Hurricanes and Gasoline Price Gouging

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Abstract:

Conventional wisdom suggests that gasoline price gouging before and after natural disasters is widespread. To explore this conjecture, we compile data on more than 4.7 million daily station-level retail gasoline prices. We combine these data with wholesale rack prices, hurricane threat and landfall information, and time-varying factors such as weather, traffic, and power outages. We investigate the effect of hurricane landfalls on retail prices, wholesale prices, retailer margins, fuel price pass-through, and share of stations reporting transactions. We exploit the fact that the exact timing and location of hurricane landfalls is conditionally exogenous for identification. We find no evidence consistent with price gouging. Instead, we document suggestive evidence of shortages predicted by simple economic theory in the presence of restrictions on price movements.

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1. Introduction

Price increases on essential goods before, during, and after emergencies lead to public outrage. Philosophers argue that "price gouging" is morally wrong. Arguments emphasize a basic failure of respect for persons and simple injustice (Sandel 2009; Snyder 2009a, 2009b). Governors and Attorneys General of hurricane-prone states publicly accuse businesses and individuals of 'unconscionable' price increases around disasters (Rapp 2005). After Hurricane Katrina, President George W. Bush likened gas station operators to looters (Ball 2011).

In contrast, economists and some legal scholars argue that price increases around natural disasters can be welfare enhancing. Although gouging attributable to excess market power may reduce efficiency, price increases may also reflect real shocks to supply and demand, allocate resources efficiently in times of scarcity, prevent overbuying and hoarding, and incentivize producers and retailers to proactively prepare (Deck and Wilson 2004; Zwolinski 2008, 2009). Alternatives like price controls may lead to severe shortages, unproductive allocations, and even physical altercations (Hayek 1968; Olmstead and Rhode 1985; Zwolinski 2008). Nobel Laureate Milton Friedman memorably remarked, "gougers deserve a medal" (Stossel 2018).

Despite widespread attention and controversy, we lack systematic evidence on price rises during and after disasters. Is price gouging common in practice? If so, when, where, and how does it occur? This paper provides early evidence. To do so, we compile more than 4.8 million daily station-level gasoline prices from roughly 11,600 retail stations operating in Florida and Louisiana during the 2004 to 2008 hurricane seasons. We merge in bulk upstream prices, wholesale rack prices, and hurricane threat and landfall data. We add detailed station-level characteristics, weather data, hourly traffic data, and power outage information. We focus on gas prices because consumers, the popular press, and the small existing literature presume that gouging is especially rampant for gasoline (Deck and Wilson 2004; Rapp 2005). We focus on Florida and Louisiana between 2004 and 2008 because of storm activity. This period includes several of the costliest hurricanes in US history, including Charley, Frances, Ivan, Jeanne, Dennis, Katrina, and Wilma (Blake and Gibney 2011).

The simplest and most transparent way to establish causality is to combine rich micro data with conditionally exogenous treatments. Here, our extensive station-level data facilitate easily interpretable difference-in-difference and event study research designs. We exploit the fact that the exact timing and location of hurricane strikes is plausibly exogenous. We address possible omitted variable concerns, as well as the possibility that impacted populations may be non-representative due to Tiebout sorting or other social dynamics, with station-by-day controls and fixed effects. We ensure results are not sensitive to violations of the stable unit treatment value assumption and other assumptions, and we confirm robustness across empirical choices. We investigate heterogeneity in treatment effects across branded vs. unbranded stations, measures of competition, and proximity to major highways.

We find no evidence consistent with price gouging. We fail to reject the null hypothesis of no effect of hurricanes on wholesale and retail gasoline prices before and during hurricane landfalls. We find statistically significant 7 to 11 cent increases in wholesale and retail gasoline prices 4 to 14 days after nearby hurricane landfalls.[2] However, once we control for input price changes, these post-landfall price

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[2] Single storm analyses suggest the effects are larger after Hurricanes Katrina, Rita, and Ike.

effects become small and negative. Point estimates from preferred specifications show that retail price margins declined on average by a statistically significant 3 cents after hurricanes made nearby landfall.

In contrast to small effects on margins, we find large impacts on price reporting, a proxy for fuel availability. We observe a more than 35% average reduction in the share of stations reporting gas prices after nearby hurricane landfalls. The reduction in the share of stations persists for roughly 8 days. Even after controlling for changes in local traffic (a proxy for demand shocks) and local power outages and disaster declarations (a proxy for operational shocks), we find a more than 20 percent decline in the share of retail stations reporting.

One interpretation of our collective results is that gas stations feel obliged to not raise prices above costs during and immediately after disasters to avoid public scrutiny. Conditional on remaining open, gasoline stations' pricing behavior follows business as usual or amounts to small temporary losses. Heterogeneity explorations suggest that some retailers fare better than others. Retailers most negatively affected by reduced margins after hurricanes are independent, have fewer nearby competitors, and are located near highways. These stations may face the greatest challenges publicly defending the need to raise prices. In short, while conventional wisdom suggests that gasoline price gouging is rampant, we provide evidence to the contrary. We instead document suggestive evidence of the shortages predicted by simple economic theory in the presence of restrictions on price movements.

We make three contributions. First, we provide systematic evidence on the extent and nature of gasoline price gouging around disasters. Reports of gasoline price gouging are widespread (Maxouris and Silverman 2018; Puleo 2019). Due to data limitations, however, the most complete existing evidence involves hand-collected data from a single city after a single hurricane (Neilson 2009).[3] Second, we explore the causes and consequences of price shocks in gasoline markets. A growing literature uses exogenous shocks to illuminate the industrial organization of fuel markets (Borenstein et al. 1997; Hastings 2004; Blair and Rezek 2008; Lewis 2009; Taylor et al. 2010; Fink et al. 2010; Anderson and Elzinga 2014). Related studies explore determinants of gasoline prices and retail margins (Myers et al. 2011, Barrage et al. 2020). We build off these studies to examine a new context: price gouging. Third, we contribute to the literature investigating the effects of hurricanes on economic market outcomes (Vigdor 2008; Groen and Polivka 2008; De Silva et al. 2010; Michel-Kerjan and Kousky 2010; National Academies 2012; Pindyck and Wang 2013; Gallagher 2014; Deryugina 2017; Gallagher and Hartley 2017; Deryugina et al. 2018; Beatty et al. 2019; Deryugina and Molitor 2019).

2. Background

Price Gouging. Legal definitions of price gouging are imprecise and vary across states. Most definitions at least indirectly presume opportunism on the part of the seller (Rapp 2005). Price gouging laws target price increases on possibly essential goods during emergencies. Florida law compares prices to average prices charged over the 30-day period prior to the disaster, and a "gross disparity" constitutes price gouging. Louisiana law requires prices not to exceed those "ordinarily charged" in the same market area at or immediately before the emergency declaration. Florida and Louisiana laws, however, go on to note that retail price increases attributable to changes in input prices or general market trends are not considered price gouging.

[3] Beatty et al. (2019) noted no statistically significant changes in the prices of batteries, flashlights, and bottled water before, during, or after hurricanes.

Gouging laws take effect following formal gubernatorial emergency declarations and last up to 30 days after declarations expire. Although statutes apply to many essential emergency commodities, gasoline is a common focus. Florida law provides for civil penalties capped at $1,000 per transaction and $25,000 per day for multiple violations by the same seller. Louisiana law permits civil penalties and criminal sanctions capped at $500 or 6 months imprisonment for violations committed willfully; $5,000 or 5 years imprisonment for violations leading to serious injury or property damage; and 21 years of hard labor imprisonment for violations associated with one or more deaths.

Citizen concerns about gasoline price gouging around hurricanes are common. Google Trends data suggest that internet searches with keywords like “gasoline prices” and “gas gouging” spike dramatically during landfall weeks and in the weeks immediately following landfall (Appendix A). Consumers concerned about price gouging around disasters are encouraged publicly to report suspicions to local law enforcement, district attorney offices, or state Attorneys General. Reports may be submitted by web hotline, phone, or in person. Media reports indicate that Attorneys General and Consumer Protection agencies receive and investigate hundreds to thousands of complaints of unconscionable gasoline price increases per day during major hurricane emergencies (Maxouris and Silverman 2018; Puleo 2019). Many of these complaints are ultimately proven unfounded, and only a very small fraction result in penalties or reimbursements (Puleo 2019).

Gasoline Marketing and Supply. Gasoline is marketed and traded at spot, rack, and retail levels. The upstream spot market for Louisiana and Florida is the Gulf Coast refining hub located near the Texas-Louisiana border. Here, large volume (‘bulk’) transactions are traded at prices influenced by New York Mercantile Exchange trading and regional supply shocks (Berhang 2017). From the spot / bulk market, refined gasoline travels by pipeline or ship to wholesale fuel terminals called racks. Louisiana racks are typically served by pipelines and most Florida racks are served by shipping routes. Rack prices, adjusted daily, are largely determined by spot pricing, transportation costs, fees, and branding requirements (Berhang 2017). Branded Gasoline is typically blended at the rack with additives including proprietary chemicals and ethanol.

Gasoline is purchased at wholesale racks by trucking companies called jobbers. Jobbers transport branded or unbranded fuel to downstream retail gasoline stations.[4] Branded retailers are contractually obligated to purchase branded gasoline from racks and jobbers, with trading prices typically pinned to the brand’s rack price or other index.[5] Unbranded retailers may purchase gasoline from any supplier at more flexible rack and jobber prices. Retail prices are ultimately determined by rack prices (including branding premiums), local transportation costs, taxes, and station-level margins.

At all points in the fuel distribution chain, prices are also influenced the type of refined product. We focus on conventional regular gasoline with an octane rating between 85 and 88. Conventional gasoline prices are also influenced by vapor pressure, a measure of volatility and thus volatile organic compound

[4] Some large retailers and independent jobbers purchase gasoline directly from bulk pipeline locations or refineries, bypassing racks. We assume the price advantage from these marketing strategies is limited through arbitrage.
[5] Branded stations can either be ‘company-owned,’ owned by the upstream refiner, or operated by leasees. Leasees typically sign long-term contracts with refiners to purchase branded fuel and pay a fee back to the refiner.

(VOC) pollution discharges. In areas with multiple vapor pressure requirements, we average across prices.[6]

3. Data

Gasoline price and station data. We obtain daily proprietary retail-level regular grade gasoline prices between June and October for each of 2004 to 2008 from the Oil Price Information Service (OPIS).[7] OPIS collects data from stations through fleet credit card swipes, relationships with credit card companies, surveys, and direct station reporting. We observe transactions from 11,603 unique stations in the raw data, including roughly 90 percent of Florida stations and 75 percent of Louisiana stations operating between 2004 and 2008. OPIS retail data are the most extensive gasoline price data available, and sample stations are representative of all owner or operator types (Lewis 2012). Appendix B provides maps of stations by state.

For each station-day, we merge in daily wholesale gasoline prices using proprietary rack prices also obtained from OPIS. Non-branded stations are matched to average regular grade wholesale price at the nearest fuel rack terminal. Branded stations are matched to the average branded fuel price at the nearest fuel rack terminal. Appendix B provides further matching details. We also merge in daily refinery-level Gulf Coast spot / bulk prices from the Energy Information Association.

