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TITLE:

Modeling Causal Effects of Disasters and Disaster Relief Activity on Truckload Spot Rates

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ABSTRACT:

Freight transportation is an important part of the US economy, of which 60% is movement of goods by trucks. We are particularly interested in full truckloads that move goods for a single customer, from a single origin to a single destination. During disasters, as the demand for truckload transportation increases to stock up and distribute emergency supplies, the ability decreases due to infrastructure damage. The increase in demand is not only from private sector but more importantly from public sector agencies for disaster relief. Moreover, as the public and private sector shippers compete for the same carrier resources, it can result in constrained truckload availability and consequently higher prices. With the increase in frequency of natural disasters it is important to model historical impact in order to be prepared for truckload procurement for future disasters. We contribute to disaster modeling and management literature by measuring causal effects of disasters on a critical system's performance. We quantify the magnitude, geographical spread, timing, and duration of the causal effects of disaster conditions (Hurricane Harvey and Hurricane Irma) and consequent public sector disaster relief activity on private sector truckload spot rates using a difference-in-differences methodology. We find that long-haul loads inbound to nodes near the hurricane's paths are most affected by both disaster conditions and disaster relief activity, experiencing a large magnitude of statistically significant increase in spot rates during hurricane periods. Moreover, the increase in spot rates is both localized and short-lived.

KEYWORDS:

Causal Inference, Difference-in-Differences, Disaster Relief Distribution, Freight Transportation, Truckload Spot Rates

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(Authors' names blinded)

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1. Introduction

The trucking industry is an important part of the U.S. economy as it moves over 60% of the domestic freight by weight and value (Bureau of Transportation Statistics 2022), and is the largest contributor to business logistics costs at $896 billion (Kearney 2023). We focus on full truckloads which refers to loads, usually over $10,000$ pounds, moved for a single customer, from a single origin to a single destination, in $48-53$ feet trailers. The truckload transportation market includes *shippers*, organizations that have goods which need to be transported; *carriers*, that provide the transportation service; and sometimes *brokers*, that serve as middle men between shippers and carriers.

Private sector shippers and carriers/brokers interact via long-term contracts or in the transitory spot market. In the strategic phase of truckload procurement, shippers forecast demand on the origin-destination lanes (e.g. zip code-to-zip code, city-to-city, market region-to-market region) of their network and send a request for proposal to a select group of carriers. The carriers respond with proposed bids of rates (e.g. cost per mile, load, or weight) for the specified lanes and potential number of loads. In some cases, there are multiple rounds of bidding where the carriers receive feedback and negotiate with the corresponding shipper. After the bid process, the shipper creates a *routing guide* which is a priority list of carriers for a particular lane, based on the rates submitted, carrier characteristics, and network characteristics. The first preference carriers on a lane are called *primary carriers* and the rest are called *back-up carriers*. The final agreed upon rates at the end of the bidding process are referred to as contract rates and are usually valid for 1 year.

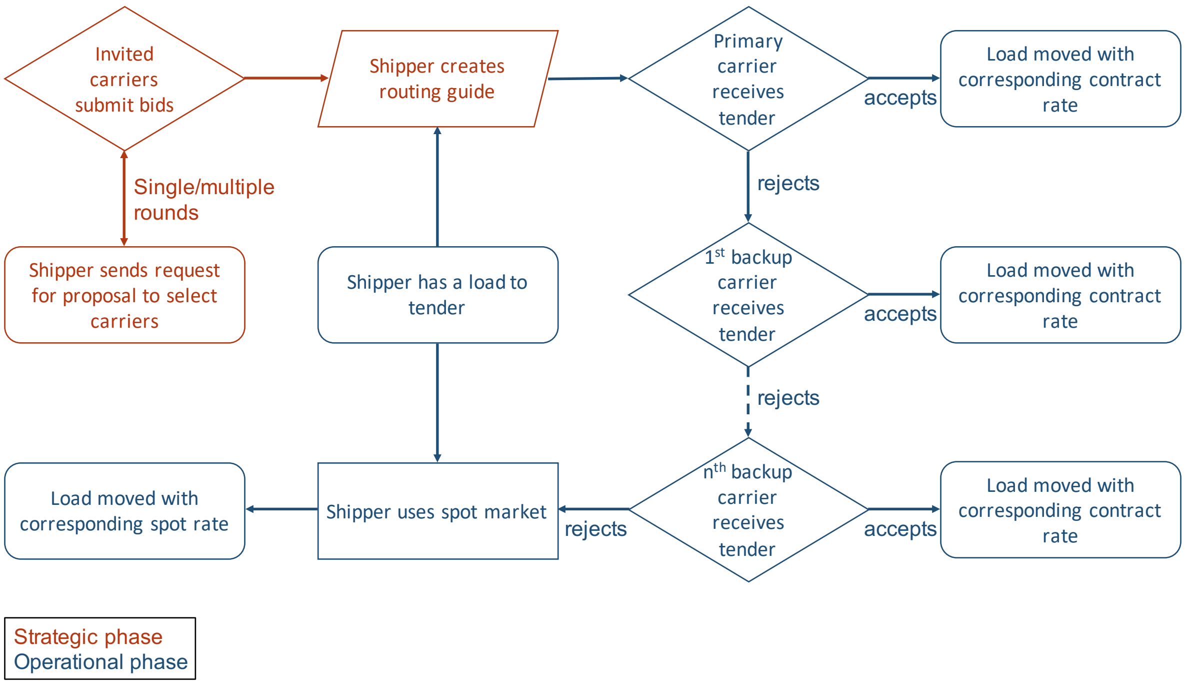
In the operational phase when a load needs to be moved, the shipper tenders it to the primary carrier of the corresponding lane. Unlike most industries, the contracts in truckload market are cost binding but not volume binding. Thus, the primary carrier can choose to accept or reject the tendered load. Similarly, the shipper is not obliged to guarantee tender of any minimum number of loads. If the primary carrier accepts the load, then they are paid the *contract rate* on file. If the primary carrier rejects, then the shipper offers it to the first back-up carrier and so on. As shippers go down the routing guide, the contract rates can be up to 12% higher and it also takes them more time to find truckload capacity (Aemireddy and Yuan 2019).

Another option available to the shippers is to access capacity in the spot market at the time of shipment, via load-boards or brokers, and pay a one-time *spot rate* on a load-by-load basis. Shippers may use the spot market after some number of rejections from their contract carriers or use it as the first option directly. Carriers may reject tendered loads when they don't have truckload capacity at the required location and time. They may also reject the load if they expect to get a higher rate in the spot market when the market demand is higher than capacity, for example during disasters. During such market conditions, the rates in spot market can be as high as 35% above contract rates (Aemireddy and Yuan 2019). Shippers may choose to use the spot option directly if the rates are lower than contract, i.e., when the market demand is lower than capacity, or when there are unexpected loads such as during disasters. (Caplice 2007, Acocella et al. 2020). This procurement process is summarized in Figure 1.

During disasters, as the demand for essential freight increases the ability to distribute freight decreases. Retailers may stock up on bottled water, packaged food, clothing, bedding, stoves, fuel etc. prior to a disaster to distribute and sell post disaster. More importantly, government agencies like The Federal Emergency Management Agency (FEMA), stock up relief and construction supplies close to the potential affected zones, at distribution centers or military bases. After the disaster conditions subside they distribute the relief supplies to affected populations. For example, during Hurricane Ian in 2022, inbound volume in key regions in Florida and Georgia increased 20% week-over-week (Taube 2022). Due to increased demand for transportation in these regions, prices tend to increase (Dorf 2017, Fuller 2022).

FEMA's truckload procurement process (Federal Emergency Management Agency 2023) differs from standard industry practice. First, FEMA's Standard Tender of Service (STOS) requires that

Figure 1 **Private sector truckload procurement process.**

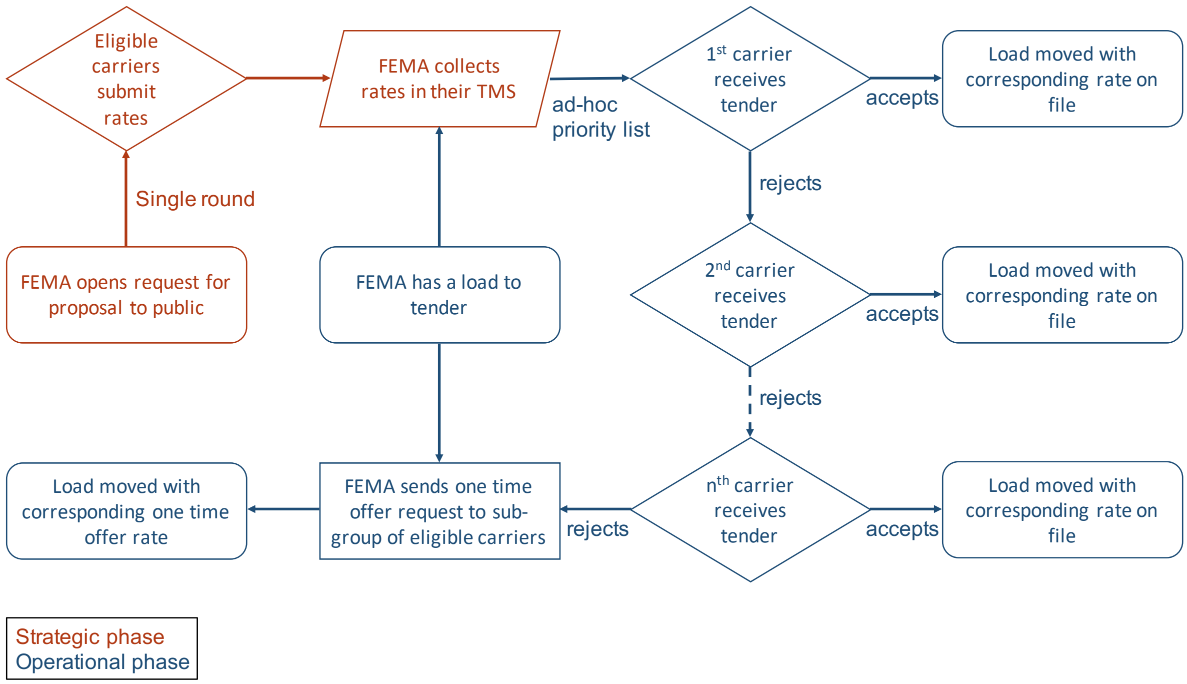


the request for proposal is open to the public and any carrier that fulfills FEMA's basic requirements can submit linehaul rates (cost per mile) and various accessorial charges for $2,401$ state-to-state (including Washington DC) lanes in the contiguous United States (CONUS). The requirements for carriers to qualify to haul loads for FEMA are listed in Section EC.1 of the appendix. Moreover, there is only a single round of rate submission where the rates are collected but a primary carrier is not selected for any of the lanes. The submitted rates are active for a year, from 1st May to 31st April, but they can be extended for another year.

Next, FEMA does not create a routing guide. When a load needs to be moved, they access the rates submitted for that particular lane from their Transportation Management System (TMS) and consider the past performance of corresponding carriers to select ad-hoc a carrier that they believe would provide the best service. FEMA's carriers are not given any prior information on their position relative to others in the priority list. Carriers are manually contacted via phone or email, and if they accept the tendered load they are paid the *rate on file* for the linehaul and the corresponding *accessorial charge*.

Furthermore, if there are no rates on file for a particular lane, if they think the rates on file do not reflect current market rates, or if the tender is rejected by multiple carriers on file then FEMA relies on one time offers. They manually send alerts to a sub-group of about $25-30$ of the eligible carriers and pick the carrier that responds with the best, all-inclusive *one time offer rate* within a specific time frame. Furthermore, the carriers may be paid *accessorial charges* if they

Figure 2 **FEMA's truckload procurement process.**



provide additional services than first offered. Again, the criteria are decided ad-hoc. The carrier sub-groups are manually shuffled once per month to provide equal opportunities to all carriers. FEMA's truckload procurement process is summarized in Figure 2.

In case of private shippers, the lanes in the request for proposal are usually more granular than state-to-state and have expected number of loads information. Carriers are often given feedback on submitted rates to be more competitive and are explicitly awarded primary or back-up status in the routing guide. Thus, contract carriers can plan their capacity for the shipper more accurately. Moreover, private sector shippers rely on brokers or load-boards to access a larger group of carriers on the spot market than just their contract carriers. Furthermore, FEMA has unpredictable transportation needs in terms of location and number of loads. Thus, their carriers have an incentive to submit higher rates to hedge risks and are also more likely to reject their loads as they might not have trucks available. Since it is important to move relief loads in time, FEMA is willing to pay higher rates for one time offers. This may drive up carrier rejection for private shippers and consequently truckload spot rates in the regions they operate in, especially during disasters.