We collect several time invariant station-level characteristics. OPIS data provide station address, brand, and station name.[8] We use brand information to construct indicators for whether a station is affiliated with a vertically integrated oil company ('branded') or a major independent retailer (`major retailer'). The former typically have arrangements with their parent companies to purchase branded wholesale fuel and both types of stations have more sophisticated marketing arrangements compared to independent stations (Hastings, 2004; Lade and Bushnell, 2019). We enter address information into a Google Maps application programming interface to construct latitude and longitude. Given latitude and longitude, we create measures of competition including the number of stations within 1, 5, and 10 km of the retailer as well as distance to the nearest competing retailer. We also combine latitude and longitude data with US Census Bureau road data to construct distance to the nearest major highway. Finally, we construct an indicator for whether a station lies within one of NOAA's coastal hurricane forecast ('watch' or 'warning') zones.

For each station-day, we construct measures of local weather, traffic, and power outages. We collect weather data from the Global Historical Climatology Network. We assign weather measures to each location based on observations at the nearest weather station with complete data. We obtain traffic volume data from the Florida and Louisiana Departments of Transportation. We assign traffic measures to each location based on observations at the nearest of 381 permanent (geographically fixed) traffic monitors. We hand construct power outage data at the county-by-day level from Department of Energy, National Energy Technology Lab Emergency Situation Report outage maps. Outages are measured as the

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[6] Results are not sensitive to using Reid Vapor Pressure (RVP) 7.8 prices during summer months and RVP 9.0 prices during fall months.

[7] June through October are the hurricane intensive months in FL and LA. No hurricanes formally threatened or struck FL or LA in November of our sample years. Absent treatments outside of June - October, we saved data acquisition costs by restricting the sample period.

[8] Our sample includes thirteen branded companies: Shell, Citgo, Chevron, BP, ExxonMobil, Sunoco, Hess, Texaco, Marathon, Murphy, Valero, Conoco, and Gulf. Major retailers include 7-11, Circle K, etc.

share of county residents without power on a given day. Results are robust to other assignment mechanisms for weather, traffic, and outage data. Lastly, we collect disaster declaration data at the county-by-day level from the Federal Emergency Management Agency (FEMA).

Hurricane data. We define hurricane "treatments" based on nearby landfalls. We collect latitude, longitude, time, date, and intensity of landfall from NOAA's National Hurricane Center Atlantic Basin Best Tracks HURDAT2 database. We define landfalls following National Weather Service conventions as the intersection of the surface center of a hurricane with coastal land. Although hurricanes may make multiple landfalls, for simplicity we define treatments based on first landfall.[9] Appendix B summarizes hurricanes making landfall in Florida and Louisiana during the 2004 to 2008 hurricane seasons. Fifteen hurricanes made landfall within 100 miles of at least one of our retail stations during the sample period, including seven of the costliest hurricanes in US history (Charley, Frances, Ivan, Jeanne, Dennis, Katrina, and Wilma, as per Blake and Gibney 2011).

Final sample. We combine prices, time invariant station characteristics, and daily weather / traffic / outage / disaster declaration data with hurricane treatments constructed at the station-by-day level. Many station-days have missing retail price data. We follow the literature and limit our primary analysis to stations with the most consistent reporting outside of treatment periods (Barrage et al. 2019, Lade and Bushnell 2019). Our preferred sample includes data from all stations with retail price data from over 75 percent of possible sample days not immediately preceding or following a nearby hurricane landfall. Our final analysis sample includes roughly 3.19 million retail prices observed over 765 possible days at 4,673 retail stations. Remaining missing data are left missing. Results are not sensitive to sample restriction choices including using a sample without station selection. Appendix B provides further detail.

Table 1: Summary Statistics (2004-2008)

	Mean	Std. Deviation	N	N (Stations)
Prices				
Retail Price ($/gal)	2.76	0.64	3,196,641	4,673
Branded Major	2.78	0.64	1,203,949	1,777
Major Retailer	2.74	0.63	1,324,135	1,889
Coastal	2.76	0.64	1,266,735	1,863
Inland	2.75	0.64	1,929,906	2,810
Wholesale Price ($/gal)	2.07	0.62	3,574,845	18
Bulk Price ($/gal)	1.98	0.64	3,574,845	--
Station Characteristics				
Distance to Highway (km)	0.42	1.01	3,574,845	4,673
Distance to Competitor (km)	0.78	1.49	3,574,845	4,673
Competitors within 5km	2.19	1.92	3,574,845	4,673

Table 1 presents summary statistics for the analysis sample of 4,673 stations. Average retail gasoline prices were $2.76 but ranged widely over years (Appendix C). Retail prices exhibited heterogeneity by

[9] Results are not sensitive to this choice. Some specifications also control for official National Weather Service hurricane watches and warnings.

type of station, with branded stations charging roughly 4 cents/gallon higher prices than major retailers. Coastal and inland stations had very similar prices. Retail margins - defined as retail prices less wholesale prices and reflecting taxes, transportation costs from racks to stations, and retail markups - averaged just under $0.70/gallon.[10] Stations, on average, were close to highways (0.4 kilometers), but the distribution was highly skewed with the median station under 0.05 kilometers from the nearest highway. We also observe substantial heterogeneity in local market concentration. The average station had two competitors within 5 kilometers but over 10% of the sample had no competitors within 5 kilometers. Some stations had as many as eight competitors within 5 kilometers.[11]

4. Empirical Strategy

In this section, we lay out our generalized difference-in-difference and event study research designs. In principle, both approaches establish causal inference by exploiting the fact that the exact timing and location of hurricane landfalls is plausibly exogenous. Difference-in-difference (DID) approaches compare changes in outcomes around landfall date for treatment stations near a given landfall relative to control stations not near that landfall. An advantage of the familiar DID method is transparent interpretation of results. The disadvantage is strong assumptions, including the stable unit treatment value assumption (SUTVA), which may be violated due to spillovers or other effects of hurricanes on control stations. Event study designs are an alternative that require fewer assumptions. Our event studies explore if and how outcomes at treatment stations depart from counterfactual outcomes for the same station and time had there been no hurricane impacts on that day. The maintained hypothesis in the event studies is "no incremental change in outcomes attributable to hurricanes."

Our initial outcomes of interest are retail prices, wholesale rack prices, and retailer margins (i.e. differences between retail and wholesale prices). We explore wholesale cost pass-through to retail prices in some detail. We then investigate the effects of hurricanes on the share of retail gas stations reporting sales on a given day. One notable feature of our data is that price data is disproportionately missing during and after hurricane landfalls. We explore whether reporting behavior can be explained by demand shocks, as proxied by local traffic volume on that day and/or operational shocks, as proxied by local power outages and local FEMA disaster declarations. For all outcomes, we consider the possibility of heterogeneous treatment effects by branding, local competition, and distance to the highway.

Prices and Margins. We begin with a difference-in-differences analysis of retail prices, wholesale prices, and retailer margins. We focus on the two weeks before and after each hurricane first made landfall.[12] To ease interpretation, we aggregate days into three periods: fourteen days to four days before landfall (Before), three days before to three days after landfall (Landfall), and four days after to fourteen days after landfall (After). Results are not sensitive to these specific aggregations. We estimate:

$$Y_{ist} = \beta_1 1[Before]_{ist} + \beta_2 1[Landfall]_{ist} + \beta_3 1[After]_{ist} + \alpha_{i(s)} + \delta_m + \pi_y + \varphi_w + X'_{ist}\Gamma + \epsilon_{ist} \quad (1)$$

[10] The federal gas tax is 18.4 cents/gal, Louisiana's gas tax is 20 cents/gal, and Florida's gas tax is 41.4 cents/gal. OPIS estimates transportation costs are typically 1.5 cents/gal.

[11] Appendix C and Figures C.1 and C.2 present additional summary statistics. The simple plot of prices against time in Figure C.1 supports our more formal assertions that follow. We see strong evidence that bulk and wholesale prices respond more sharply and more quickly to hurricanes than retail prices.

[12] We standardize landfall data to the first day a hurricane made landfall in either state. The one exception is Hurricane Katrina that made landfall in Florida on August 25, 2005 and in Louisiana on August 29, 2005.

where Y_{ist} is the retail or wholesale price at station i located in state s on day t. *Before*, *Landfall*, and *After* are indicator variables equal to one if station *i* is within 100 miles of a landfall during the relevant time period.

To control for seasonality and trends within and across years, we include fixed effects for year (π_y), month-of-year (δ_m), and day-of-week (φ_w). Parsimonious specifications include state fixed effects (α_s) to account for different tax rates and other time invariant factors varying across states. Our preferred specifications include station-level fixed effects (α_i) to account for station-specific cost factors and other time invariant station characteristics.[13] X'_{ist} represents a vector of controls including indicators for whether a station was under a tropical storm or a hurricane warning or watch on day and quadratic temperature controls. Standard errors for retail price regressions are clustered at the county-level and wholesale price regression standard errors are clustered at the rack-level.

In specifications with retail prices as the dependent variable, we estimate (1) with and without controls for upstream (wholesale or bulk) fuel prices. Regressions without upstream price controls provide evidence of retail price impacts, but do not distinguish between price changes attributable to changes in stations' costs and those attributable to changes in stations' margins above costs. Unconditional retail price estimates capture the average price impacts of hurricanes as seen by consumers. By contrast, regressions with upstream price controls provide evidence on retail price impacts net of changes in input prices. In other words, regressions with upstream price controls explore margins and inform the question of whether retailers engage in behavior consistent with legal definitions of price gouging.[14]

The difference-in-difference approach in equation (1) is familiar and readily interpreted in levels. A natural concern is that hurricanes have impacts on prices beyond 100 miles of landfall. Given potential regional or national impact of hurricanes on fuel markets, finding a valid control group is challenging. Other potential violations of difference-in-difference assumptions are also possible.

We therefore consider an event study research design. We limit the sample to stations within 100 miles of a landfall point and focus only on the fourteen days before and after landfall. We estimate the model:

$$y_{ist} = \sum_{j=-\tau}^{\tau} \beta_j 1\,[t=j] \; + \; \alpha_i + \delta_m + \pi_y + \varphi_w + X'_{ist}\Gamma + \epsilon_{ist} \quad . \qquad (2)$$

Regressions of the form of (2) include the same controls as our preferred difference-in-difference specifications in equation (1). We allow for differential treatment effects by event-day, β_j. One difference from the standard event study setting is that some storms in our sample arrived in quick succession, so stations may fall into two event windows at a single time. As a hypothetical example, the same station might be observed both 10 days after one storm and 12 days before another. As a result, unlike classic event studies, the indicators $1\,[t=\tau]$ are not perfectly collinear. Since the level is unidentified in equation (2), we normalize the coefficients to be relative to β_{-14}, the coefficient on

[13] Station margins may include costs that are common to all stations (e.g., federal and state taxes), region-specific costs (e.g., average trucking costs from wholesale racks), and station-specific costs and markups over wholesale costs (which may account for factors such as local monopoly power).