Additionally, truck trailers may have to sit idle in staging areas for days/weeks, waiting for the disaster conditions to pass and for distribution activity to be completed. As they are a finite resource, they may become unavailable for other activity (Redwood Logistics 2017, Smith 2017, Straight 2017, Fuller 2022). This capacity crunch can cause higher truckload prices in various parts of the transportation network not physically affected by the disaster as well (Redwood Logistics 2017, Spelic 2018).

Truckload capacity is also affected by dangerous road conditions during disasters. Routes become inaccessible due to infrastructure damage, possibly leading to longer travel times and increased number of refused loads by carriers. This can also result in higher prices (Spelic 2018). For example during Winter Storm Uri in Texas in February 2021, trucks were idle due to icy conditions on the road (Kapadia 2021). Cassidy (2021) estimate that California forest fires can increase travel time by a day and half when major roads are closed.

Increase in truckload prices from increased demand and reduced capacity has been experienced in previous disasters. For example, truckload prices were 66% higher on the Dallas-Houston lane post Hurricane Harvey in August 2017 than the previous week (Smith 2017). Similarly in 2019, during Hurricane Dorian spot prices increased by 3% nationwide (Montague 2019). In extreme situations, natural disasters can cause $100 million per day in delay costs (Straight 2017).

The frequency of natural disasters and resulting economic loss has increased in the last 50 years (World Meteorological Organization 2021). Thus, there is a need to study their historical impact to be better prepared for limited situational awareness in the future. Private shippers that need to haul relief and non-relief goods during disasters can better plan their emergency budgets in case of future disasters by modeling the intensity, timing, and duration of the effects of disaster conditions on truckload prices. Such information can be used to quantify the trade-offs between paying higher prices to ship during peak impact vs waiting for impact of disasters to subside.

Moreover, there is a general perception in the private sector that FEMA's disaster relief activity depletes truckload capacity and consequently increases prices. However, the industry reports do not quantify the effect. Even though FEMA's primary objective is to move all relief loads in time during disasters and reduce costs, it is also important to reduce externalities on the private sector. Thus, modeling the contribution of FEMA's truckload activity on increase in private sector truckload prices, in addition to effect of the disasters, can motivate better procurement practices and educate shippers and carriers.

Furthermore, most existing disaster modeling literature focus on macroeconomic or firm level effects and not on transportation procurement prices. Additionally, general disaster management literature usually study transportation infrastructure resilience and restoration, re-routing of vehicles, or fleet management. However, it is essential to first ensure that transportation service *can* be procured to satisfy increased demand in the setting of constrained resources.

Thus, our research objective is to quantify the causal effects of disaster conditions and public sector disaster relief activity on private sector truckload prices. We focus on the truckload spot market as it is more reactive to sudden shocks like disasters. As part of our ongoing collaboration with FEMA, we answer the following research questions:

1. ***What is the effect of disasters on private sector truckload spot rates?***

2. ***What is the effect of FEMA's truckload procurement on private sector truckload spot rates?***

The remainder of the paper is organized as follows. In Section 2 we review literature on modeling effects of disasters and transportation planning during disasters. Next, we outline the data-sets and the difference-in-differences methodology used to measure the causal effects in Section 3 and Section 4, respectively. In Section 5 we present the results of the effects of disaster conditions and disaster relief activity on truckload spot rates, and in Section 6 we further discuss the mechanisms and practical insights. Finally, we summarize our research and discuss potential directions for future extensions in Section 7.

2. Literature Review

Quantitative research in humanitarian logistics and crisis management tend to focus on supplier selection, relief inventory pre-positioning, facility location, network design, relief allocation, forecasting and order planning, relief and evacuation routing, fleet management, rescue and repair scheduling, and service network restoration (Baxter et al. 2020, Besiou and Van Wassenhove 2020). Researchers highlight the importance of working on real needs of humanitarian logistics practitioners. From our close collaboration with FEMA we identify the need to analyze transportation procurement during disasters. This also addresses the gap of studying shared services in current disaster management literature (Besiou and Van Wassenhove 2020).

Natural and man-made disasters can cause large economic losses. Quantitative models for measuring macroeconomic impact of disasters have been reviewed by Okuyama and Santos (2014). They surveyed studies that measure system wide total losses including pre-disaster mitigation costs and post-disaster recovery costs. These studies popularly use input-output model, computable general equilibrium model, or social accounting matrix to incorporate inter-system dependencies. Some also measure long-run impact of climate change. Similarly, Botzen et al. (2019) reviewed papers that use input-output, computable general equilibrium, vintage capital, neoclassic growth, productivity-capital, learning, endogenous growth, and institutional growth models to measure the short-term and long-term impact of disasters on gross domestic product, labor, and various sector outputs.

Fomby et al. (2013) tracked the changes in macroeconomic indices of developed and developing countries, for agriculture and non-agriculture sectors, following multiple natural disasters. Meanwhile, Inoue and Todo (2019) particularly analyzed the direct and indirect impact of the 2011 Great East Japan earthquake on the gross domestic product estimated using industrial production index of one million firms. Carvalho et al. (2020) also modeled the macroeconomic impact of the 2011 Great East Japan earthquake, but used a general equilibrium model considering propagation of the shocks.

Such research is useful for estimating losses from disasters and for government agencies to administer informed economic policies for future disasters. However, apart from economic impact, it is also important to investigate individual critical systems' performances during disasters to facilitate better operational decision making by all stakeholders. Few researchers have modeled the impact of various disasters on supply chain, logistics, and transportation metrics.

For example, Mariana (2021) used deviation in delivery time as an indicator of impact of disaster on supply chain performance. They tabulated results for 32 cases of natural disasters around the world. Similarly, Cardoso et al. (2022) surveyed papers that model impact of various natural disasters on supply chain in terms of changes in inventory, production, operation, supply, demand, human resources, income, cash, price, transportation infrastructure, and critical services.

Meanwhile, Cavallo et al. (2014) reported on the changes in product prices and shelf inventory in supermarkets during the 2010 Chile earthquake and the 2011 Great East Japan earthquake. Gagnon and López-Salido (2020) also studied the change in prices in U.S. supermarkets as a result of labor conflicts in California and St. Louis, Hurricane Katrina in 2005, and winter storms in Washington D.C. in 2009. Finally, Kashiwagi et al. (2021) measured the effects of Hurricane Sandy in 2012 on sales growth of firms within and outside the U.S.

Aydin et al. (2012) investigated the effects of I-40 bridge collapse in 2002 and Shen and Aydin (2014) analyzed the impact of Hurricane Katrina in 2005 on the U.S. highway freight movement at state and national levels. They estimated freight flows on the highway networks pre and post disruption using traffic assignment. Then, they reported the impact in terms of changes in vehicle miles traveled, vehicle hours traveled, vehicle to capacity ratio, weighted absolute flow difference, and consequent economic loss. Similarly, Wen et al. (2014) modeled the impact of Hurricane Katrina in 2005 on intermodal transportation systems in the Gulf Coast region of Mississippi, U.S. Likewise, Kim et al. (2019) outlined the effects of heavy flooding in April 2018 and the volcanic eruption in May 2018 that occurred in Hawai'i, U.S. They reported the locations and durations of road closures due to flooding, crack, and lava, and the consequent isolation of communities for evacuation.

As opposed to physical impact on transportation, Caza and Shekhar (2022) studied the impact of natural disasters and national holidays on truckload routing guide performance of shippers in the U.S. They conducted hypothesis tests to verify if primary carrier acceptance rate, route guide depth, percentage spot loads, and cost per mile were statistically significantly different in the post-disaster period as compared to the benchmark in pre-disaster period. They highlight that routing guide performance is dependant on market conditions, and the frequency and number of loads on the lanes, and suggest that lanes should be accurately segmented for appropriate truckload procurement strategies.

In contrast to short-term natural disasters, some researchers have studied the impact of longer disruptions, such as the COVID-19 pandemic, on passenger and freight transportation. Aloi et al. (2020) measured the decrease in urban mobility and the consequent increase in accidents and emissions in the city of Santander, Spain during the COVID-19 quarantine period. Similarly, Loske (2020) analyzed how COVID-19 cases and deaths influenced food transport volumes in Germany. The drop in taxi demand in Chongqing, China following the COVID-19 pandemic was measured by Nian et al. (202). Wielechowski et al. (2020) studied the relationship between COVID-19 cases and regulation policies in Poland and public transportation usage. Finally, Bauranov et al. (2021) studied the changes in airline passenger volume and network efficiency during the COVID-19 pandemic.

Meanwhile, some studies (Mongiovì et al. 2013, Raiyn and Toledo 2014, Riveiro et al. 2017, Davis et al. 2020, Tang et al. 2020) have also used various anomaly detection techniques for transportation networks to identify unknown disruptive events, like accidents, from road traffic and passenger mobile travel data. However, the aforementioned research do not attribute causality, of the measured impacts, to disasters.

Some studies have used causal inference methods to measure effects of natural disasters on macroeconomic and firm performance metrics. Hsiang and Jina (2014) showed the long-term causal impact of tropical cyclones on gross domestic product of countries using difference-in-differences methodology. Barrot and Sauvagnat (2016) also used difference-in-differences to estimate the effects of various disasters on U.S. firms' sales growth. Meanwhile, Boehm et al. (2019) used normalized propensity score re-weighting to study how the 2011 Great East Japan earthquake deferentially affected firms in the U.S. with affiliations in Japan compared to firms with no Japanese affiliations. They measured the earthquake's effects on firm's value of imports. Again, Carvalho et al. (2020) used difference-in-differences to find that firms in the disaster area and connections to firms in the disaster area had lower growth rates, than rest of the country, post-disaster. Finally, Barriola and Schmidt (2022) used triple-difference to estimate how different income communities were affected by grocery store prices changes in Atlantic hurricane affected areas.

Causal inference has also been used to measure effects of disaster risk on land and housing prices (Kiel and Matheson 2018, Bernstein et al. 2019, Dubé et al. 2021). Nevertheless, not many papers conduct causal analysis of effects of disasters on transportation systems, especially transportation procurement pricing. For example, Wang et al. (2022) measure the causal effects of the COVID-19 pandemic on ride-share drivers' labor supply and earnings.

As noted earlier, transportation planning for humanitarian logistics has also been studied widely. Researchers have modeled transportation infrastructure resilience and repair during disasters (Duque et al. 2016, Kasaei and Salman 2016, Zhou et al. 2019, Pan et al. 2021, Almeida et al.

2022), vehicle routing for humanitarian operations (Huang et al. 2012, Amideo et al. 2019, Anuar et al. 2021), and fleet size and mix for relief distribution (Pedraza-Martinez and Van Wassenhove 2012, Besiou et al. 2014, Pedraza-Martinez et al. 2020). Moreover, studies on procurement during disasters focus on supplier selection for the relief goods themselves (Hu et al. 2022). However, not many researchers examine the procurement of transportation services for distribution of relief goods during disasters.

We contribute to disaster modeling, management, and transportation planning literature by analyzing the procurement of a critical shared service, i.e., truckload transportation, during disasters and modeling the causal effects of disaster and disaster relief activity on truckload procurement prices.

3. Data Description

In this study we analyze two major hurricanes, $h \in H = \{\text{Hurricane Harvey, Hurricane Irma}\}$, that made landfall in CONUS. Hurricane Harvey made landfall as a category 3 hurricane on $t^{landfall}_{Harvey} =$ 26th August, 2017 in Texas and Hurricane Irma made landfall as a category 3 hurricane on $t^{landfall}_{Irma} =$ 10th September, 2017 in Florida (Knapp et al. 2010, 2018).

The spatial granularity of analysis is 3-digit-zip nodes, $n \in N$, in CONUS and the temporal granularity is days, $t \in T$, between 1st July, 2017 and 29th November, 2017.

First, we specify some important time periods. Benchmark period, $T_{benchmark}$, is defined as 1st July, 2017 to 11th August, 2017. Pre-hurricane period, $T_{pre-hurricane}$, is defined as 12th August, 2017 to 18th August, 2017. Finally, hurricane period is defined as $T_h = \{t^{landfall}_h, t^{landfall}_h + 1, ..., t^{landfall} + 6\}\ \forall h \in H$.

Then, we measure the haversine distance $d_{n,t,h}$ from each node n's centroid to hurricane h's centroid on each day t when Saffir-Simpson Hurricane Wind Scale (SSHS) rating was ≥ 0.

We use truckload spot market data from a leading market intelligence company. For each node, $n \in N$, and each day, $t \in T$, we know the following aggregated metrics for dry-van spot truckloads:

- $c_{n,t} =$ average cost per mile of loads for node n on days $\{t-2, t-1, t\}$
- $m_{n,t} =$ average miles traveled by loads for node n on days $\{t-2, t-1, t\}$
- $a_{n,t} =$ total load posts for node n on day t

For these metrics, we define subscripts $o =$ loads outbound from an origin node, $i =$ loads inbound to a destination node, $s =$ short haul loads (origin-destination distance ≤ 225 miles), and $l =$ long haul loads (origin-destination distance > 225 miles).