[14] So long as wholesale and retail prices are cointegrated, including contemporaneous wholesale prices sufficiently controls for the long-run relationship between wholesale and retail prices. Results are robust to allowing for lagged retail price adjustment to wholesale costs by including lagged wholesale prices.

$1[t = -14]$.[15] This normalization should be innocuous since, after controlling for station-level fixed effects, we find no impact of hurricanes two weeks before landfall in our difference-in-differences model.

We study heterogeneous price and margin impacts by interacting event-day indicators in equation (2) with station and location characteristics. As noted, we test for differential impacts across branded, major retail, and unbranded (or independent) stations. We test whether stations with limited local competition experience differential impacts than stations with nearby competitor stations. Finally, we test whether stations near highways experience different impacts than those far from highways.

We also test for differential cost pass-through between hurricane periods and untreated periods. The literature studying gasoline markets notes a delayed response of retail fuel prices to changes in upstream fuel costs (Borenstein et al. 1997; Lewis and Noel 2011; Lewis 2011). Pass-through patterns may differ during hurricanes if fuel supply chains are interrupted or stations are hesitant to pass-through increased wholesale costs in the aftermath of a storm. Formally, we follow the standard approach in the literature (e.g. Borenstein, Cameron, and Gilbert 1997) and estimate pass-through on sub-samples of our data as follows:

$$y_{it} = \alpha_i + \sum_{j=0}^{L-1} \beta_j \Delta w_{it-j} + \beta_L w_{it-L} + \delta_m + \pi_y + \varphi_w + X'_{it}\Gamma + \epsilon_{it} \qquad (3)$$

Equation (3) is a cumulative dynamic multiplier (CDM) model that estimates the average retail price response in our sample to changes in wholesale fuel costs (w_{it}). Coefficients β_j represent cumulative pass-through rates of wholesale fuel costs to retail prices after *j* days. Based on data exploration and consistent with previous work, we set *L=30* to allow prices to exhibit lagged adjustment to wholesale cost shocks within a month.

Price Reporting. We also use the methods summarized by (1) and (2) above to explore whether stations remain open before, during, and after nearby hurricane landfalls. Because OPIS tracks gasoline prices through reporting arrangements with stations, we cannot fully distinguish between missing price data due to a station closure / stockout versus missing data due to no station-report or credit card swipe.

We first replicate our event study design to establish estimates of the station reporting in baseline and during hurricane periods. These event studies include station, day of week, month of year, and year fixed effects. We estimate the same specifications on a control group of inland stations as a placebo exercise. We then re-estimate event study regressions including proxies for demand (traffic serves as a proxy for the likelihood of observing a swipe) and supply shocks (power outages - pumps require electricity to operate). Comparing differences in coefficients offers insight into how much of missing price information is unrelated to proxies for supply and demand. Finally, we explore heterogeneity.

5. Hurricanes and Retail Prices, Retail Margins, and Fuel Price Pass-Through

Table 2 summarizes results from difference-in-differences analyses of the form of (1). Panel A presents results for retail and wholesale prices without conditioning on upstream prices. Panel B presents results

[15] Results are similar when we drop all stations that fall in more than one event windows concurrently and estimate a traditional event-study regression relative to the landfall day.

from regressions that include upstream price controls, providing evidence of hurricane impacts on fuel price margins.

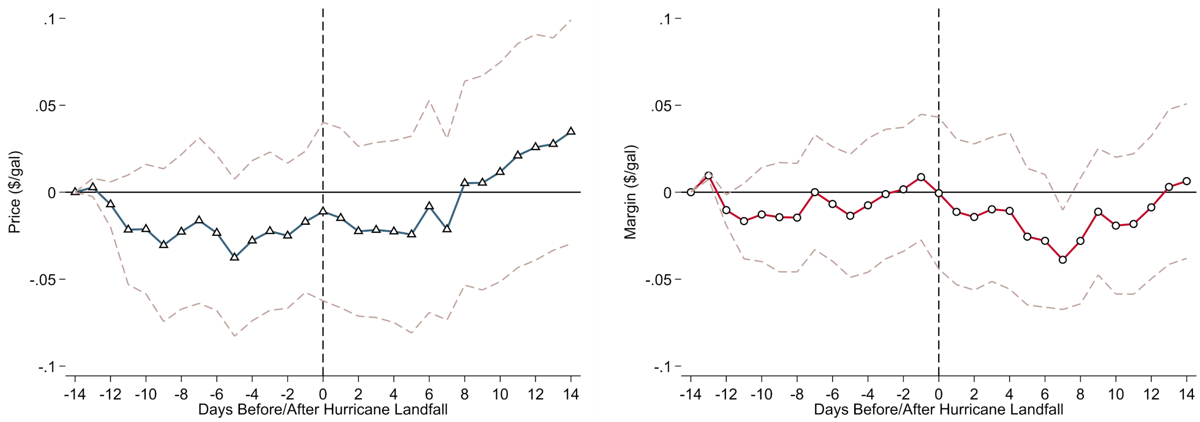
Table 2: Average Effect of Hurricanes on Retail and Wholesale Prices and Margins

	(1)	(2)	(3)	(4)
Dep. Var	Retail	Retail	Wholesale	Wholesale
Panel A: No upstream price controls				
Pre-Hurricane	0.042	0.022	0.017	0.020
	(0.036)	(0.035)	(0.038)	(0.040)
Hurricane	0.050	0.028	0.035	0.038
	(0.033)	(0.032)	(0.027)	(0.030)
Post-Hurricane	0.089**	0.069	0.114*	0.116
	(0.045)	(0.043)	(0.065)	(0.067)
Observations	3,196,641	3,196,641	3,574,845	3,574,845
Stations/Racks	4,673	4,673	18	18
Panel B: Upstream price controls				
Pre-Hurricane	0.022	-0.001	0.028	0.025
	(0.016)	(0.014)	(0.016)	(0.016)
Hurricane	0.033	0.007	0.009	0.007
	(0.021)	(0.019)	(0.018)	(0.017)
Post-Hurricane	-0.006	-0.028**	-0.033	-0.036
	(0.014)	(0.011)	(0.026)	(0.025)
Wholesale Price	0.785***	0.786***		
	(0.006)	(0.006)		
Bulk Price			0.719***	0.719***
			(0.005)	(0.004)
Observations	3,196,641	3,196,641	3,574,845	3,574,845
Stations/Racks	4,673	4,673	18	18
State FE	Yes	No	Yes	No
Station/Rack FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Month-of-Year FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is station-level retail/wholesale price. "Hurricane" is an indicator for whether a station is within 100 miles of a hurricane landfall in the three days before, during, or three days after landfall. "Pre-Hurricane" and "Post-Hurricane" are similar indicator variables for stations in landfall areas ten to four days before and after landfall, respectively. All regressions include controls for whether a station is under a storm/hurricane watch or warning and quadratic temperature controls. Standard errors are clustered at the county for retail regressions and wholesale rack for wholesale regressions. *, **, and *** denote significance at the 10%, 5% and 1% level.

In Table 2 Panel A, we document modest evidence that unconditional wholesale and retail prices increase before, during, and after hurricanes. Increases in prices before and during landfall are small and not statistically significant. We find statistically significant 7 to 11 cent increases in wholesale and retail gasoline prices 4 to 14 days after nearby hurricane landfalls. These increases on observable prices are statistically significant in regressions with state-level fixed effects and not statistically significant in regressions with station-level fixed effects.

In Table 2 Panel B, we provide evidence that any post-landfall price increases become small and negative once we control for changes in upstream prices. In our preferred specification in column (2) of Panel B, we document that retail price margins declined on average. In specifications with station-level fixed effects, margins fell by a statistically significant 3 cents after hurricanes made nearby landfall. Results for other specifications are similar, but less precisely estimated.



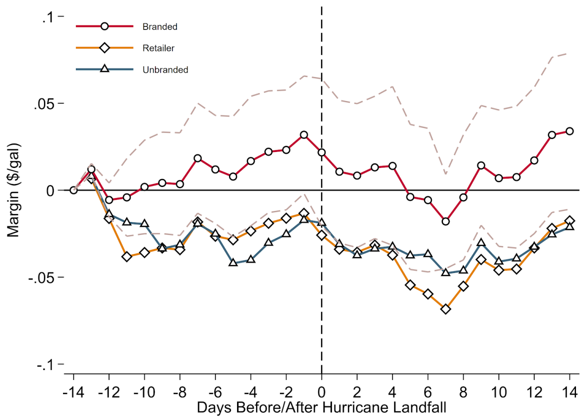
1(a): Price Impacts *1(b): Margin Impacts*

Figure 1 – Retail Price and Margin Event Studies

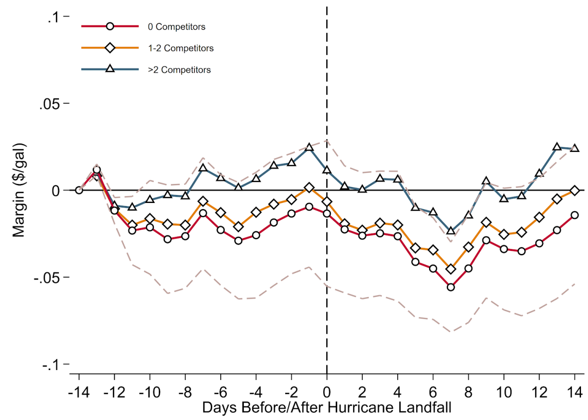
Figure 1 summarizes results from event study regressions of the form of (2). Figure 1a provides event study results for observed retail prices and Figure 1b provides event study results for retailer margins. Figure 1a suggests that retail prices remain statistically similar before, during, and after nearby hurricane landfalls. Figure 1b suggests that retailer margins remain statistically unchanged before and during hurricane landfalls but fall by 2 to 4 cents per gallon in the roughly 4 to 10 days after a landfall. Margins appear to recover within 14 days after landfall. Declining retailer margins after landfall are consistent with difference-in-difference results and with wholesale price increases that are not fully passed through to retail prices. Appendix C and Figures C.4 - C.7 document that key results are robust to different sample choices, event window construction, and models with distributed lags on wholesale prices.

Figure 2 explores heterogeneity in event study results with retailer margins as the outcome. Although we plot all coefficient estimates, we present standard errors (dashed lines) for the baseline category only (i.e. the first category in the legend). Results in Figure 2 show that all stations experience declines in margins after hurricane landfall. Point estimates in Figures 2a, 2b, and 2c suggest post-landfall declines in margins are greater among major retailer and independent/unbranded stations, stations with fewer nearby competitors, and stations located away from major highways. Corresponding difference-in-differences results suggest similar patterns for the branded vs. retailer / unbranded station comparisons and for the nearby competitor vs. few nearby competitor comparisons (Figure C.3).

We next consider the extent to which retail stations may experience losses after hurricanes by formally comparing wholesale price pass-through (to retail prices) for treated stations and periods to wholesale price pass-through to non-treated stations and periods. We compare estimates from the cumulative dynamic multiplier model in equation (3) for treated stations reporting transactions before, during, and after hurricane landfalls to estimates from the cumulative dynamic multiplier model in equation (3) for all stations in our sample over all periods. To do so, the analysis for treatment stations and periods extend the event window to 30 days before and after landfall.



2(a)



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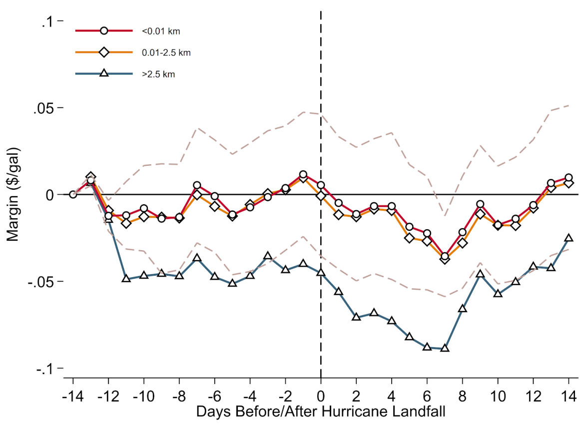


2(c)

Figure 2: Treatment Effect Heterogeneity

Figure 3 presents pass-through results. Each point estimate represents the cumulative pass-through of a $1.00/gallon increase in wholesale fuel costs after the corresponding number of days. The cost shock occurs on day 0. Blue diamonds denote pass-through rates for all stations in all periods and red triangles denote pass-through rates at stations in landfall areas in the 30 days before and after landfall. We document faster cost pass-through after a cost shock at treated stations during treatment periods, relative to baseline pass-through for the full sample. In the treatment sample and the full baseline sample, full pass-through takes 25 to 30 days. [16]

[16] There are a few interpretations of lagged retail price adjustment in the literature. First, are sticky prices due to, for example, menu costs (Barro 1972; Mankiw, 1985). This is unlikely in fuel markets given the observed frequency of price changes. Others include slow inventory adjustment, market power, imperfect information, and consumer

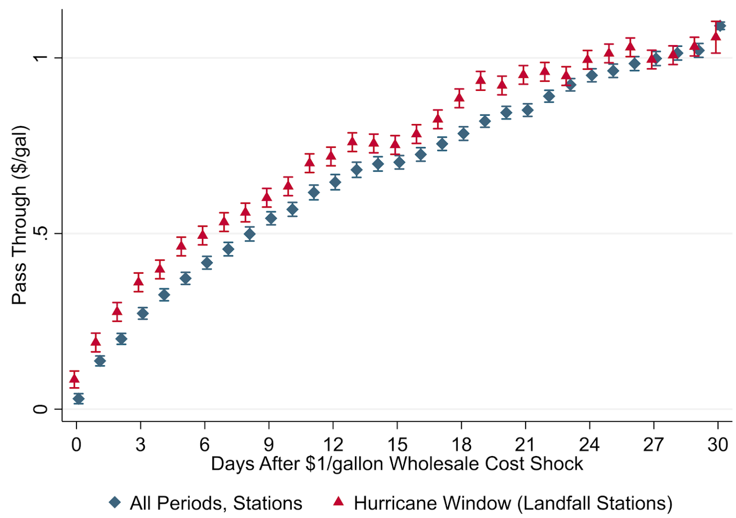


Figure 3: Wholesale Cost Pass-Through to Retail Prices

Interpreting the faster pass-through during treatment periods requires some care. Although wholesale price shocks are passed through somewhat faster in the two weeks after hurricane landfall than in other periods, it is still the case that the economically meaningful wholesale price shocks starting 4 days after landfall take several weeks to fully pass-through to retail prices. As such, retailer margins in the 4-14 days after landfall are smaller than steady state margins and retailers that continue to sell fuel are worse off (in terms of margins) during post-landfall periods than in other periods. Over the longer-run, roughly one month, all wholesale price shocks (from hurricanes or anything else) are passed on to consumers.

Collectively, we find no evidence that stations change retail prices in ways that are consistent with price gouging. Retail prices observed by consumers rise a small amount, or not at all, on average. Moreover, retail prices do not rise more than wholesale input prices. Although wholesale price shocks induced by hurricanes are eventually passed through fully to consumers, this pass-through occurs with a delay. Our best evidence suggests that margins at treated retail stations decline in the two weeks following hurricanes. Heterogeneity suggests some stations' margins decline more than others.

6. Hurricane Impacts on Station Reporting and Closures

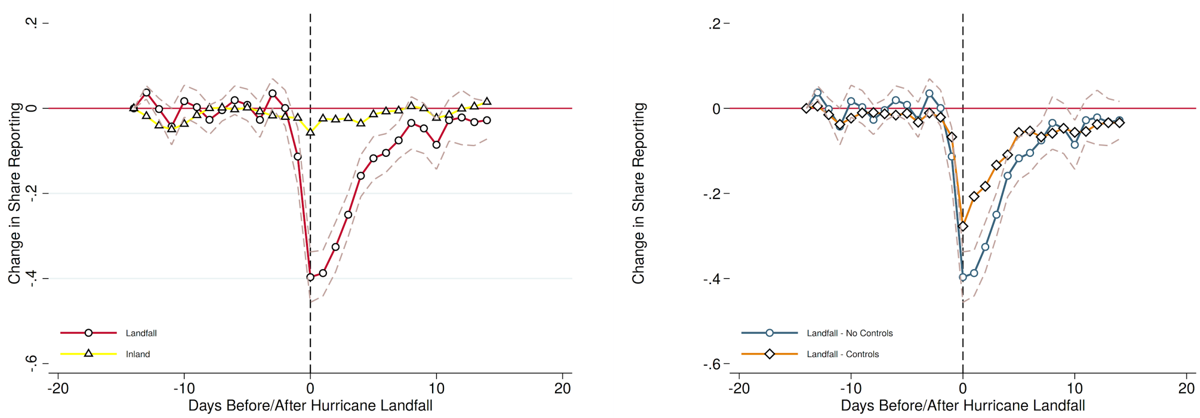
Stations are missing in our data when OPIS does not collect price information on a station-day.[17] This happens when either no fleet card is swiped or the station doesn't report a price. Missing station data can be attributed to many factors, particularly around hurricanes. On the demand side, a fleet driver may not stop at a station due to low demand; fleets may not operate on certain days or during emergencies. Alternatively, a station may be closed, i.e., no prices are reported due to supply issues.

search costs (Deltas 2008; Lewis 2011; Lewis and Noel, 2011). Consider the slow inventory adjustment interpretation. Fuel stations store fuel on site and purchase fuel from jobbers or racks infrequently. In this light, a 50% pass-through rate after two weeks could represent 50% of stations turning over tanks.

[17] By construction, stations included in our sample report price information at least 75% of the time during non-landfall periods. Details of sample construction are outlined in Appendix A.

Stations may be closed for several reasons, including stock outs, damage, safety concerns, and strategic closure due to inability to charge scarcity rents or pass through wholesale fuel costs.

We first test whether missingness is correlated with landfall. To this end, we replicate our event study for hurricane landfalls described above. We estimate a linear probability model where the outcome is whether or not a store reports any price on a given day and include event-time dummies as well as station, day of week, month, and year fixed effects. We run regressions separately for the impacted stations and a placebo group, inland stations in areas not under a hurricane watch or warning. Figure 4(a) summarizes the results. We see a large statistically significant drop in the share of stations reporting prices in impacted areas in the days following landfall. Reporting rates fall 40% on average on the day of landfall. Within eight days of a storm making landfall, the share of stations missing price data is not statistically different from baseline levels – though point estimates remain small and negative.



4(a)

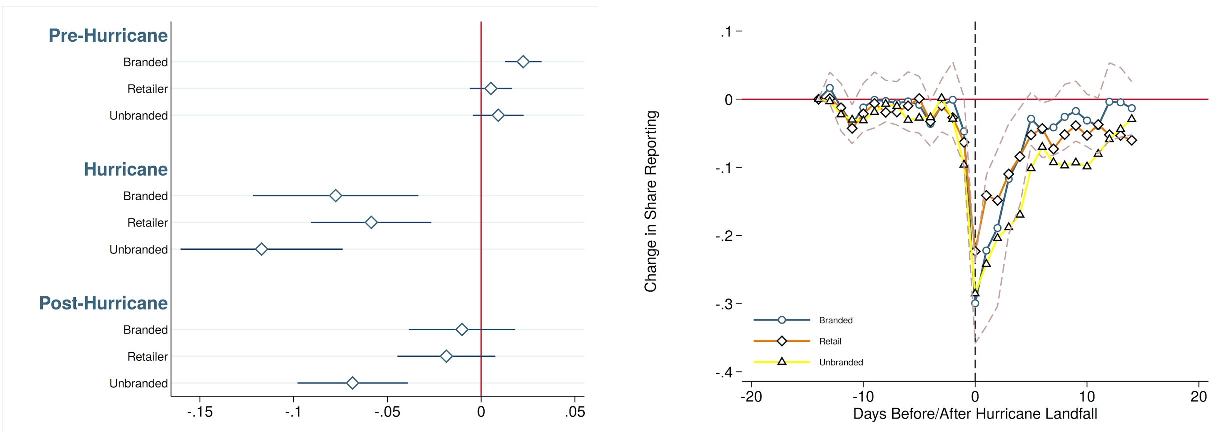
4(b)

Figure 4: Changes in Reporting Behavior

We next explore how much of the variation in missing prices can be explained by proxies for supply and demand. We attribute the residual variation in missing prices after controlling for these supply and demand conditions to the other factors discussed above such as poor management, disrupted supply chains, or strategic closures. We proxy for supply factors using county-level price outage data and FEMA disaster declarations. The average station in a landfall area is in a county that goes from having no power outages before landfall to roughly 30% of the county experiencing some disruption on the day after landfall (Figure C.9). Outages return to baseline levels within seven days of landfall. We proxy for demand conditions using nearby traffic flows. Traffic falls sharply after a hurricane makes landfall, roughly 1.5 standard deviations from baseline, but returns to normal within four days (Figure C.8).

Figure 4(b) replicates the analysis in 4(a) with traffic controls, the share of the county experiencing a power outage, and controls for whether the station is located in a FEMA disaster area. The controls explain an important and statistically significant share of the missing retail prices. In the first three days after landfall, additional controls explain roughly 50 percent of the overall decline in reporting. Even with these controls, however, there remains an economically meaningful share of missing prices unexplained.

Unbranded (independent) retailers experienced the largest decrease in margins. Given this, we also test whether unbranded stations have a larger share of unexplained missing prices. If they do, this would support the hypothesis that unexplained price reporting is due to strategic closure - stations closing because they are unable to pass-through increased wholesale costs. Recall that branded station retail prices is typically more directly pinned to a branded wholesale rack price. We replicate both the difference-in-differences and event study regressions, controlling for demand and supply shocks, for branded, retail, and unbranded stations separately. The results are summarized in Figure 5. Figure 5a plots the difference-in-differences coefficients. Unbranded stations are not significantly more likely to fail to report prices before landfall but are significantly more likely to not report prices during and after landfall. Event study results are less precise but tell a similar story.