The average cost per mile and average miles are calculated with the load information submitted by participating shippers and brokers. Information for each node-day is contributed by $3 - 14$ participants, thus may be limited in the representation of the market. The total loads posted are from the load-board of the company and include all the loads that were posted on it. Additionally, we ignore fuel surcharges in the cost per mile and only keep the linehaul costs.

Apart from the effects of hurricanes, we also want to measure how public sector's truckload procurement activity disrupts the private sector truckload spot market. Thus, we use FEMA's historical shipment data. We know the total FEMA dry-van truckloads that were moved, $v_{n,t}$, for each node $n \in N$ on each day $t \in T$.

4. Methodology

In this section we outline the difference-in-differences methodology used to answer the research questions.

4.1. Causal Effects of Hurricanes

We want to identify whether nodes near a hurricane's path experience larger increase in spot rates during hurricanes compared to nodes with similar market characteristics away from the hurricane's path. Thus, we first define hurricane nodes as a set of all nodes n whose centroid is within 150 miles of hurricane h's center on some day, i.e., $N_h = n : d_{n,t,h} \leq 150$ miles $\exists t$, $\forall h \in H$. We have $|N_{Harvey}| = 24$ and $|N_{Irma}| = 41$.

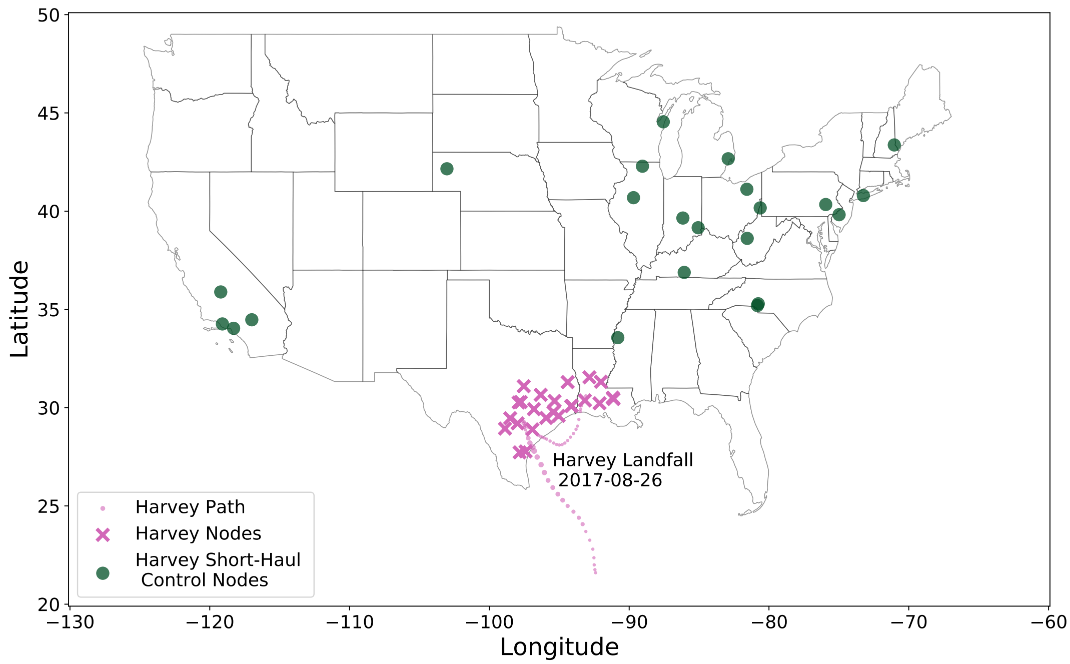
In order to account for the endogeneity of the hurricane nodes, we use nearest neighbor matching to find control nodes, N_h^C, that are most *similar* to the defined hurricane nodes, N_h $\forall h \in H$. We define control node options, $n \in N_{all\_control}$, as a set of nodes that:

- are away from both the hurricanes' paths, i.e., $d_{n,t,h} > 300$ miles $\forall t \in T$, $\forall h \in H$
- don't have any FEMA activity, i.e., $v_{n,t} = 0$ $\forall t \in T$
- have parallel trend in outbound and inbound spot rates in the benchmark period compared to the hurricane nodes, i.e., $[c_{o,n} - \bar{c}_{o,n \in N_h}]_{t \in T_{benchmark}}$ and $[c_{i,n} - \bar{c}_{i,n \in N_h}]_{t \in T_{benchmark}}$ are both stationary $\forall h \in H$, $\forall \{s, l\}$. To test for stationarity we use the augmented Dickey-Fuller test at a significance level of 0.05.

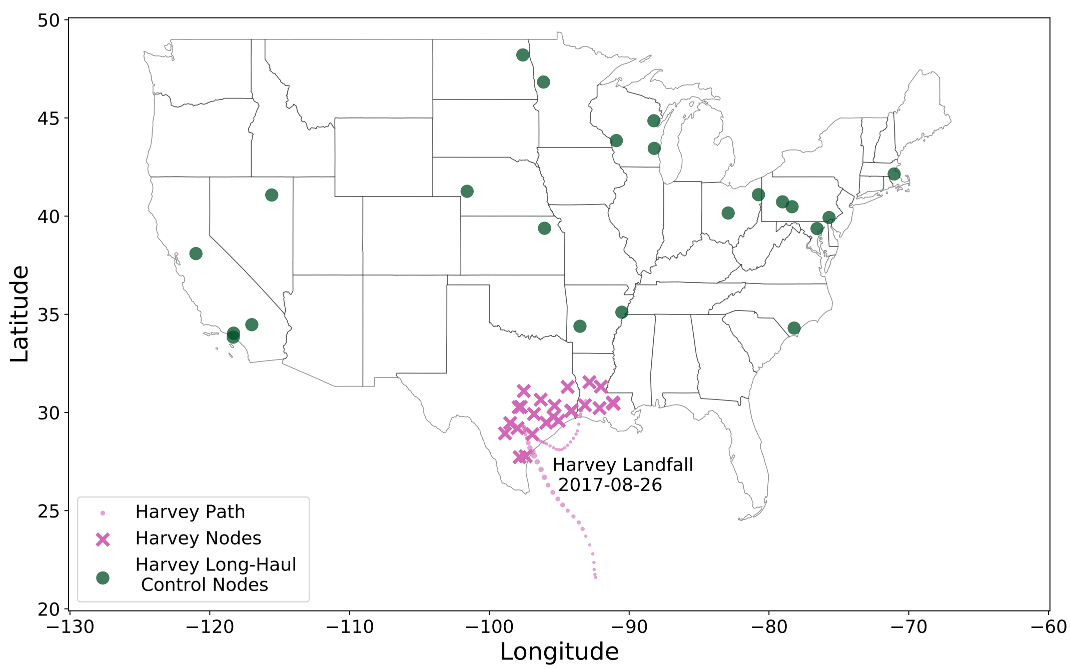
Next, we measure the similarity between $[c_{o,n_1}, c_{i,n_1}, m_{o,n_1}, m_{i,n_1}, a_{o,n_1}, a_{i,n_1}]_{t \in T_{benchmark}}$ and $[c_{o,n_2}, c_{i,n_2}, m_{o,n_2}, m_{i,n_2}, a_{o,n_2}, a_{i,n_2}]_{t \in T_{benchmark}}$ for each $n_1 \in N_{all\_control}$ and each $n_2 \in N_h$ using normalized dynamic time warping $\forall h \in H$, $\forall \{s, l\}$. To maintain a balanced data-set for the regression models, we select a single node $n_1 \in N_{all\_control}$ with the highest similarity to each node $n_2 \in N_h$ and group them as the final control nodes, N_h^C. Thus, we get $|N_{Harvey,s}^C| = 22$, $|N_{Harvey,l}^C| = 22$, $|N_{Irma,s}^C| = 29$, and $|N_{Irma,l}^C| = 26$.

The maps of Hurricane Harvey nodes and corresponding control nodes are shown in Figure 3 and the relationship between spot rates vs time for these nodes are graphed in Figure 4. Similarly, for Hurricane Irma we refer to Figure 5 and Figure 6. On visual inspection, the spot rates for hurricane nodes and corresponding control nodes do show parallel trends in the benchmark period, in Figure 4 and Figure 6.

Figure 3 **Map of Hurricane Harvey nodes and corresponding control nodes.**



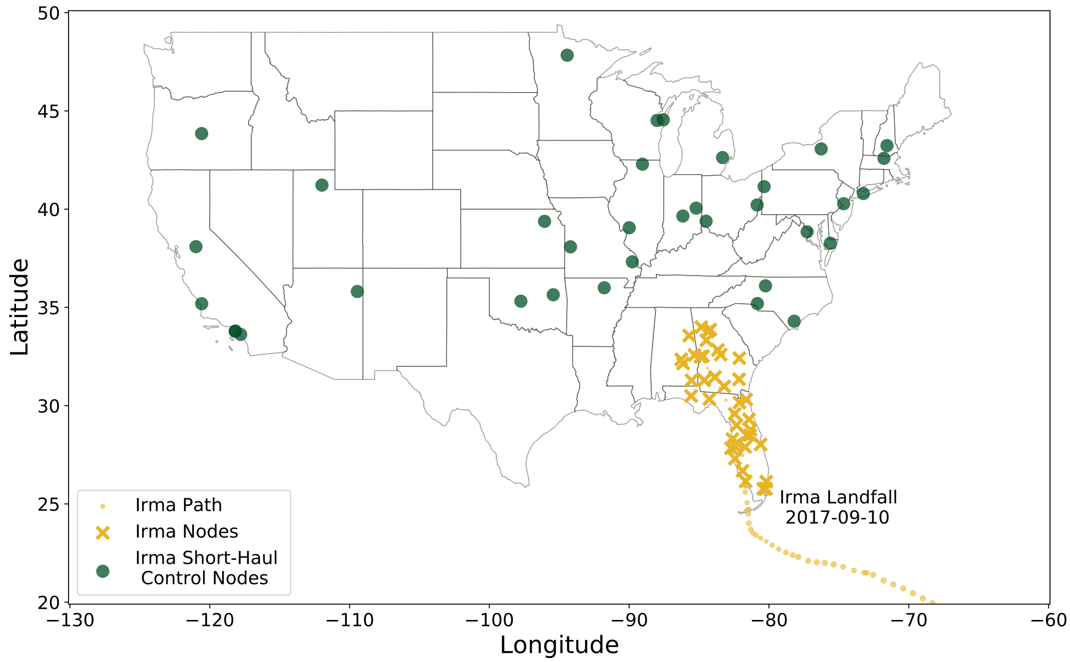
(a) Short-haul



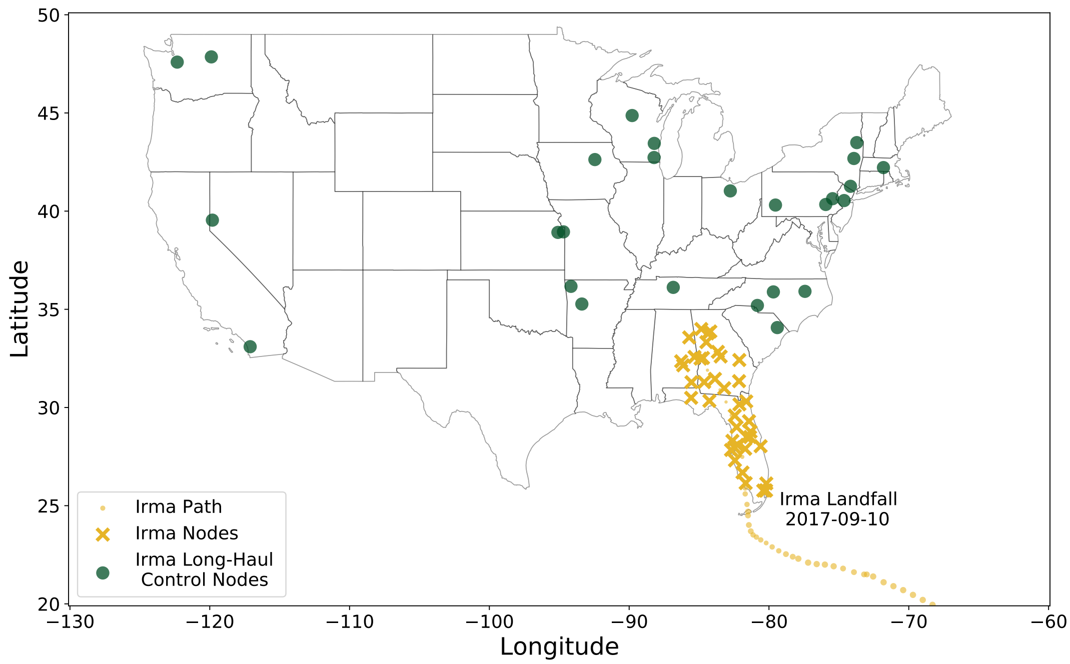
(b) Long-haul

Figure 4 **Spot rates ($/mile) vs time relationship for Hurricane Harvey nodes and corresponding control nodes.**