5(a) *5(b)*

Figure 5: Changes in Reporting by Station Type

7. Discussion and Conclusion

We provide new evidence on the effect of hurricanes on downstream fuel markets. Most importantly, we establish that retailers do not increase gasoline prices above and beyond increases in wholesale rack prices before, during, or after hurricanes. Point estimates indicate that retailers that continue to sell gasoline do so at margins below steady-state margins. Moreover, we document the share of stations selling gasoline after hurricanes falls markedly - even after using local traffic, emergency declarations, and power outages to control for demand and operational shocks.

We note several caveats. First, we do not rule out the possibility that a small number of stations price gauge. Our main results document that the average station does not increase prices opportunistically around hurricane landfalls. Our heterogeneity results suggest that some stations' margins fare worse than others', but we find no evidence of unscrupulous or coercive pricing among any subgroup. Nevertheless, our econometric exercise may obscure behavior by a few outlying 'bad apples'. Second, our results are conditional on the Florida and Louisiana 2004 to 2008 hurricane season context. Florida and Louisiana are disproportionately prone to hurricane landfalls, and 2004 to 2008 rank among the most active Atlantic hurricane seasons on record. Different market structures, population characteristics, and other factors may generate different results for other states. Since the 2004 to 2008 FL and LA hurricanes were highly salient, it is possible that results do not necessarily generalize to other settings.

The above caveats notwithstanding, our results have natural implications for economics and policy. First, we find no evidence consistent with price gouging. In terms of retail pricing, hurricanes either have no effects or make stations worse off. Common beliefs that price gouging around hurricanes is widespread are unfounded. Second, we find evidence consistent with strategic stockouts. Although other explanations are possible, our results may suggest that stations choose to remain closed given an inability or unwillingness to recoup higher input prices in the short run. Around hurricane landfalls, supply shifts inward and demand shifts outward, so short-run scarcity pricing might naturally be expected to clear markets. Instead, given intense consumer and media scrutiny, stations may respond to social pressures and fear of legal action by strategically stocking out or underinvesting in the physical capital (like generators) needed to sell fuel after hurricanes. Inefficient short and long run outcomes are plausible, and a complete welfare analysis represents a promising area of future research.

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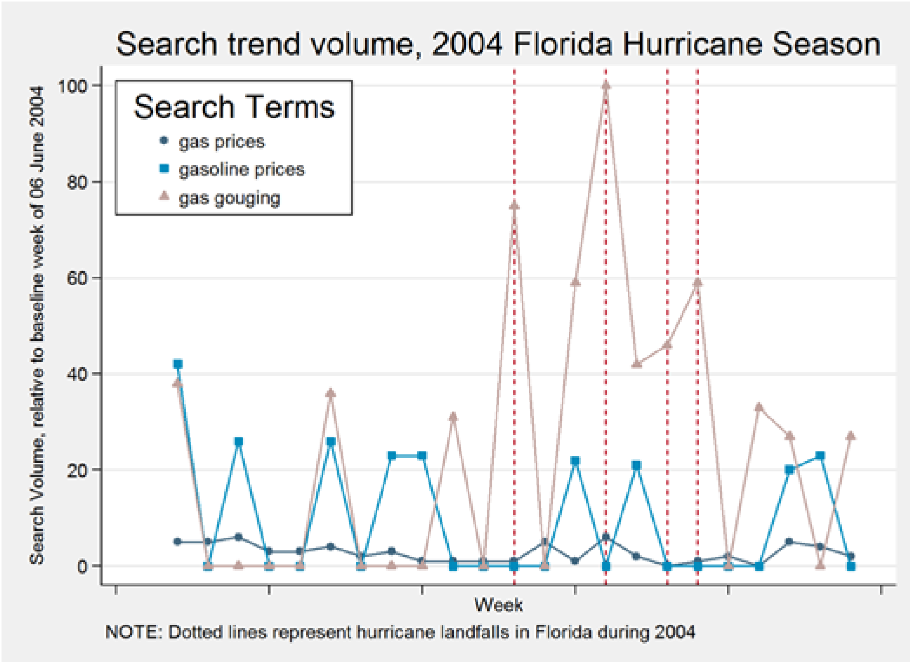
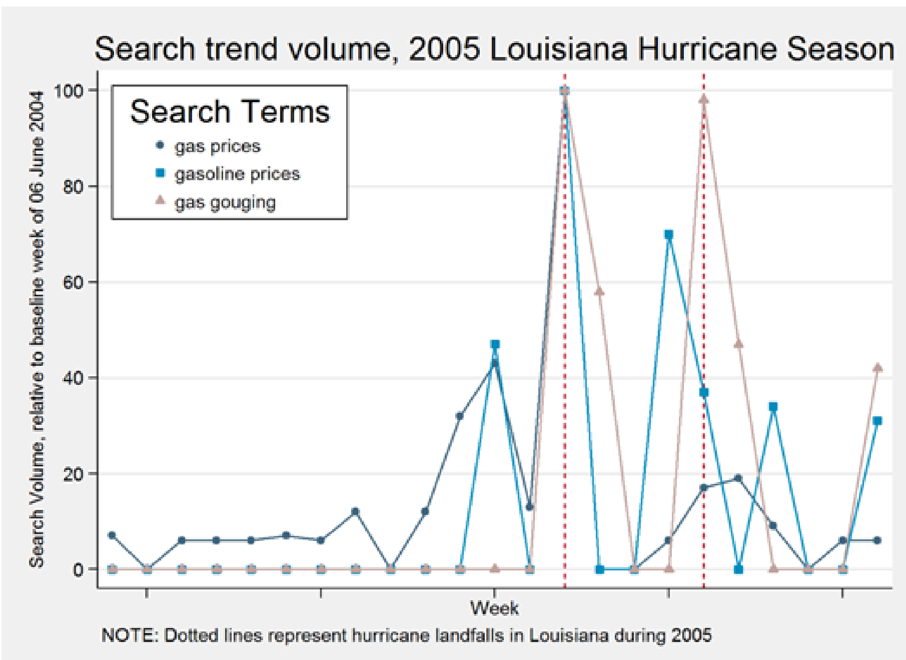
Online Appendix for
Hurricanes and Gas Price Gouging
Tim Beatty, Gabriel E. Lade, and Jay Shimshack

A Google Trends Data

Search Volume Trends: 2004 FL and 2005 LA hurricane seasons

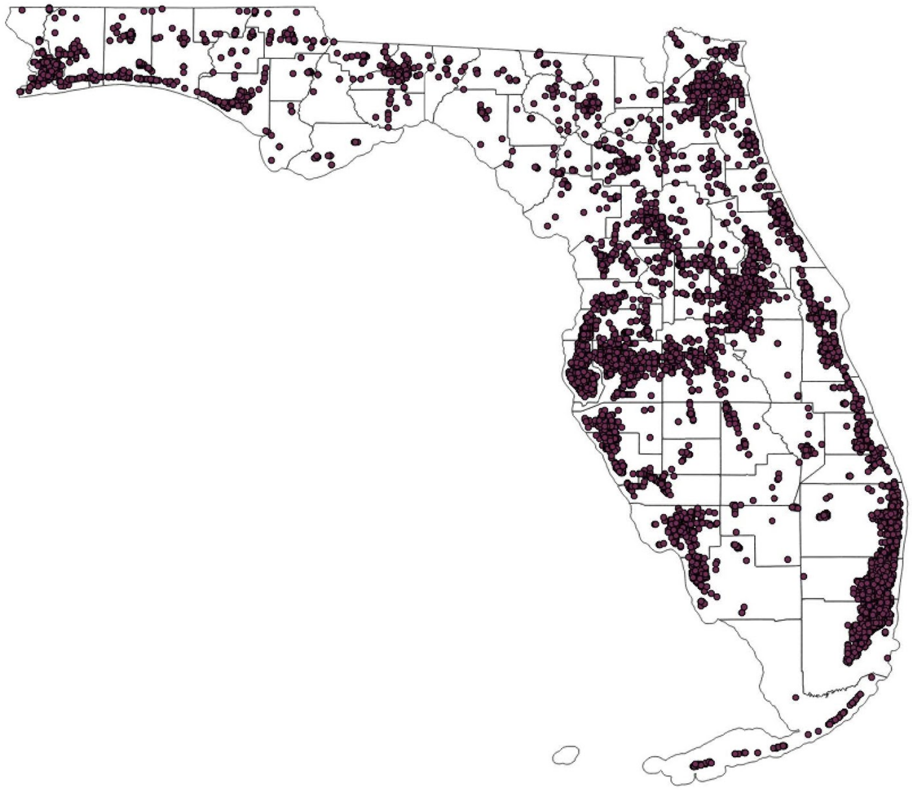


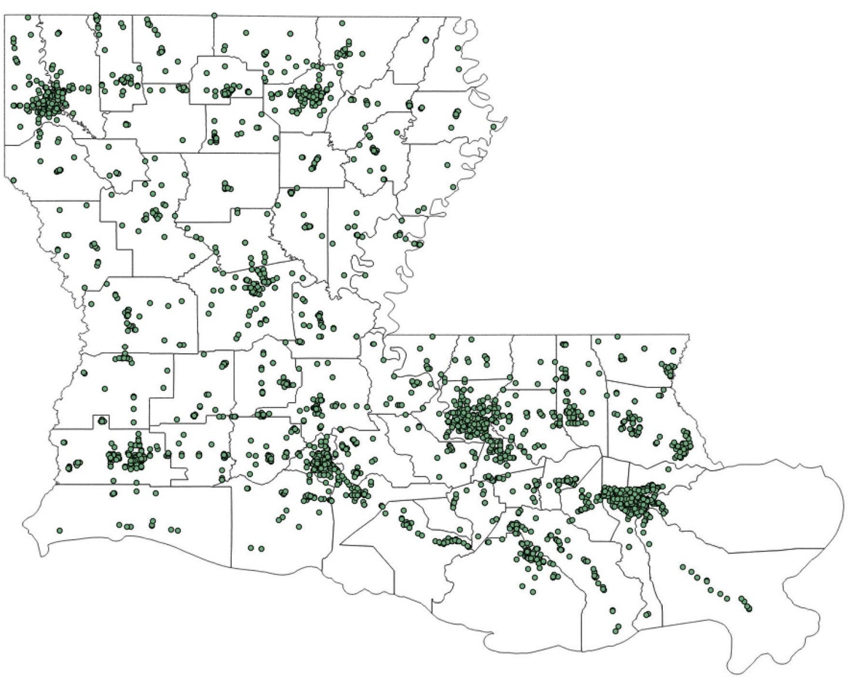


Other state and year combinations illustrate the same patterns, although less starkly.

B Supplemental Data Details

Station maps.





Wholesale terminal data. We purchased wholesale terminal (or rack) price data from OPIS for all gasoline terminals in Florida and Louisiana for hurricane-season months (June to October) for 2004 to 2008. The data include daily wholesale gasoline prices for a total of 19 racks. OPIS reports several wholesale prices for each rack. We keep the OPIS average price for each rack and all major branded gasoline prices if reported by the stations.[18]

OPIS average gasoline prices have full data coverage over our sample. Branded wholesale prices is sparse at some racks. Thus, we calculate the fraction of days with non-missing prices over the full sample and keep only rack-brand prices with greater than 75% reporting over our full sample. We replace all remaining missing branded prices with the average OPIS gasoline price at each corresponding rack.