Figure 5 **Map of Hurricane Irma nodes and corresponding control nodes.**

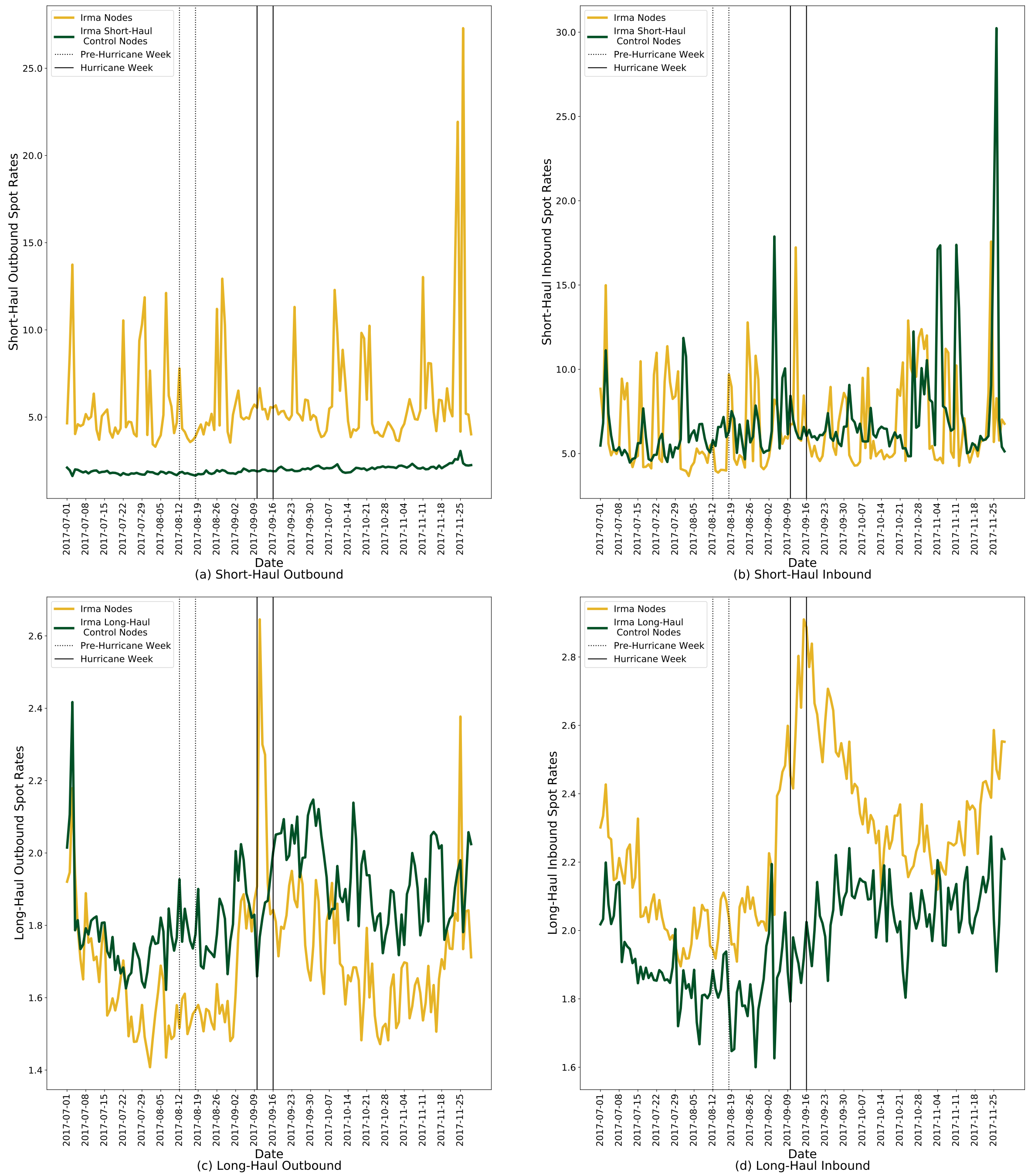


(a) Short-haul



(b) Long-haul

Figure 6 **Spot rates ($\$$/mile) vs time relationship for Hurricane Irma nodes and corresponding control nodes.**



To answer the first research question, we model the difference-in-differences regression to measure the causal effects of the hurricanes as:

$$c_{n,t} = \alpha_0 + \alpha_1 D_n + \alpha_2 D_t + \alpha_3 D_n D_t + \epsilon_{n,t} \tag{1}$$

Where D_n is a binary variable for node type and D_t is a binary variable for time period. We define $D_n = 0\ \forall n \in N_h^C$ and $D_n = 1\ \forall n \in N_h$. Moreover, $D_t = 0\ \forall t \in T_{pre-hurricane}$ and $D_t = 1\ \forall t \in T_h$. We separately model $c_{n,t}\ \forall h \in H,\ \forall\{s,l\},\ \forall\{o,i\}$. Coefficient α_0 measures the level, α_1 measures the node effect, i.e., fixed difference in hurricane and control nodes, α_2 measures the time effect of the market, and finally α_3 measures the causal effect of the hurricanes on the spot rate.

We select a difference-in-differences approach since we have pre-treatment and post-treatment spot rates data for sizable treated and control groups, but not all possible confounding variables are present in the data-set. Additionally, we note that in the modeled natural experiment we account for the exogeneity of the treatment, i.e., hurricane nodes are defined independent of their spot rates, and the comparability of treatment and control groups, i.e., through control group matching, thus preserving the validity of the causal evidence.

Moreover, we conduct multiple robustness checks for the difference-in-differences models. First, we change the hurricane group definition to measure geographical radius of effect. We re-define hurricane nodes as $N_h = n : d_{n,t,h} \leq d\ \forall d \in \{50, 100, 150, 200, 250\}$miles, $\exists t,\ \forall h \in H$. We use the same matching methodology to find the new corresponding control nodes, $N_h^C\ \forall h \in H$. Additionally, we re-define the hurricane period $T_h = \{t_h^{landfall} - 7 + \tau, ..., t_h^{landfall} - 7 + \tau + w - 1\}$. Where $w = \{3, 7, 10, 14, ..., 35\}$ represents the size of time window to measure duration of the effect and $\tau = \{0, 1, ..., 42 - w\}$ represents the lead/lag of the effect compared to landfall day. Furthermore, we re-define the control nodes. We redo control group matching using Euclidean distance instead of dynamic time warping, as well as use $N_h^C = N_{all\_control}$. Again, we separately model $c_{n,t}\ \forall h \in H,\ \forall\{s,l\},\ \forall\{o,i\}$.

4.2. Causal Effects of FEMA

We additionally want to identify whether FEMA's relief activity during Hurricane Harvey and Hurricane Irma increased spot rates for the private sector.

First, we define FEMA nodes, $n \in N_{FEMA}$, as a set of nodes that:

- are either within 150 miles one of the hurricanes or are more than 300 miles away from both of the hurricanes, i.e., $d_{n,t,h} \leq 150$ miles $\exists t,\ \forall h \in H \mid d_{n,t,h} > 300$ miles $\forall t \in T,\ \forall h \in H$
- have more than 5 FEMA loads on some day around either of the hurricane's landfalls, i.e., $v_{n,t} >= 5\ \exists t \in \{t_{Harvey}^{landfall} - 14, ... t_{Irma}^{landfall} + 41\}$

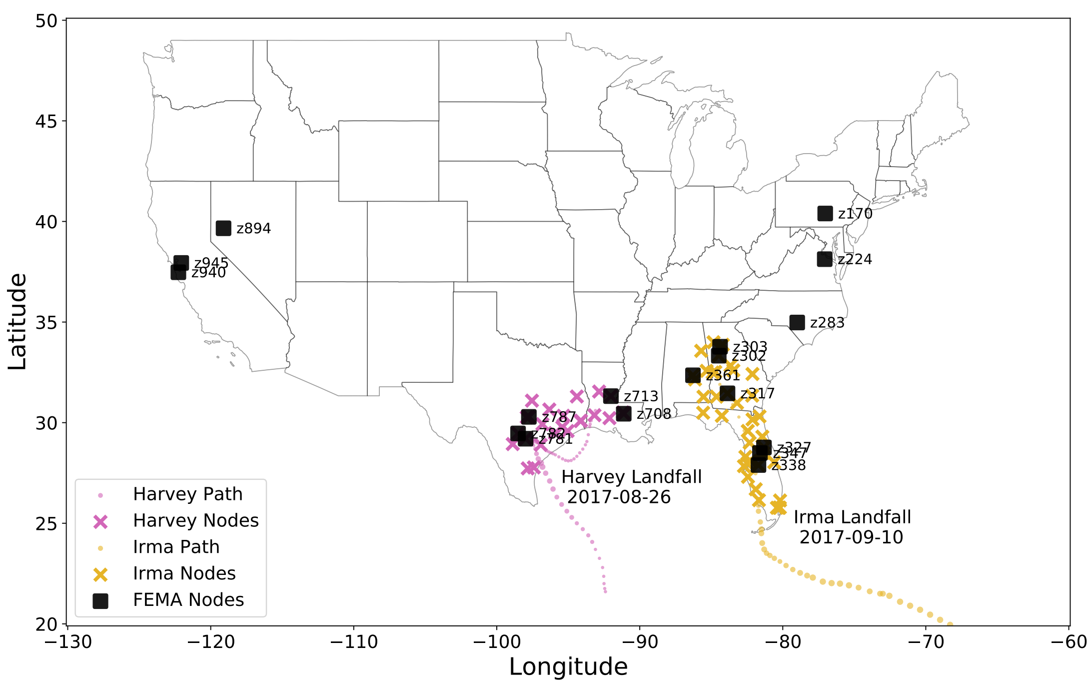
The FEMA nodes and hurricane nodes are mapped in Figure 7.

Then, to measure the causal effects of FEMA, we use the difference-in-differences methodology similar to the previous sub-section. We consider weekly windows, $w = 7$, before and after the hurricanes' landfalls and define the treated period as $T_{treated} = \{t_h^{landfall} + \tau, ..., t_h^{landfall} + \tau + 6\}$ $\forall h \in H$, $\forall \tau = \{-14, -7, ..., 35\}$.

If all the FEMA nodes in the treated period are within 150 miles of the hurricane's path, then we use Equation 1 to measure the causal effect. Here we define three cases of treated nodes, $D_n = 1$: (i) n is a FEMA node, i.e., $\forall n \in N_{FEMA}$, (ii) n is a hurricane node, i.e., $\forall n \in N_h$, or (iii) n is a hurricane node but not a FEMA node, i.e., $\forall n \in N_h \setminus N_{FEMA}$. For all these cases $D_n = 0$ if it is a corresponding control node of the hurricane, i.e., $\forall n \in N_h^C$. Similarly, $D_t = 0$ $\forall t \in T_{pre-hurricane}$ and $D_t = 1$ $\forall t \in T_{treated}$. Again, α_3 measures the causal effect of FEMA or the hurricanes on the spot rates and we separately model $c_{n,t}$ $\forall h \in H$, $\forall \{s, l\}$, $\forall \{o, i\}$.

Next, if all the FEMA nodes in the treated period are more than 300 miles away from the hurricane's path, then we use Equation 1 to measure the causal effect. We identify new control nodes $n \in N_{FEMA}^C$ for the FEMA nodes using the same matching process discussed in the previous sub-section. Thus, we define $D_n = 0$ $\forall n \in N_{FEMA}^C$ and $D_n = 1$ $\forall n \in N_{FEMA}$. Moreover, $D_t = 0$ $\forall t \in T_{pre-hurricane}$ and $D_t = 1$ $\forall t \in T_{treated}$. Once again, α_3 measures the causal effect of FEMA on the spot rates and we separately model $c_{n,t}$ $\forall h \in H$, $\forall \{s, l\}$, $\forall \{o, i\}$.

Figure 7 Map of hurricane nodes and FEMA nodes.



Finally, if FEMA nodes are both within 150 miles of the hurricane's path and more than 300 miles from the hurricane's path, then we use a triple-difference model to measure the causal effect:

$$c_{n,t} = \alpha_0 + \alpha_1 D_n + \alpha_2 D_t + \alpha_3 D_F + \alpha_4 D_n D_t + \alpha_5 D_t D_F + \alpha_6 D_F D_n + \alpha_7 D_n D_t D_F + \epsilon_{n,t} \quad (2)$$

Where $D_n = 1 \; \forall n \in N_h$ and $D_n = 0 \; \forall n \in N_h^C \cup (N_{FEMA} \setminus N_h)$. Then, $D_F = 1 \; \forall n \in N_{FEMA}$ and $D_F = 0 \; \forall n \in N_h^C \cup (N_h \setminus N_{FEMA})$. Finally, $D_t = 0 \; \forall t \in T_{pre-hurricane}$ and $D_t = 1 \; \forall t \in T_{treated}$. Here, α_7 estimates whether hurricane nodes with FEMA loads have a difference in increase in spot rates compared to hurricane nodes without FEMA loads. Once again, we separately model $c_{n,t} \; \forall h \in H$, $\forall \{s, l\}$, $\forall \{o, i\}$.