We match stations to the nearest wholesale rack. If the nearest wholesale rack includes a branded wholesale price, we match branded stations to those prices. All other stations, and branded stations where no reliable branded price is available, are matched to the average OPIS wholesale price.

Retail Sample Restrictions. Retail price data from OPIS include 4,782,500 daily prices reported for 11,603 gasoline stations in Florida and Louisiana. Prices are reported at irregular intervals spanning hurricane-season months (June to October) for 2004 to 2008.

We filter the retail price data in the following ways to define our final sample. First, we create a balanced panel for each station, filling in all days with no reported prices with missing prices. The resulting data include the original 11,603 stations with missing and non-missing retail price data for 765 days for a total of 8,876,295 observations. We define a hurricane-window as the 14 days before, during, or after any hurricane made landfall in Florida or Louisiana. We then calculate the percentage of days that a station reports prices in each year and over the entire sample outside of hurricane windows.[19]

Our main station sample includes only stations that report price data for at least 75% of non-hurricane days over all five years. This includes just over 3.5 million observations of 4,673 stations reporting over 3.19 million prices. First, we use the sample of stations that report prices for 75% of non-hurricane days but impose the restriction by year instead of over the entire sample. Second, we use the sample of stations that report prices for 75% of non-hurricane days in 2004, our first year, and follow them through all years regardless of reporting in later years.[20] Last, we use all stations included in the original OPIS data.

Hurricane and Landfall Data. Hurricane and landfall data are from NOAA. Fourteen hurricanes made landfall in Florida or Louisiana over our sample. Table A.1 lists the hurricanes, the first day a hurricane warning was issued in either state, the first day the hurricane made landfall in either state, the stations impacted by the hurricane and the stations reporting prices in a landfall area, and the average and highest sustained wind speed in the landfall areas. Two hurricanes, Bonnie and Charlie, came in quick succession. As such, we treat the two hurricanes as a single storm. Katrina made landfall in Florida three days before making landfall in Louisiana, so we treat Katrina as two separate hurricanes.

[18] We observe reliable wholesale price data at various racks for Chevron, Conoco-Phillips, Marathon, Sunoco, Texaco, and Valero.
[19] We have 460 days outside of the 14-day window before or after a hurricane made landfall in Florida or Louisiana.
[20] These two alternative sample restrictions include 7,301 stations reporting over 3.6 million prices and 4,653 stations reporting just over 3 million prices, respectively.

The number of stations impacted by each hurricane and average wind of each hurricane vary substantially. Katrina impacted over 1,250 stations, almost 300 of which don't report prices during the landfall event. Six of the hurricanes had sustained winds exceeding 100 miles per hour. As expected, the storms with the highest winds are typically the same storms with the largest gap between stations in the landfall area and stations reporting prices in the landfall area.

Table B.1 - Hurricanes in Sample

Hurricane	First Warning	First Landfall	Stations in Landfall Area (Reporting)	Wind (High)
Bonnie/Charlie	8/11/2004	8/12/2004	887 (548)	130 (130)
Frances	9/2/2004	9/6/2004	184 (113)	50 (125)
Ivan	9/14/2004	9/16/2004	153 (7)	105 (145)
Jeanne	9/24/2004	9/26/2004	1007 (246)	105 (105)
Arlene	6/10/2005	6/11/2005	143 (90)	50 (60)
Dennis	7/7/2005	7/10/2005	176 (5)	105 (130)
Katrina (FL)	8/24/2005	8/25/2005	1038 (966)	70 (150)
Katrina (LA)	8/27/2005	8/29/2005	216 (5)	110 (150)
Rita	9/18/2005	9/24/2005	99 (4)	100 (155)
Wilma	10/22/2005	10/24/2005	988 (146)	105 (160)
Alberto	6/12/2006	6/13/2006	324 (306)	40 (60)
Humberto	9/13/2007	9/13/2007	67 (64)	80 (80)
Gustav	8/31/2008	9/1/2008	567 (68)	90 (135)
Ike	9/11/2008	9/13/2008	8 (2)	95 (125)

C Summary Statistics and Results

1. Additional Summary Statistics

Figure C.1 shows daily average retail, wholesale, and bulk prices for each year in our sample. Gray vertical bars represent a hurricane. We include the average wholesale and retail price across all stations in our sample in the bolded line. Thinner lines around each overall average are averages for subsamples of our data. These include stations and corresponding wholesale racks in each state, in coastal areas, and in the landfall area of each storm that made landfall in each year.

The Figure shows how the limited heterogeneity in retail and wholesale price responses around each storm. The Figure also highlights that while bulk and wholesale prices show substantial volatility, particularly around hurricanes, retail prices are much smoother in comparison. Another notable feature of the data are the large bulk price spikes after Katrina, Rita and Ike. These are due to the hurricanes impacting Gulf refinery operations. In all cases, wholesale and retail prices do not respond with nearly the same magnitude, likely due to low transactions occurring around these events and availability of emergency supplies.

Figure C.2 presents corresponding figure for precipitation. The Figure highlights the substantial variation in the intensity of hurricanes, both across storms and across different areas during the same storm.

2. Additional Results: Difference-in-Differences Heterogeneity

Figure C.3 presents coefficient plot estimates from estimating our difference-in-differences model (equation 3) and interacting with each treatment variable the same indicators as used to produce Figure 2. While the levels are different (likely due to the normalization in the event study) the relative effects of hurricanes before, during, and after landfall are generally consistent between Figure 2 and C.3.

Branded stations see no to very small impacts while independent stations see negative margins in all periods. One area of difference is among retail stations, who in the event study also experience negative margins, but in the difference-in-differences model show similar patterns as branded stations. We again find limited evidence of heterogeneity based on the competitiveness of local markets. We see some slight differences in the highway estimates. We find more limited heterogeneity in distance to highway in the difference-in-differences model where the event-study estimates show that stations >2.5 kms from a highway experience steady, negative margins around hurricanes.

3. Robustness Checks: Price and Margin Event Studies

Figures C.4 and C.5 explore the sensitivity of our price and margin event study results to the sample restrictions discussed in Appendix B. We show results using three alternative sample restrictions. The first panel (a) shows results for a sample where we impose the same 75% reporting requirement, but we do so by year. Thus, if a station has consistent reporting in 2004 but not 2005, it is in our sample in the former but not the latter year. Panel (b) shows results imposing the 75% reporting requirement in 2004 and carrying that sample forward for all years. Panel (c) presents results when we do not impose any sample restrictions and include all retail prices from OPIS. All results are very similar to our preferred estimates.

4. Robustness Checks: Lagged Adjustment

Our difference-in-differences model (Table 2) estimates long-run wholesale and bulk cost pass-through rates around 80% instead of the expected full cost pass-through. Meanwhile, the distributed lag model (Figure 3) shows full wholesale-to-retail cost pass-through after 30 days. To resolve this, we re-estimate equations (1) and (2) with distributed lag wholesale cost terms instead of the level of wholesale costs.

Table C.1 presents corresponding results to Table 2 Panel B. Results are largely similar to our main findings, especially in our preferred station- and rack-fixed effects models. We no longer find small negative retail margin after landfall. Instead, we estimate a 1.6 cent/gallon increase in the margin that is statistically insignificant. Wholesale-to-retail pass-through rates increase to (slightly over) 100%, and bulk-to-wholesale pass-through rates increase to 90%. Figure C.6 presents corresponding event-study results confirming that retail margins are unaffected by hurricanes.

While the results here suggest that the distributed lag form may be more appropriate, we prefer to maintain the contemporaneous wholesale cost control model for a few reasons. Most importantly, including thirty lags necessarily drops June from our model given that we only observe prices during hurricane months. Hurricanes Alberto and Arlene are not included in our estimates as a result. Second, the distributed lag model requires absorbing a large number of degrees of freedom.

5. Robustness Checks: Extended Event Window

Figure C.11 shows the extended event study. We extend our window around landfall stations to include 21 days before and after landfall. For comparison purposes, we present all results relative to the fourteenth day before landfall. We find largely similar results, and observe that both the positive price results and negative margins after hurricanes are temporary, recovering back to pre-hurricane levels by the third week after landfall.

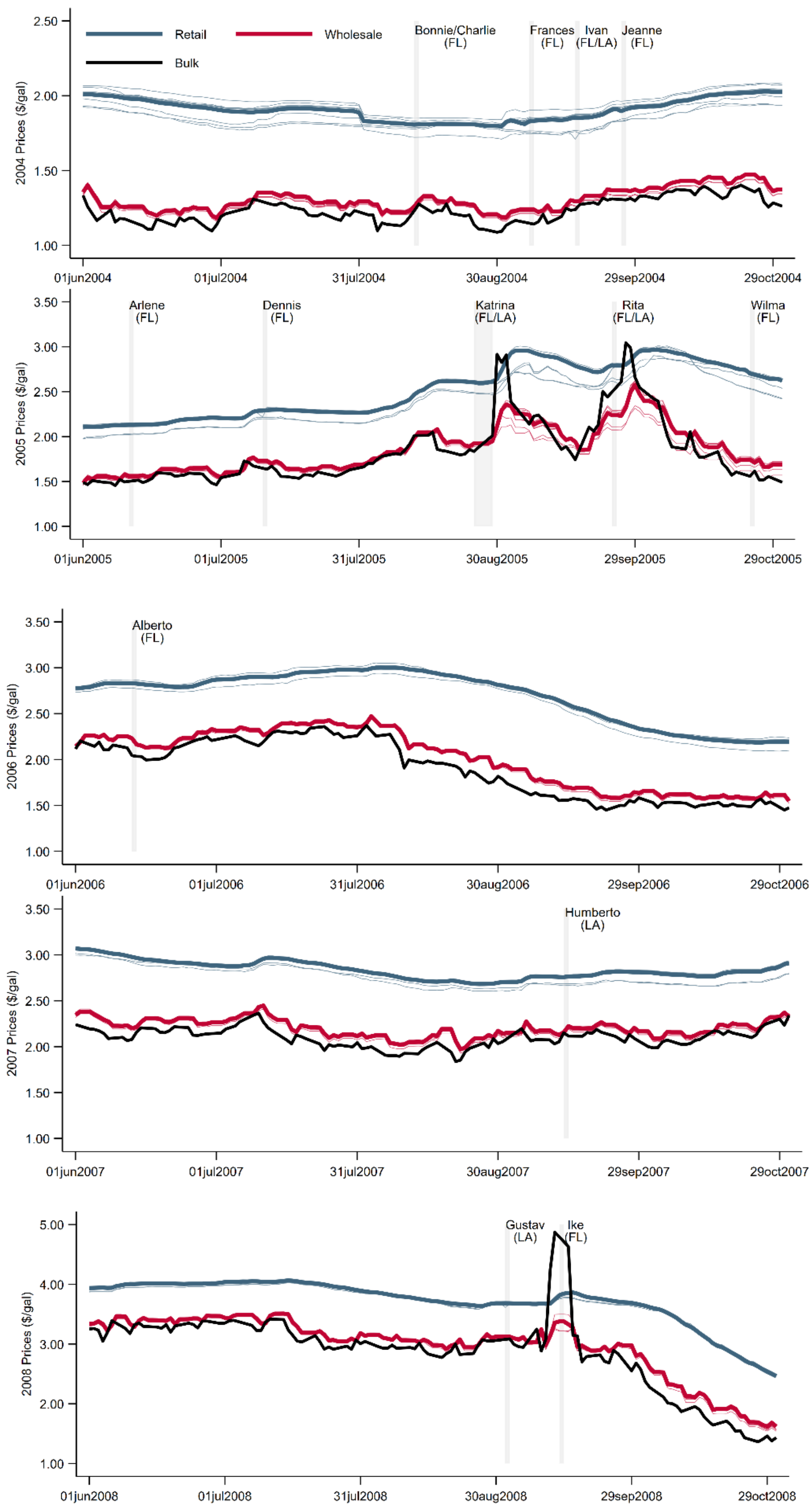


Figure C1: Average retail, wholesale, and bulk prices.