5. Results

In this section we discuss the results of implementing the discussed methodology, and answer the research questions.

5.1. Causal Effects of Hurricanes

The results for the hurricanes' effect on spot rates are shown in Table 1 and Table 2 for Hurricane Harvey and Hurricane Irma, respectively. First, we observe that only long-haul loads inbound to Hurricane Harvey nodes had a statistically significant increase in spot rates during the week of Hurricane Harvey's landfall. Similarly, during Hurricane Irma, only long-haul loads inbound and outbound from Hurricane Irma nodes were affected. Additionally, the increase in spot rates due to Hurricane Irma was higher for long-haul inbound loads than outbound loads. Finally, Short-haul loads did not experience any effect during both the hurricanes.

We also note that the adjusted R-squared of all the models are low. Additional node characteristics may be required to fully explain the increase in spot rates. However, in this research we are only interested in quantifying to what extent the hurricanes themselves had an effect on spot rates.

Table 1 Causal effect of Hurricane Harvey on spot rates ($/mile).

Variable	Short-Haul Outbound	Short-Haul Inbound	Long-Haul Outbound	Long-Haul Inbound
Intercept	4.20^{***} (0.18)	4.80^{***} (0.18)	1.74^{***} (0.04)	1.76^{***} (0.08)
D_n	1.16 (1.39)	−0.60 (0.28)	-0.20^{***} (0.05)	0.04 (0.09)
D_t	1.28 (0.72)	0.23 (0.27)	0.13^{**} (0.07)	0.02 (0.12)
$D_n D_t$	−0.78 (1.62)	3.65 (2.70)	0.05 (0.10)	0.48^{***} (0.14)
Observations	267	358	325	313
Adjusted R-squared	−0.004	0.008	0.074	0.129

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 2 **Causal effect of Hurricane Irma on spot rates (\$/mile).**

Variable	**Short-Haul Outbound**	**Short-Haul Inbound**	**Long-Haul Outbound**	**Long-Haul Inbound**
Intercept	5.08^{***} (0.22)	6.42^{***} (0.41)	1.80^{***} (0.05)	1.85^{***} (0.05)
D_n	-0.70 (0.54)	-1.41 (0.95)	-0.25^{***} (0.06)	0.18^{**} (0.06)
D_t	0.58 (0.46)	0.30 (0.58)	0.06 (0.07)	0.07 (0.07)
D_nD_t	0.57 (0.74)	2.71 (1.90)	0.42^{***} (0.11)	0.60^{***} (0.10)
Observations	367	418	447	548
Adjusted R-squared	0.011	0.002	0.079	0.246

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Then, we present the robustness results for each combination of $\{d, \tau, w\}$ in Section EC.2 of the appendix. The magnitude of causal effect, α_3, decreases with increase in d and w because of aggregation, as expected. We summarize these results in Table 3 and Table 4 for Hurricane Harvey and Hurricane Irma, respectively. We call the value of d, for which α_3 values were statistically significant at significance level of 0.05, as 'overall effect radius'. And similarly, we refer to the range of T_h, for which α_3 values were statistically significant at significance level of 0.05, as 'overall effect duration'. Finally, 'peak effect' refers to the the largest magnitude of α_3.

We observe that long-haul inbound spot rates are the most affected by hurricanes. Nodes within 250 miles from the hurricanes' paths had a statistically significant increase in spot rates, 1 week pre-landfall to $4-5$ weeks post-landfall, for both the hurricanes. During Hurricane Harvey, the peak effect, for nodes within 50 miles of the hurricane, was an increase of \$1.02/mile (53%), 1 week post-landfall. Similarly, the peak effect during Hurricane Irma was \$1.52/mile (82%), 2 weeks post-landfall. Spot rates for short-haul inbound and outbound as well as long-haul outbound were less impacted by the hurricanes. The effect radius was only 50 miles, except for long-haul outbound during Hurricane Irma. Moreover, outbound spot rates had a smaller magnitude of effect than inbound spot rates and short-haul spot rates had a smaller duration of effect than long-haul spot rates. Finally, the robustness results for different control node matching criteria are presented in Section EC.2 of the appendix. We find that the general insights remain unchanged.

Table 3 Summary of causal effect of Hurricane Harvey on spot rates ($/mile).

	Outbound	Inbound
Short-Haul	Overall effect radius: 50 miles Overall effect duration: 1 week pre-landfall to 2 weeks post-landfall Peak effect for 50 miles radius and 7 day window: $1.56 Peak effect timing: 1 week post-landfall	Overall effect radius: 50 miles Overall effect duration: 1 week post-landfall Peak effect for 50 miles radius and 7 day window: $30.56 Peak effect timing: 1 week post-landfall
Long-Haul	Overall effect radius: 50 miles Overall effect duration: 1 week pre-landfall to 4 weeks post-landfall Peak effect for 50 miles radius and 7 day window: $0.37 Peak effect timing: 1.5 week post-landfall	Overall effect radius: 250 miles Overall effect duration: 1 week pre-landfall to 4 weeks post-landfall Peak effect for 50 miles radius and 7 day window: $1.02 Peak effect timing: 1 week post-landfall

Table 4 Summary of causal effect of Hurricane Irma on spot rates ($/mile).

	Outbound	Inbound
Short-Haul	Overall effect radius: 50 miles Overall effect duration: 1 week pre-landfall Peak effect for 50 miles radius and 7 day window: $2.43 Peak effect timing: 1 week pre-landfall	Overall effect radius: 50 miles Overall effect duration: 1 week pre-landfall to 4 weeks post-landfall Peak effect for 50 miles radius and 7 day window: $8.00 Peak effect timing: 1 week pre-landfall
Long-Haul	Overall effect radius: 250 miles Overall effect duration: 1 week pre-landfall to 1.5 weeks post-landfall Peak effect for 100 miles radius and 7 day window: $0.50 Peak effect timing: 1 week around landfall	Overall effect radius: 250 miles Overall effect duration: 1 week pre-landfall to 5 weeks post-landfall Peak effect for 50 miles radius and 7 day window: $1.52 Peak effect timing: 2 weeks post-landfall

5.2. Causal Effects of FEMA

The weeks when FEMA had a statistically significant effect on spot rates are outlined in Tables 5 to 7, and the relationship between spot rates vs time for these cases are graphed in Figure 8. On visual inspection, the spot rates for hurricane nodes, FEMA nodes, and corresponding control nodes do show parallel trends in the benchmark period, in Figure 8.

First, we observe that FEMA's activity had no effect on short-haul inbound and short-haul outbound spot rates. Then, we see that long-haul outbound spot rates increased $0.49/mile (28%) due to FEMA's truckload activity 2 weeks after Hurricane Harvey's landfall. Similarly, 1 week before Hurricane Irma's landfall, long-haul outbound spot rates increased $0.44/mile (24%) in nodes with outbound FEMA loads. For both these weeks, the hurricane nodes with no FEMA loads had no statistically significant increase in long-haul outbound spot rates.

Similar to the hurricanes, long-haul inbound spot rates were the most affected by FEMA. In the week following Hurricane Harvey's landfall, FEMA's inbound loads to destinations near Hurricane Harvey caused an increase of $0.83/mile (47%) in spot rates. Whereas, hurricane nodes with no

FEMA activity only experienced an increase of \$0.41/mile (23%) in spot rates. Similarly, in the two weeks following Hurricane Irma's landfall, FEMA's inbound loads to destinations near Hurricane Irma caused an increase of \$0.89/mile (48%) and \$0.54/mile (29%) in spot rates, respectively. Again, corresponding hurricane nodes with no FEMA activity had a lower magnitude of increase in spot rates, i.e, \$0.58/mile (31%) and \$0.46/mile (25%), respectively. Moreover, a month post Hurricane Irma's landfall, nodes with inbound FEMA long-haul loads still had an increase of \$0.35/mile (19%) in spot rates. Whereas, hurricane nodes with no FEMA loads had no statistically significant increase in long-haul inbound spot rates.

Table 5 Causal effect of FEMA and Hurricane Harvey on long haul spot rates (\$/mile).

Treated Group	**Hurricane**	**FEMA**	**Hurricane \ FEMA**
Variable	(a) $c_{l,o}$, $h =$ Harvey, $\tau = 14$		
Intercept	1.74*** (0.05)	1.74*** (0.05)	1.74*** (0.05)
D_n	−0.20*** (0.07)	−0.30* (0.17)	−0.19*** (0.07)
D_t	0.19*** (0.07)	0.19*** (0.07)	0.19** (0.07)
D_nD_t	0.01 (0.10)	0.49** (0.23)	−0.02 (0.10)
Observations	344	163	330
Adjusted R-squared	0.08	0.08	0.07
$N_{treated}$	–	'z781'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	963	963	0
$\lvert N_{treated}\rvert$	24	1	23
$\lvert N_h^C\rvert$	22	22	22
Variable	(b) $c_{l,i}$, $h =$ Harvey, $\tau = 0$		
Intercept	1.76*** (0.07)	1.76*** (0.08)	1.76*** (0.08)
D_n	0.04 (0.10)	0.23 (0.21)	0.01 (0.10)
D_t	0.05 (0.10)	0.05 (0.11)	0.05 (0.10)
D_nD_t	0.45*** (0.14)	0.83*** (0.30)	0.41*** (0.14)
Observations	318	153	298
Adjusted R-squared	0.124	0.147	0.097
$N_{treated}$	–	'z713', 'z781'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	996	996	0
$\lvert N_{treated}\rvert$	24	2	22
$\lvert N_h^C\rvert$	22	22	22

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 6 Causal effect of FEMA and Hurricane Irma on long haul outbound spot rates (\$/mile).

Treated Group	**Hurricane**	**FEMA**	**Hurricane \ FEMA**
Variable	(c) $c_{l,o}$, $h =$ Irma, $\tau = -7$		
Intercept	1.80^{***} (0.06)	1.80^{***} (0.05)	1.80^{***} (0.06)
D_n	-0.24^{***} (0.08)	-0.09 (0.18)	-0.26^{***} (0.08)
D_t	0.09 (0.08)	0.09 (0.08)	0.09 (0.08)
$D_n D_t$	0.18^{*} (0.11)	0.44^{*} (0.26)	0.16 (0.11)
Observations	451	240	431
Adjusted R-squared	0.041	0.015	0.041
$N_{treated}$	–	‘z303’, ‘z361’	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	47	47	0
$\lvert N_{treated} \rvert$	41	2	39
$\lvert N_h^C \rvert$	26	26	26

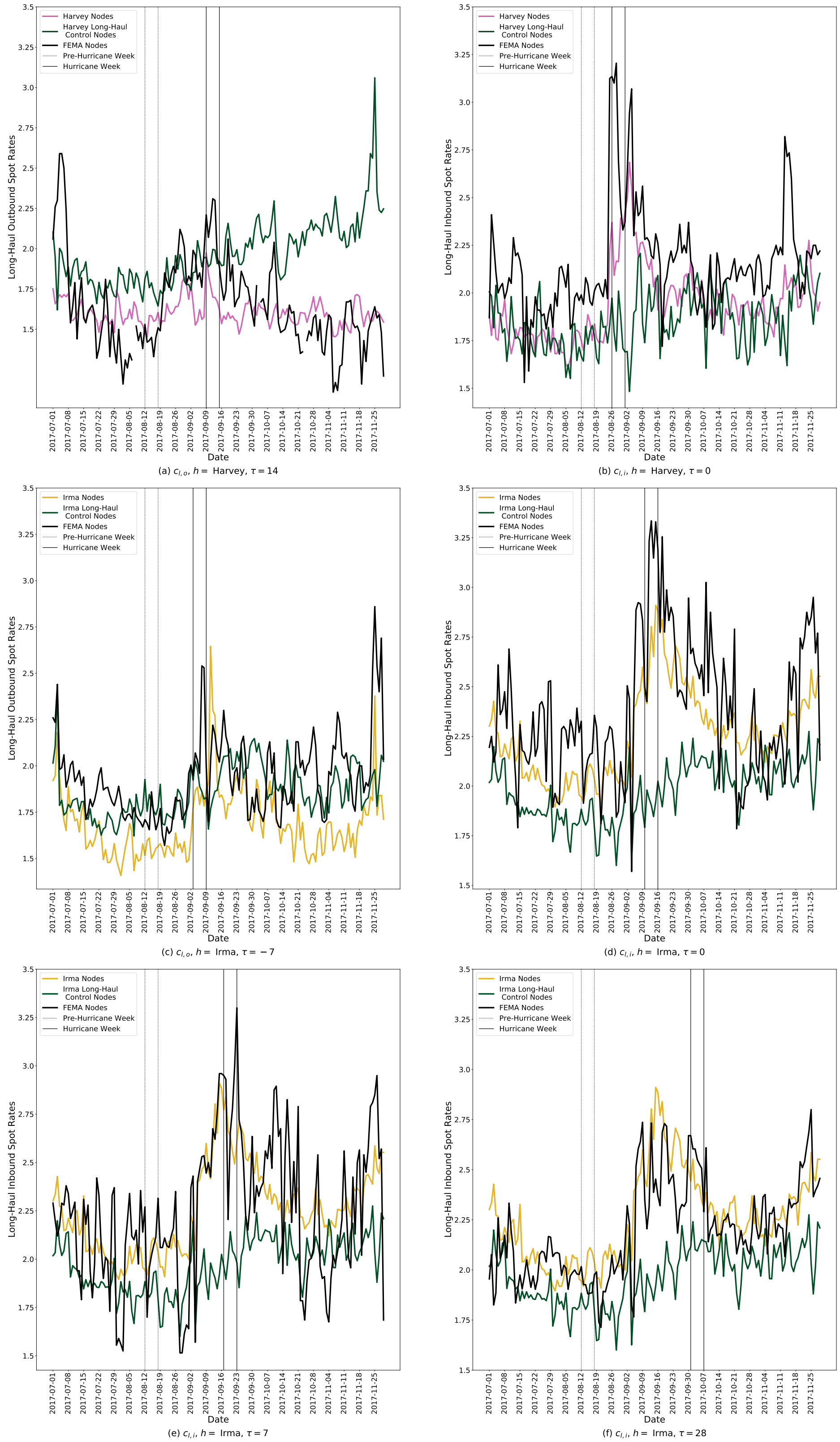
Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 7 Causal effect of FEMA and Hurricane Irma on long haul inbound spot rates ($/mile).