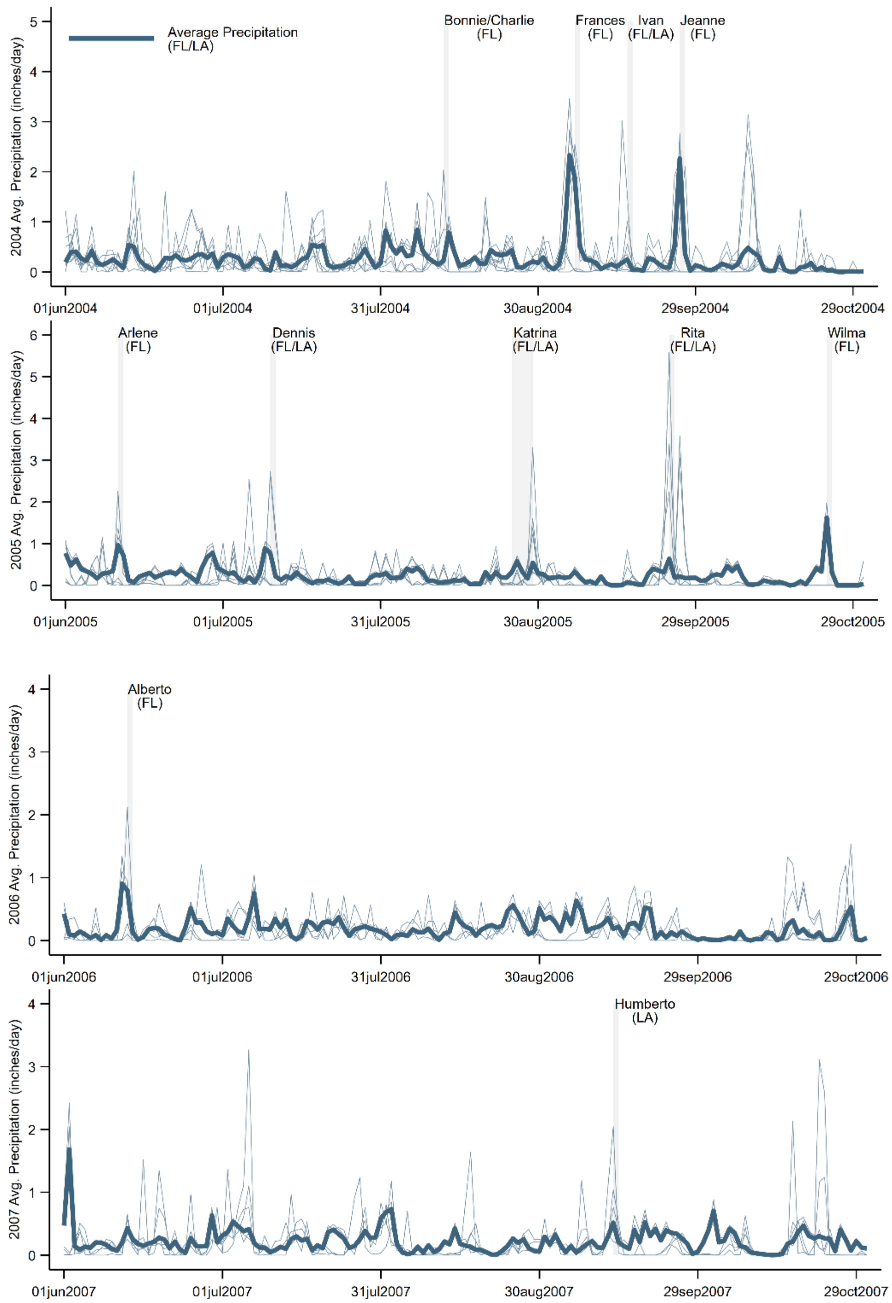
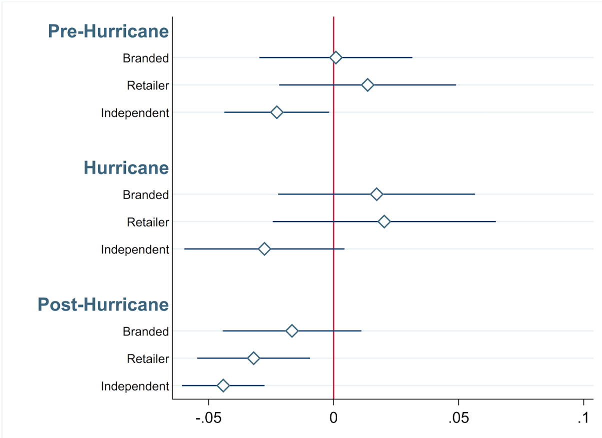
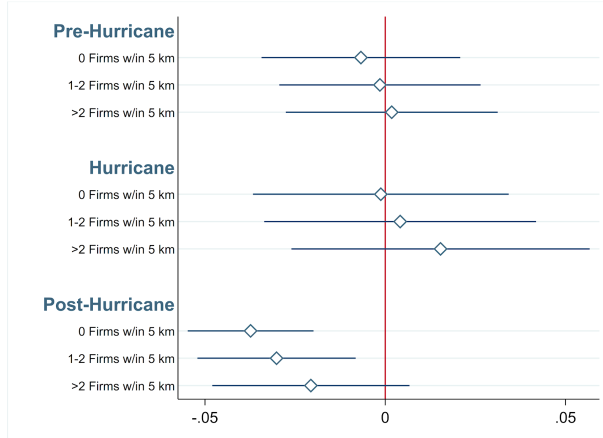


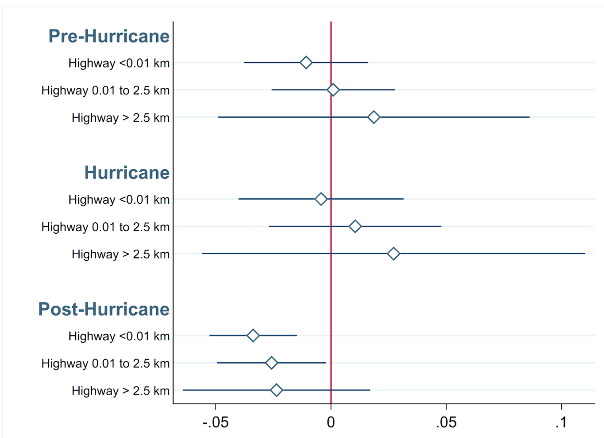
Figure C2: Average precipitation.



(a)

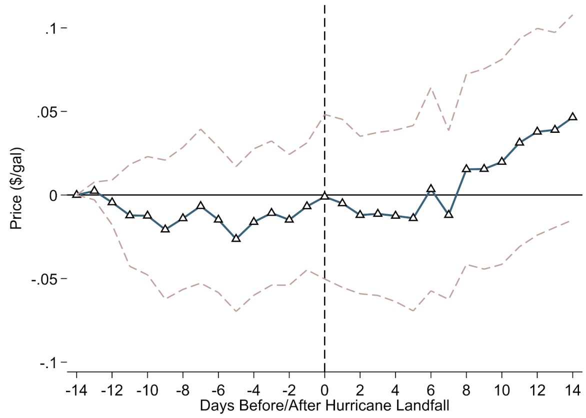


(b)

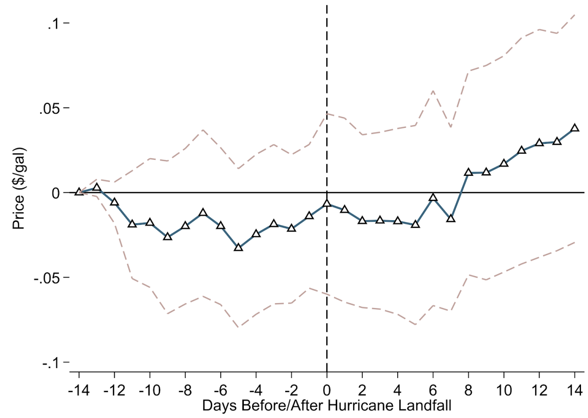


(c)

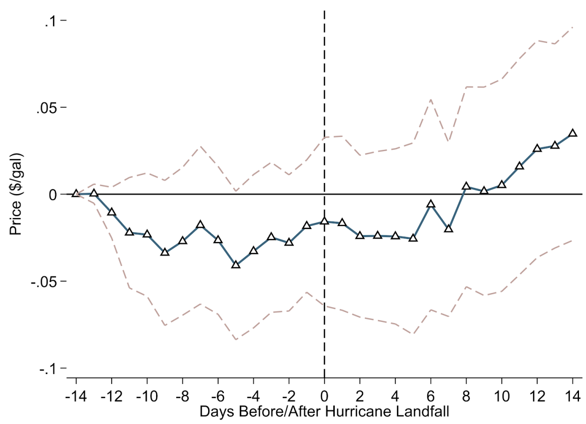
Figure C.3 - Treatment Effect Heterogeneity (Difference-in-Differences)



(a)

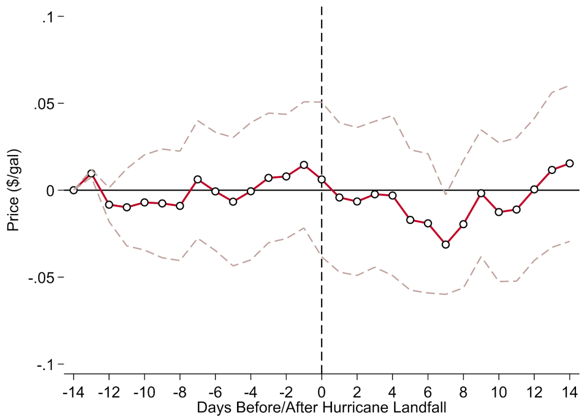


(b)