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
Variable	(d) $c_{l,i}$, $h =$ Irma, $\tau = 0$		
Intercept	1.86*** (0.05)	1.86*** (0.05)	1.86*** (0.05)
D_n	0.17** (0.07)	0.30** (0.12)	0.14* (0.07)
D_t	0.05 (0.07)	0.05 (0.07)	0.05 (0.07)
D_nD_t	0.62*** (0.10)	0.89*** (0.17)	0.58*** (0.10)
Observations	541	298	496
Adjusted R-squared	0.254	0.257	0.219
$N_{treated}$	–	'z327', 'z338', 'z347', 'z361'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	86	86	0
$\lvert N_{treated}\rvert$	41	4	37
$\lvert N_h^C\rvert$	26	26	26
Variable	(e) $c_{l,i}$, $h =$ Irma, $\tau = 7$		
Intercept	1.86*** (0.05)	1.86*** (0.04)	1.86*** (0.05)
D_n	0.17** (0.07)	0.19 (0.14)	0.17** (0.07)
D_t	0.15** (0.07)	0.15** (0.06)	0.15** (0.07)
D_nD_t	0.46*** (0.10)	0.54** (0.22)	0.46*** (0.10)
Observations	586	283	564
Adjusted R-squared	0.233	0.086	0.227
$N_{treated}$	–	'z338', 'z361'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	86	86	0
$\lvert N_{treated}\rvert$	41	2	39
$\lvert N_h^C\rvert$	26	26	26
Variable	(f) $c_{l,i}$, $h =$ Irma, $\tau = 28$		
Intercept	1.86*** (0.04)	1.86*** (0.04)	1.86*** (0.04)
D_n	0.17*** (0.06)	0.07 (0.12)	0.19*** (0.06)
D_t	0.27*** (0.06)	0.27*** (0.07)	0.27*** (0.06)
D_nD_t	0.11 (0.09)	0.35** (0.17)	0.07 (0.09)
Observations	542	279	501
Adjusted R-squared	0.144	0.115	0.130
$N_{treated}$	–	'z303', 'z338', 'z347'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	26	26	0
$\lvert N_{treated}\rvert$	41	3	38
$\lvert N_h^C\rvert$	26	26	26

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Figure 8 **Spot rates (\$/mile) vs time relationship for FEMA nodes, hurricane nodes, and corresponding control nodes.**



(a) $c_{l,o}$, $h =$ Harvey, $\tau = 14$

(b) $c_{l,i}$, $h =$ Harvey, $\tau = 0$

(c) $c_{l,o}$, $h =$ Irma, $\tau = -7$

(d) $c_{l,i}$, $h =$ Irma, $\tau = 0$

(e) $c_{l,i}$, $h =$ Irma, $\tau = 7$

(f) $c_{l,i}$, $h =$ Irma, $\tau = 28$

6. Discussion of Results

The results of the difference-in-differences analysis indicate that both Hurricane Harvey and Hurricane Irma, and their corresponding relief activity by FEMA, caused a statistically significant impact on private sector truckload spot rates. Moreover, both the hurricanes made landfall as category 3 storms and had similar qualitative effect on spot rates in terms of magnitude, geographical spread, timing, and duration. The increase in spot rates were not random effects since we account for parallel trends and robustness in our models.

We observe that long-haul inbound spot rates were most affected by the hurricanes. Spot rates for loads inbound to hurricane nodes increased with a larger magnitude compared to outbound loads from those nodes. This could be due to the aggregation of relief demand for inbound shipments, leading to higher competition and rate increases. In contrast, outbound demand could be lower due to disaster conditions, resulting in less competitive pressure. Furthermore, the effect on inbound spot rates extended over a larger geographic radius than outbound rates, suggesting that demand driven factors played a more substantial role than infrastructure related factors in these rate increases. Additionally, the increase in long-haul spot rates persisted for a longer period and over a wider geographic radius compared to short-haul spot rates, possibly because short-haul spot rates are already characterized by their higher magnitude and variance.

We note that FEMA did not affect short-haul spot rates at all. Again, this may be attributed to characteristic higher magnitude and variance of short-haul spot rates or FEMA's relatively low volume compared to the broader market. Meanwhile, nodes with long-haul FEMA loads did have a statistically significant increase in spot rates but it was not continuous throughout the observed weeks. For nodes near hurricanes' paths and with FEMA activity had many weeks with significant impact of the hurricanes without the concurrent FEMA impact on spot rates of the hurricane nodes. Moreover, nodes with FEMA activity but away from the hurricanes' paths had no statistically significant effect in any case.

However, when FEMA cause statistically significant increase in spot rates, the magnitude exceeded that of the hurricane's effect. Furthermore, FEMA's effect coincided with the peak hurricane effects, i.e., close to the hurricanes' landfalls. Long-haul inbound spot rates witnessed a larger increase due to FEMA activity than long-haul outbound rates, perhaps due to higher relief demand to important destinations. In cases where FEMA had a statistically significant effect, it was observed that FEMA paid between 1.75 to 5 times more than the prevailing private sector spot rates. The impact of FEMA on increase in spot rates could be because FEMA's rates were either directly part of the analyzed private sector data-set or FEMA's demand induced carriers to charge higher prices to private sector shippers going to the same destinations. Thus, FEMA's activity adds to the impact of disasters on spot rates, but does not create an effect independently.

7. Conclusion

During disasters, as the demand for truckload transportation to distribute relief supplies increases, the prices to procure transportation also increase due to disaster damage and competition for carrier resources by public and private sector actors. Given the increase in the frequency and intensity of natural disasters, it is important to model the causal impact during historical disasters in order to be better prepared for future ones.

We contribute to disaster management literature by modeling the effects of disasters on a critical shared system, i.e., freight transportation prices. This enables the assessment and planning of transportation procurement even before addressing the allocation and routing of relief supplies. We quantify the magnitude, geographical spread, timing, and duration of the increase in truckload spot rates and find that both hurricanes and their corresponding FEMA activity impacted private sector spot rates. Long-haul inbound rates were the most effected, and the effect was localized in geography close to the hurricane's path as well as limited in duration to periods around landfall dates.

Our results offer valuable insights that shippers may leverage to formulate transportation procurement budgets for disaster shipments, for example, deciding whether to endure higher costs in the short term or to wait for rates to stabilize. For the public sector, our findings identify the severity of the impact on private sector rates and encourage alternative truckload procurement practices to ensure economical relief operations without externalities.

We note a few limitations in our study. First, our analysis is based on only on two specific disasters. However, the methodology can be extended to other events to compare different types of disasters. Next, we do not include node-specific and time-specific control variables. Nonetheless, these variables will help further explain the conditions affecting spot rates. Finally, the data-set includes a subset of the U.S. market, but we believe that the general insights are a starting point for motivating future research.

Additional causal analysis can be done considering effects of disaster categories and conditions, such as amount of cumulative rainfall. Moreover, measuring effects on carrier rejection rates can reveal whether FEMA significantly uses up carrier capacity during disasters. Another avenue to explore is truckload procurement strategies for unplanned high volume of loads, for both public and private sector actors, especially with an emphasis on reducing costs and externalities associated with relief efforts.

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Appendix for "Modeling Causal Effects of Disasters and Disaster Relief Activity on Truckload Spot Rates"

EC.1. FEMA STOS Requirements

To haul goods for FEMA, carriers need to have an operating authority certification from the Department of Transportation, a valid commercial driver's license, a medical qualification card, a Transportation Worker Identification Credential (TWIC), a Standard Carrier Alpha Code (SCAC), cargo insurance coverage of $300,000, obtain a Data Universal Numbering System (DUNS) number, be enrolled in System for Award Management (SAM), sign a Logistics Supply Chain Management System Cloud (LSCMS-C) User Request Form, complete the System Rules of Behavior and User Security Agreement, pass an online LSCMS training course with more than 80% score to get full access to LSCMS, register for Syncada to receive payment, and agree to carry a transponder while hauling the goods when required by FEMA.

EC.2. Causal Effects of Hurricanes - Robustness Checks

Following are the links to robustness results with different control group matching criteria:

1. dynamic time warping matching
2. Euclidean matching
3. all control options

EC.3. Causal Effects of FEMA

In Table EC.1 we tabulate additional results of FEMA's causal effect on truckload spot rates.

Table EC.1: Causal effect of FEMA and hurricanes on spot rates ($/mile).