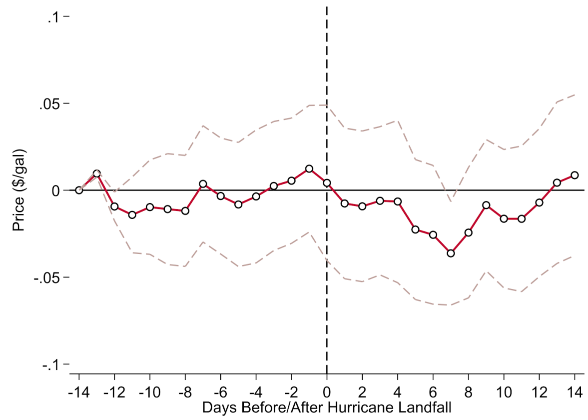


(c)

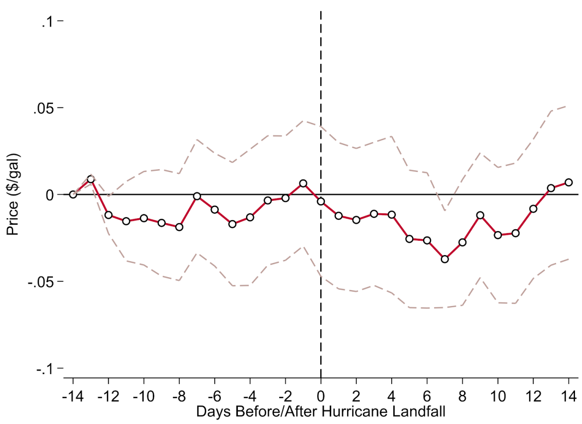
Figure C.4 - Price Event Study Sample Sensitivity



(a)



(b)



(c)

Figure C.5 - Margin Event Study Sample Sensitivity

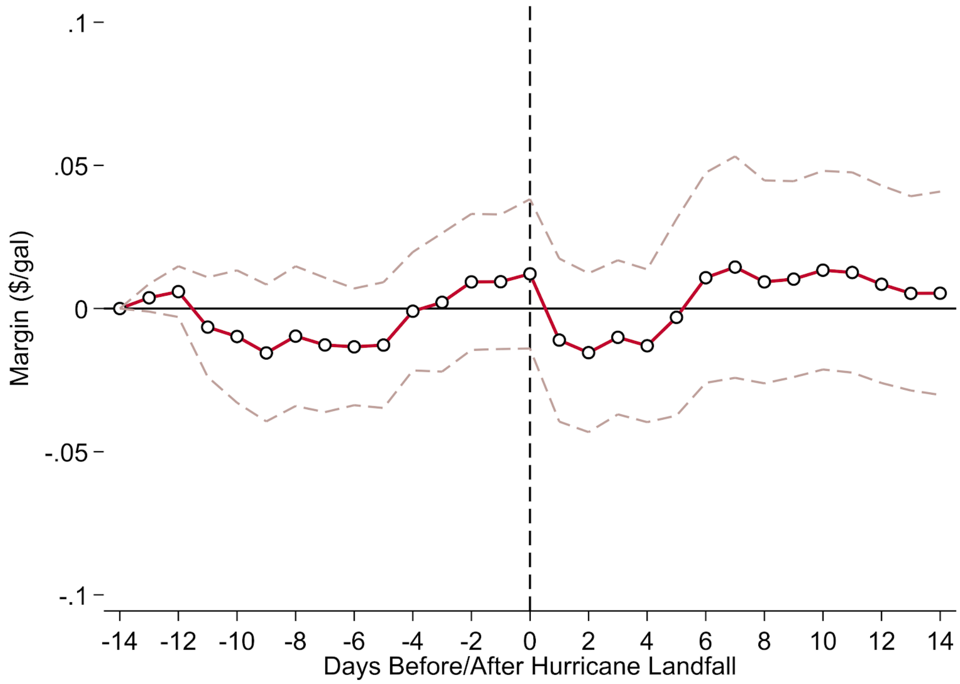
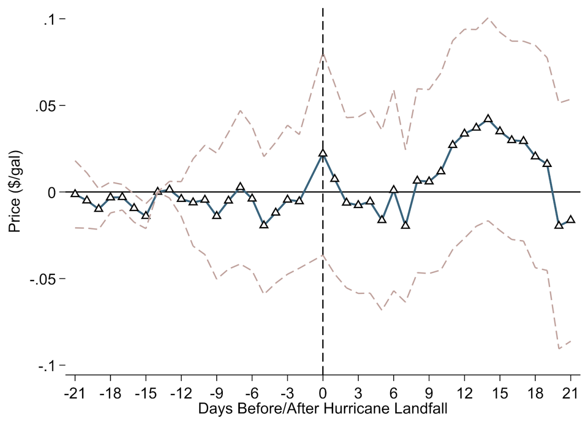
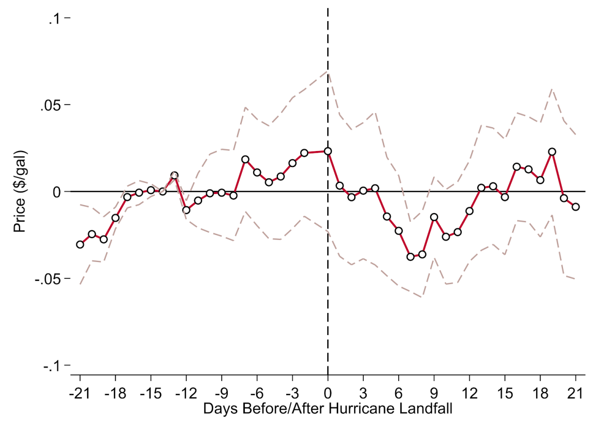


Figure C.6: Margins Event Study with Distributed Lag Wholesale Controls.



(a): Price Impacts



(b): Margin Impacts

Figure C.7: 21-Day Price and Margin Event Study

Table C1: Average Effect of Hurricanes on Retail and Wholesale Prices and Margins

	(1)	(2)	(3)	(4)
Dep. Var	Retail	Retail	Wholesale	Wholesale
Pre-Hurricane	0.024***	-0.003	0.013	0.011
	(0.009)	(0.006)	(0.018)	(0.018)
Hurricane	0.031***	0.003	0.009	0.007
	(0.010)	(0.007)	(0.013)	(0.014)
Post-Hurricane	0.040***	0.016	-0.010	-0.011
	(0.015)	(0.012)	(0.023)	(0.022)
Wholesale Price	1.091***	1.091***		
	(0.005)	(0.005)		
Bulk Price			0.910***	0.910***
			(0.005)	(0.005)
Observations	2,556,192	2,556,192	2,867,745	2,867,745
Stations/Racks	4,663	4,663	18	18
State FE	Yes	No	Yes	No
Station/Rack FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
Month-of-Year FE	Yes	Yes	Yes	Yes
Day-of-Week FE	Yes	Yes	Yes	Yes

Notes: The dependent variable is station-level retail/wholesale price. "Hurricane" is an indicator for whether a station is within 100 miles of a hurricane landfall in the three days before, during, or three days after landfall. "Pre-Hurricane" and "Post-Hurricane" are similar indicator variables for stations in landfall areas ten to four days before and after landfall, respectively. All regressions include controls for whether a station is under a storm/hurricane watch or warning and quadratic temperature controls. Standard errors are clustered at the county for retail regressions and wholesale rack for wholesale regressions. *, **, and *** denote significance at the 10%, 5% and 1% level.

6. Traffic

As a proxy for demand we use a normalized measure of traffic at the traffic monitor closest to each station. We see that potential demand falls by about one and a quarter standard deviations on the day of landfall, but by the fourth day after landfall, traffic has largely returned to normal.

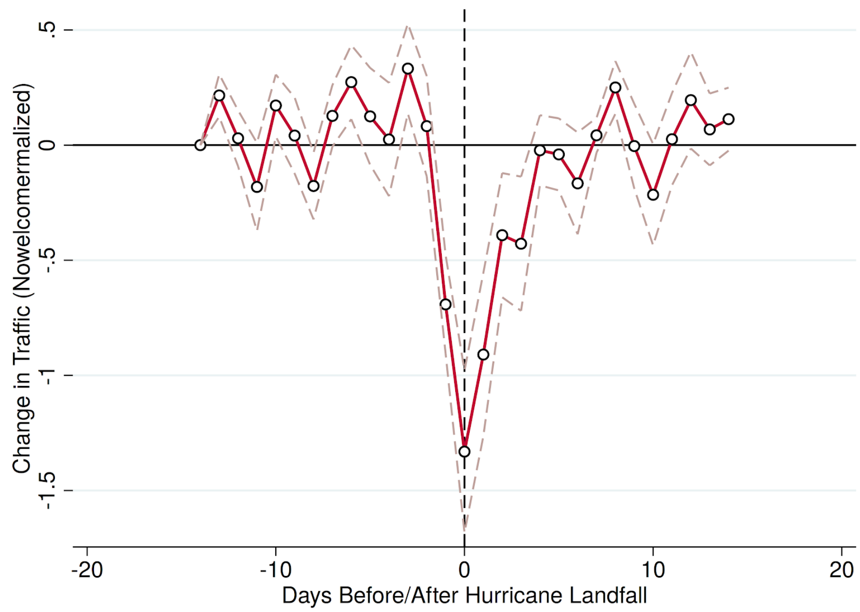


Figure C.8 Normalized Traffic Levels Event Study

7. Power Outages

As a proxy for supply disruptions we use a measure of power outages at the county level. Power outages are widespread in the immediate aftermath of a hurricane landfall but return to pre-landfall levels within 6 to 7 days.

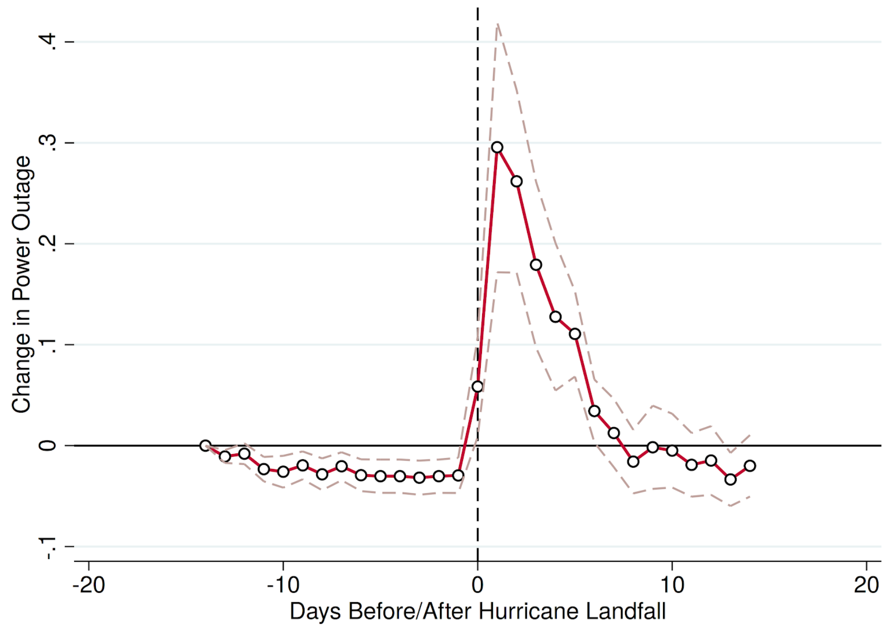


Figure C.9 Power Outage Event Study