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
Variable	$c_{s,o}$, $h=$ Harvey, $d=255$ miles, $w=7$, $\tau=0$		
Intercept	4.31*** (0.70)	4.31*** (0.41)	4.31*** (0.71)
D_n	0.47 (0.89)	0.14 (1.44)	0.49 (0.92)
D_t	1.16 (1.02)	0.16* (0.60)	1.16 (1.03)
D_nD_t	−0.78 (1.31)	−0.79 (2.04)	−0.77 (1.36)
Observations	379	165	365
Adjusted R-squared	−0.004	0.005	−0.004
$N_{treated}$	–	'z761'	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	19	19	0
$\lvert N_{treated}\rvert$	47	1	46
$\lvert N_h^C\rvert$	38	38	38
Variable	$c_{s,o}$, $h=$ Harvey, $d=50$ miles, $w=7$, $\tau=14$		
Intercept	4.02*** (0.19)	4.02*** (0.19)	4.02*** (0.21)
D_n	−0.24 (0.26)	−0.24 (0.36)	−0.23 (0.33)
D_t	0.56* (0.28)	0.56* (0.28)	0.56* (0.31)
D_nD_t	−0.12 (0.39)	−0.43 (0.51)	0.26 (0.53)
Observations	62	45	48
Adjusted R-squared	0.090	0.079	0.085
$N_{treated}$	–	‘z781’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	31	31	0
$\lvert N_{treated}\rvert$	5	1	4
$\lvert N_h^C\rvert$	5	5	5
Variable	$c_{s,o}$, $h=$ Harvey, $d=150$ miles, $w=7$, $\tau=14$		
Intercept	4.42*** (0.79)	4.42*** (0.25)	4.42*** (0.81)
D_n	0.94 (1.09)	−0.64 (0.82)	1.10 (1.14)
D_t	0.78 (1.14)	0.78 (0.36)	0.78 (1.17)
D_nD_t	−1.56 (1.57)	−0.65 (1.61)	−1.64 (1.64)
Observations	287	148	273
Adjusted R-squared	−0.007	0.030	−0.007
$N_{treated}$	–	‘z781’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	31	31	0
$\lvert N_{treated}\rvert$	24	1	23
$\lvert N_h^C\rvert$	22	22	22
Variable	$c_{s,o}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=-7$		
Intercept	4.86*** (1.21)	4.86*** (1.75)	4.86*** (1.23)
D_n	−0.51 (1.63)	−0.94 (6.43)	−0.48 (1.69)
D_t	5.47*** (1.89)	5.47** (2.75)	5.47*** (1.93)
D_nD_t	−4.54* (2.44)	−3.98 (9.17)	−4.58* (2.52)
Observations	362	161	348
Adjusted R-squared	0.025	0.008	0.024
$N_{treated}$	–	‘z303’	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	182	182	0
$\lvert N_{treated}\rvert$	41	1	40
$\lvert N_h^C\rvert$	35	35	35
Variable	$c_{s,o}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=14$		
Intercept	4.86*** (0.89)	4.86*** (0.92)	4.86*** (0.91)
D_n	−0.51 (1.20)	−0.94 (3.39)	−0.48 (1.24)
D_t	2.30* (1.35)	2.30 (1.40)	2.30* (1.37)
D_nD_t	−0.47 (1.75)	−1.35 (4.82)	−0.42 (1.81)
Observations	376	168	362
Adjusted R-squared	0.008	0.001	0.007
$N_{treated}$	–	‘z303’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	8	8	0
$\lvert N_{treated}\rvert$	41	1	40
$\lvert N_h^C\rvert$	35	35	35
Variable	$c_{s,i}$, $h=$ Harvey, $d=100$ miles, $w=7$, $\tau=0$		
Intercept	5.24*** (1.52)	5.24*** (0.21)	5.24*** (1.56)
D_n	−1.01 (2.10)	−2.48*** (0.71)	−0.87 (2.20)
D_t	0.27 (2.19)	0.27 (0.31)	0.27 (2.24)
D_nD_t	4.77 (3.09)	0.06 (1.00)	5.42* (3.25)
Observations	275	150	261
Adjusted R-squared	0.010	0.127	0.014
$N_{treated}$	–	‘z787’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	18	18	0
$\lvert N_{treated}\rvert$	16	1	15
$\lvert N_h^C\rvert$	14	14	14
Variable	$c_{s,i}$, $h=$ Harvey, $d=150$ miles, $w=7$, $\tau=0$		
Intercept	5.01*** (1.18)	5.01*** (0.18)	5.01*** (0.20)
D_n	−0.82 (1.63)	−2.25*** (0.67)	−0.71 (1.69)
D_t	0.17 (1.67)	0.17 (0.26)	0.17 (1.70)
D_nD_t	3.71 (2.38)	0.16 (0.95)	4.09 (2.48)
Observations	358	194	344
Adjusted R-squared	0.008	0.086	0.010
$N_{treated}$	–	‘z787’	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	18	18	0
$\lvert N_{treated} \rvert$	24	1	23
$\lvert N_h^C \rvert$	22	22	22
Variable	$c_{s,i}$, $h =$ Harvey, $w = 7$, $\tau = 7$		
Intercept	–	4.12*** (0.27)	–
D_n	–	1.64*** (0.35)	–
D_t	–	0.16 (0.38)	–
$D_n D_t$	–	−0.3 (0.49)	–
Observations	–	24	–
Adjusted R-squared	–	0.586	–
N_{FEMA}	–	‘z224’	–
$\sum_{t \in T_h} \sum_{n \in N_{FEMA}} v_{n,t}$	–	5	–
$\lvert N_{FEMA} \rvert$	–	1	–
$\lvert N_{FEMA}^C \rvert$	–	1	–
Variable	$c_{s,i}$, $h =$ Harvey, $d = 50$ miles, $w = 7$, $\tau = 14$		
Intercept	4.70*** (0.19)	4.70*** (0.18)	4.70*** (0.19)
D_n	−1.30*** (0.28)	−1.86*** (0.39)	−1.07*** (0.31)
D_t	0.34 (0.28)	0.34 (0.27)	0.34 (0.29)
$D_n D_t$	0.08 (0.39)	−0.19 (0.56)	0.07 (0.43)
Observations	107	64	93
Adjusted R-squared	0.275	0.422	0.189
$N_{treated}$	–	‘z781’	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	31	31	0
$\lvert N_{treated} \rvert$	5	1	4
$\lvert N_h^C \rvert$	5	5	5
Variable	$c_{s,i}$, $h =$ Harvey, $d = 150$ miles, $w = 7$, $\tau = 14$		
Intercept	5.01*** (0.21)	5.01*** (0.19)	5.01*** (0.21)
D_n	−0.82*** (0.28)	−2.17*** (0.71)	−0.71** (0.29)
D_t	0.49 (0.30)	0.49* (0.28)	0.49 (0.30)
$D_n D_t$	−0.24 (0.40)	−0.34 (1.01)	−0.24 (0.41)
Observations	381	187	367
Adjusted R-squared	0.053	0.104	0.042
$N_{treated}$	–	‘z781’	–

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	31	31	0
$\lvert N_{treated}\rvert$	24	1	23
$\lvert N_h^C\rvert$	22	22	22
Variable	$c_{s,i}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=-7$		
Intercept	–	6.31*** (0.97)	–
D_n	–	−1.19 (1.28)	–
D_t	–	2.55* (1.39)	–
D_F	–	−0.55 (3.47)	–
D_nD_t	–	−1.09 (1.78)	–
D_tD_F	–	−2.73 (4.91)	–
D_FD_n	–	−2.05 (5.32)	–
$D_nD_tD_F$	–	2.18 (7.51)	–
Observations	–	444	–
Adjusted R-squared	–	0.007	–
N_{FEMA}	–	‘z224’, ‘z361’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	185	–
$\lvert N_h\rvert$	–	41	–
$\lvert N_h^C\rvert$	–	35	–
Variable	$c_{s,i}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=14$		
Intercept	6.31*** (0.87)	6.31*** (0.34)	6.31*** (0.89)
D_n	−1.30 (1.14)	−1.76 (1.29)	−1.27 (1.18)
D_t	−0.20 (1.23)	−0.20 (0.51)	−0.20 (1.25)
D_nD_t	2.20 (1.58)	0.29 (1.82)	2.29 (1.63)
Observations	423	182	409
Adjusted R-squared	0.002	0.002	0.003
$N_{treated}$	–	‘z303’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	8	8	0
$\lvert N_{treated}\rvert$	41	1	40
$\lvert N_h^C\rvert$	35	35	35
Variable	$c_{l,o}$, $h=$ Harvey, $d=255$ miles, $w=7$, $\tau=-7$		
Intercept	1.64*** (0.03)	1.64*** (0.04)	1.64*** (0.03)
D_n	−0.14*** (0.04)	−0.25 (0.16)	0 (−0.13*** (0.04))
D_t	0.00 (0.04)	0.00 (0.05)	0.00 (0.04)

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
D_nD_t	0.06 (0.06)	0.02 (0.22)	0.06 (0.06)
Observations	576	264	562
Adjusted R-squared	0.021	0.006	0.018
$N_{treated}$	–	‘z761’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	97	97	0
$\lvert N_{treated}\rvert$	47	1	46
$\lvert N_h^C\rvert$	43	43	43
Variable	$c_{l,o}$, $h=$ Harvey, $d=255$ miles, $w=7$, $\tau=0$		
Intercept	–	1.64^{***} (0.04)	–
D_n	–	-0.13^{**} (0.05)	–
D_t	–	0.05 (0.05)	–
D_F	–	0.12 (0.12)	–
D_nD_t	–	0.12^{*} (0.07)	–
D_tD_F	–	−0.19 (0.17)	–
D_FD_n	–	−0.24 (0.20)	–
$D_nD_tD_F$	–	0.03 (0.29)	–
Observations	–	594	–
Adjusted R-squared	–	0.025	–
N_{FEMA}	–	‘z170’, ‘z761’, ‘z894’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	175	–
$\lvert N_h\rvert$	–	47	–
$\lvert N_h^C\rvert$	–	43	–
Variable	$c_{l,o}$, $h=$ Harvey, $w=7$, $\tau=0$		
Intercept	–	1.59^{***} (0.09)	–
D_n	–	0.16 (0.13)	–
D_t	–	0.01 (0.13)	–
D_nD_t	–	−0.15 (0.19)	–
Observations	–	56	–
Adjusted R-squared	–	−0.017	–
N_{FEMA}	–	‘z170’, ‘z894’	–
$\sum_{t\in T_h}\sum_{n\in N_{FEMA}} v_{n,t}$	–	10	–
$\lvert N_{FEMA}\rvert$	–	2	–
$\lvert N_{FEMA}^C\rvert$	–	2	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
Variable	$c_{l,o}$, $h=$ Harvey, $d=150$ miles, $w=7$, $\tau=7$		
Intercept	1.74*** (0.04)	1.74*** (0.05)	1.74*** (0.04)
D_n	−0.20*** (0.06)	−0.19 (0.13)	−0.20*** (0.06)
D_t	0.16** (0.06)	0.16** (0.08)	0.16** (0.07)
D_nD_t	−0.09 (0.09)	0.07 (0.20)	−0.12 (0.09)
Observations	311	163	286
Adjusted R-squared	0.108	0.036	0.111
$N_{treated}$	–	'z708', 'z781'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	102	102	0
$\lvert N_{treated}\rvert$	24	2	22
$\lvert N_h^C\rvert$	22	22	22
Variable	$c_{l,o}$, $h=$ Harvey, $d=255$ miles, $w=7$, $\tau=7$		
Intercept	1.64*** (0.04)	1.64*** (0.04)	1.64*** (0.04)
D_n	−0.14*** (0.05)	−0.14 (0.11)	−0.13*** (0.05)
D_t	0.10* (0.05)	0.10* (0.06)	0.10* (0.06)
D_nD_t	0.06 (0.07)	0.10 (0.16)	0.05 (0.07)
Observations	545	270	506
Adjusted R-squared	0.039	0.012	0.035
$N_{treated}$	–	'z708', 'z761', 'z781'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	122	122	0
$\lvert N_{treated}\rvert$	47	3	44
$\lvert N_h^C\rvert$	43	43	43
Variable	$c_{l,o}$, $h=$ Harvey, $d=255$ miles, $w=7$, $\tau=14$		
Intercept	1.64*** (0.04)	1.64*** (0.05)	1.64*** (0.04)
D_n	−0.14** (0.06)	−0.22 (0.15)	−0.13** (0.06)
D_t	0.23*** (0.06)	0.23*** (0.06)	0.23*** (0.06)
D_nD_t	−0.05 (0.08)	0.17 (0.21)	−0.07 (0.08)
Observations	595	282	567
Adjusted R-squared	0.068	0.054	0.063
$N_{treated}$	–	'z761', 'z781'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	1,052	1,052	0
$\lvert N_{treated}\rvert$	47	2	45
$\lvert N_h^C\rvert$	43	43	43

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
Variable	$c_{l,o}$, $h =$ Harvey, $d = 255$ miles, $w = 7$, $\tau = 28$		
Intercept	1.64*** (0.04)	1.64*** (0.05)	1.64*** (0.04)
D_n	−0.14*** (0.05)	−0.25 (0.21)	−0.13*** (0.05)
D_t	0.28*** (0.05)	0.28*** (0.07)	0.28*** (0.05)
D_nD_t	−0.22*** (0.07)	−0.24 (0.29)	−0.22*** (0.07)
Observations	579	273	565
Adjusted R-squared	0.127	0.072	0.122
$N_{treated}$	–	'z761'	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	54	54	0
$\|N_{treated}\|$	47	1	46
$\|N_h^C\|$	43	43	43
Variable	$c_{l,o}$, $h =$ Harvey, $d = 100$ miles, $w = 7$, $\tau = 35$		
Intercept	1.84*** (0.05)	1.84*** (0.05)	1.84*** (0.04)
D_n	−0.39*** (0.06)	−0.41*** (0.11)	−0.38*** (0.07)
D_t	0.24*** (0.06)	0.24*** (0.07)	0.24*** (0.06)
D_nD_t	−0.12 (0.08)	0.12 (0.16)	−0.18* (0.10)
Observations	234	136	206
Adjusted R-squared	0.346	0.194	0.349
$N_{treated}$	–	'z781', 'z782'	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	25	25	0
$\|N_{treated}\|$	16	2	14
$\|N_h^C\|$	15	15	15
Variable	$c_{l,o}$, $h =$ Harvey, $d = 150$ miles, $w = 7$, $\tau = 35$		
Intercept	1.74*** (0.04)	1.74*** (0.04)	1.74*** (0.04)
D_n	−0.20*** (0.05)	−0.31*** (0.11)	−0.18*** (0.06)
D_t	0.24*** (0.06)	0.24*** (0.06)	0.24*** (0.06)
D_nD_t	−0.17** (0.08)	0.12 (0.16)	−0.22*** (0.08)
Observations	322	171	294
Adjusted R-squared	0.178	0.135	0.174
$N_{treated}$	–	'z781', 'z782'	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	25	25	0
$\|N_{treated}\|$	24	2	22
$\|N_h^C\|$	22	22	22

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
Variable	$c_{l,o}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=-14$		
Intercept	–	1.80*** (0.05)	–
D_n	–	−0.25*** (0.06)	–
D_t	–	0.02 (0.07)	–
D_F	–	−0.04 (0.14)	–
D_nD_t	–	−0.04 (0.09)	–
D_tD_F	–	−0.14 (0.20)	–
D_FD_n	–	0.27 (0.24)	–
$D_nD_tD_F$	–	0.38 (0.33)	–
Observations	–	494	–
Adjusted R-squared	–	0.063	–
N_{FEMA}	–	‘z170’, ‘z303’, ‘z894’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	50	–
$\lvert N_h\rvert$	–	41	–
$\lvert N_h^C\rvert$	–	26	–
Variable	$c_{l,o}$, $h=$ Irma, $d=200$ miles, $w=7$, $\tau=-14$		
Intercept	–	1.80*** (0.04)	–
D_n	–	−0.25*** (0.05)	–
D_t	–	0.01 (0.06)	–
D_F	–	−0.04 (0.13)	–
D_nD_t	–	−0.04 (0.07)	–
D_tD_F	–	−0.13 (0.19)	–
D_FD_n	–	0.38* (0.29)	–
$D_nD_tD_F$	–	0.28 (0.27)	–
Observations	–	703	–
Adjusted R-squared	–	0.072	–
N_{FEMA}	–	‘z170’, ‘z303’, ‘z367’, ‘z894’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	76	–
$\lvert N_h\rvert$	–	57	–
$\lvert N_h^C\rvert$	–	36	–
Variable	$c_{l,o}$, $h=$ Irma, $d=200$ miles, $w=7$, $\tau=-7$		
Intercept	1.80*** (0.04)	1.80*** (0.04)	1.80*** (0.05)
D_n	−0.22*** (0.06)	0.02 (0.14)	−0.25*** (0.06)

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
D_t	0.09 (0.07)	0.09 (0.06)	0.09 (0.07)
D_nD_t	0.18** (0.09)	0.48** (0.20)	0.15 (0.09)
Observations	640	329	607
Adjusted R-squared	0.042	0.043	0.043
$N_{treated}$	–	'z303', 'z361', 'z367'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	91	91	0
$\lvert N_{treated}\rvert$	57	3	54
$\lvert N_h^C\rvert$	36	36	36
Variable	$c_{l,o}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=0$		
Intercept	1.80*** (0.05)	1.80*** (0.05)	1.80*** (0.06)
D_n	−0.24*** (0.08)	−0.03 (0.20)	−0.25*** (0.08)
D_t	0.05 (0.08)	0.05 (0.07)	0.05 (0.08)
D_nD_t	0.44*** (0.11)	0.23 (0.29)	0.45*** (0.11)
Observations	433	229	419
Adjusted R-squared	0.077	−0.005	0.076
$N_{treated}$	–	'z303'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	9	9	0
$\lvert N_{treated}\rvert$	41	1	40
$\lvert N_h^C\rvert$	26	26	26
Variable	$c_{l,o}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=7$		
Intercept	1.80*** (0.05)	1.80*** (0.05)	1.80*** (0.06)
D_n	−0.24*** (0.08)	−0.03 (0.21)	−0.25*** (0.08)
D_t	0.25*** (0.08)	0.25*** (0.08)	0.25*** (0.08)
D_nD_t	0.03 (0.11)	0.14 (0.30)	0.02 (0.11)
Observations	477	227	463
Adjusted R-squared	0.071	0.040	0.073
$N_{treated}$	–	'z303'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	29	29	0
$\lvert N_{treated}\rvert$	41	1	40
$\lvert N_h^C\rvert$	26	26	26
Variable	$c_{l,o}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=35$		
Intercept	1.80*** (0.05)	1.80*** (0.05)	1.80*** (0.05)
D_n	−0.24*** (0.07)	−0.05 (0.13)	−0.27*** (0.07)

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
D_t	0.08 (0.07)	0.08 (0.07)	0.08 (0.07)
$D_n D_t$	0.10 (0.10)	0.04 (0.18)	0.11 (0.11)
Observations	458	257	423
Adjusted R-squared	0.043	−0.004	0.051
$N_{treated}$	–	'z302', 'z347', 'z361'	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	51	51	0
$\lvert N_{treated} \rvert$	41	3	38
$\lvert N_h^C \rvert$	26	26	26
Variable	$c_{l,o}$, $h =$ Irma, $d = 200$ miles, $w = 7$, $\tau = 35$		
Intercept	1.80*** (0.04)	1.80*** (0.04)	1.80*** (0.04)
D_n	−0.22*** (0.06)	0.01 (0.11)	−0.26*** (0.06)
D_t	0.10* (0.06)	0.10* (0.06)	0.10* (0.06)
$D_n D_t$	0.02 (0.08)	0.11 (0.16)	0.00 (0.08)
Observations	664	353	616
Adjusted R-squared	0.048	0.009	0.063
$N_{treated}$	–	'z302', 'z347', 'z361', 'z367'	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	61	61	0
$\lvert N_{treated} \rvert$	57	4	53
$\lvert N_h^C \rvert$	36	36	36
Variable	$c_{l,i}$, $h =$ Harvey, $d = 150$ miles, $w = 7$, $\tau = -7$		
Intercept	1.76*** (0.06)	1.76*** (0.07)	1.76*** (0.07)
D_n	0.04 (0.08)	0.15 (0.18)	0.02 (0.09)
D_t	0.02 (0.09)	0.02 (0.10)	0.02 (0.09)
$D_n D_t$	0.03 (0.12)	0.00 (0.25)	0.04 (0.13)
Observations	314	162	286
Adjusted R-squared	−0.005	−0.009	−0.008
$N_{treated}$	–	'z708', 'z781'	–
$\sum_{t \in T_h} \sum_{n \in N_{treated}} v_{n,t}$	121	121	0
$\lvert N_{treated} \rvert$	24	2	22
$\lvert N_h^C \rvert$	22	22	22
Variable	$c_{l,i}$, $h =$ Harvey, $d = 255$ miles, $w = 7$, $\tau = 0$		
Intercept	1.82*** (0.05)	1.82*** (0.05)	1.82*** (0.05)
D_n	−0.07 (0.06)	−0.01 (0.14)	−0.08 (0.06)

Standard errors are in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
D_t	0.11 (0.07)	0.11 (0.07)	0.11 (0.07)
$D_n D_t$	0.17^{*} (0.09)	0.41^{**} (0.20)	0.15 (0.10)
Observations	583	278	549
Adjusted R-squared	0.038	0.041	0.031
$N_{treated}$	–	'z713', 'z761', 'z781'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	$1,008$	$1,008$	0
$\lvert N_{treated}\rvert$	47	3	44
$\lvert N_h^C\rvert$	43	43	43
Variable	$c_{l,i}$, $h=$ Harvey, $d=100$ miles, $w=7$, $\tau=7$		
Intercept	–	1.54^{***} (0.07)	–
D_n	–	0.14 (0.10)	–
D_t	–	0.19^{*} (0.10)	–
D_F	–	-0.10 (0.23)	–
$D_n D_t$	–	0.40^{***} (0.14)	–
$D_t D_F$	–	-0.04 (0.31)	–
$D_F D_n$	–	0.58^{*} (0.30)	–
$D_n D_t D_F$	–	0.17 (0.40)	–
Observations	–	260	–
Adjusted R-squared	–	0.315	–
N_{FEMA}	–	'z283', 'z781', 'z787'	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	101	–
$\lvert N_h\rvert$	–	16	–
$\lvert N_h^C\rvert$	–	15	–
Variable	$c_{l,i}$, $h=$ Harvey, $d=150$ miles, $w=7$, $\tau=7$		
Intercept	–	1.76^{***} (0.7)	–
D_n	–	0.00 (0.10)	–
D_t	–	0.15 (0.10)	–
D_F	–	-0.32 (0.25)	–
$D_n D_t$	–	0.40^{***} (0.14)	–
$D_t D_F$	–	0.00 (0.35)	–
$D_F D_n$	–	0.72^{**} (0.33)	–
$D_n D_t D_F$	–	0.17 (0.44)	–
Observations	–	328	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
Adjusted R-squared	–	0.198	–
N_{FEMA}	–	‘z283’, ‘z781’, ‘z787’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	101	–
$\|N_h\|$	–	24	–
$\|N_h^C\|$	–	22	–
Variable	$c_{l,i}$, $h=$ Harvey, $d=50$ miles, $w=7$, $\tau=35$		
Intercept	1.94*** (0.08)	1.94*** (0.08)	1.94*** (0.10)
D_n	0.07 (0.13)	0.08 (0.13)	0.05 (0.26)
D_t	−0.25** (0.11)	−0.24** (0.10)	−0.24* (0.13)
D_nD_t	0.42** (0.16)	0.44** (0.18)	0.42 (0.30)
Observations	51	40	37
Adjusted R-squared	0.272	0.291	0.174
$N_{treated}$	–	‘z781’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	136	136	0
$\|N_{treated}\|$	5	1	4
$\|N_h^C\|$	5	5	5
Variable	$c_{l,i}$, $h=$ Harvey, $d=150$ miles, $w=7$, $\tau=35$		
Intercept	1.76*** (0.06)	1.76*** (0.08)	1.76*** (0.06)
D_n	0.04 (0.08)	0.26 (0.25)	0.02 (0.09)
D_t	0.14 (0.09)	0.14 (0.11)	0.14 (0.09)
D_nD_t	0.08 (0.12)	0.05 (0.36)	0.08 (0.12)
Observations	320	149	306
Adjusted R-squared	0.031	0.011	0.028
$N_{treated}$	–	‘z781’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	136	136	0
$\|N_{treated}\|$	24	1	23
$\|N_h^C\|$	22	22	22
Variable	$c_{l,i}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=-7$		
Intercept	–	1.86*** (0.04)	–
D_n	–	0.23*** (0.06)	–
D_t	–	0.06 (0.07)	–
D_F	–	−0.42** (0.21)	–
D_nD_t	–	0.32*** (0.09)	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	Hurricane	FEMA	Hurricane \ FEMA
D_tD_F	–	0.13 (0.29)	–
D_FD_n	–	−0.01 (0.25)	–
$D_nD_tD_F$	–	−0.40 (0.34)	–
Observations	–	530	–
Adjusted R-squared	–	0.198	–
N_{FEMA}	–	‘z283’, ‘z303’, ‘z317’, ‘z361’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	470	–
$\lvert N_h\rvert$	–	41	–
$\lvert N_h^C\rvert$	–	26	–
Variable	$c_{l,i}$, $h=$ Irma, $d=250$ miles, $w=7$, $\tau=-7$		
Intercept	–	1.86*** (0.04)	–
D_n	–	0.13** (0.06)	–
D_t	–	0.13** (0.06)	–
D_F	–	−0.42* (0.23)	–
D_nD_t	–	0.12 (0.08)	–
D_tD_F	–	0.06 (0.31)	–
D_FD_n	–	0.03 (0.26)	–
$D_nD_tD_F$	–	−0.19 (0.36)	–
Observations	–	803	–
Adjusted R-squared	–	0.084	–
N_{FEMA}	–	‘z283’, ‘z291’, ‘z303’, ‘z317’, ‘z361’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	633	–
$\lvert N_h\rvert$	–	72	–
$\lvert N_h^C\rvert$	–	43	–
Variable	$c_{l,i}$, $h=$ Irma, $d=200$ miles, $w=7$, $\tau=0$		
Intercept	1.85*** (0.05)	1.85*** (0.04)	1.85*** (0.05)
D_n	0.15** (0.06)	0.30*** (0.11)	0.12* (0.07)
D_t	0.10 (0.07)	0.09 (0.06)	0.10 (0.07)
D_nD_t	0.49*** (0.09)	0.73*** (0.16)	0.46*** (0.10)
Observations	714	381	655
Adjusted R-squared	0.189	0.205	0.158
$N_{treated}$	–	‘z327’, ‘z334’ ‘z338’, ‘z347’, ‘z361’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	123	123	0

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

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Table EC.1 – continued from previous page

Treated Group	**Hurricane**	**FEMA**	**Hurricane \ FEMA**
$\lvert N_{treated}\rvert$	57	5	52
$\lvert N_h^C\rvert$	36	36	36
Variable	$c_{l,i}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=14$		
Intercept	1.86*** (0.05)	1.86*** (0.04)	1.86*** (0.05)
D_n	0.17** (0.07)	−0.43** (0.20)	0.20*** (0.07)
D_t	0.21*** (0.07)	0.21*** (0.07)	0.21*** (0.07)
D_nD_t	0.34*** (0.10)	0.10 (0.28)	0.35*** (0.10)
Observations	562	259	548
Adjusted R-squared	0.205	0.056	0.222
$N_{treated}$	–	‘z303’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	11	11	0
$\lvert N_{treated}\rvert$	41	1	40
$\lvert N_h^C\rvert$	26	26	26
Variable	$c_{l,i}$, $h=$ Irma, $d=150$ miles, $w=7$, $\tau=35$		
Intercept	–	1.86*** (0.04)	–
D_n	–	0.20*** (0.06)	–
D_t	–	0.22*** (0.06)	–
D_F	–	−0.08 (0.15)	–
D_nD_t	–	0.02 (0.08)	–
D_tD_F	–	0.02 (0.21)	–
D_FD_n	–	−0.54** (0.24)	–
$D_nD_tD_F$	–	0.15 (0.33)	–
Observations	–	578	–
Adjusted R-squared	–	0.113	–
N_{FEMA}	–	‘z303’, ‘z940’, ‘z945’	–
$\sum_{t\in T_h}\sum_{n\in N_{treated}} v_{n,t}$	–	92	–
$\lvert N_h\rvert$	–	41	–
$\lvert N_h^C\rvert$	–	26	–

Standard errors are in parentheses. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.