

The impact of special events on the freight spot market

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Abstract

The United States freight spot market moves in patterns consistent with general economic fluctuations within the broader macro-economy. While the spot market does follow general trends, there is an underlying belief that pricing fluctuations occur as a result of external events. These external events, such as natural disasters, market holidays, terrorist attacks, etc., all fall into the category of “special events” due to their ability to gain a physical presence that alters socio-economic interactions. Socio-economic interactions change the market, but there has been little research into the effect that these special events have on the freight spot market. The aim of this study was to determine the underlying correlation between special events and the spot market and to discern any recognizable patterns that could help the solution providers craft effective strategies to respond to special events. A temporal-spatial multi-variable linear regression model was developed using historical spot market transactions provided by the solutions provider. The model’s results were transferred into a heat map, which was compared against a heat map of the actual values. After testing through 20 models and 3 key performance indicators, no linear correlation could be established. The highest correlation (R^2) value was 0.147, which was observed in the model, Outbound Volume for Hurricane Harvey, and the lowest was 0.014, which was observed in the model, CPM for Hurricane Matthew. Linear regression has been the historical modeling technique for spot market rates, but now that the field is beginning to expand into physical and temporal regions of freight understanding, linear regression does not have the capacity to recognize the nuances that extend beyond basic economic principles. While linear regression did not provide a strong correlation between special events and the spot market in this study, future testing utilizing nonlinear techniques, such as neural networks and machine learning, is likely to produce better correlation results.

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God. Family. Friends. I love you.

Toni, you are beyond the degree. Tito, thanks for bearing with dad. Roseline, great companion. Adam, you are a bar raiser, thanks for coping with me.

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A man without passion, hopes, and dreams sounds like a robot to me.

“Friends are Family.” It’s been a blast Sunkanmi.

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1.0 INTRODUCTION

Operations in the transportation industry tend to focus on reliability, contract-fulfillment, and cost-reduction. These three key factors are at the center of the industry and are delineating metrics of whether a carrier will survive. Freight transportation as an industry was responsible for over \$738.9 billion in gross revenue in 2016 (Trucking.Org, 2018). Not only does this figure equate to nearly 8% of the United States' GDP, but it is also a major sector for employment with over 700 thousand active carriers in 2016 (Trucking.Org, 2018). With such a large industry it becomes important to recognize datasets that affect the sector through analytic synthesis. In general, the spot market provides an avenue for transactions based on a specific commodity that is traded in exchange for goods provided. Freight spot markets take that general concept and further delineate it into carriers providing transport services to shippers. Third-Party Logistic firms (3PL) provide services for deal brokering between the carriers and shippers when contracts are either dropped or not yet created. The project focuses on the interactions between shippers, carriers, brokers, and this data-driven entity known as the spot market. Using historical data from a service provider in North America, the project attempts to identify and quantify the temporal-spatial impact of external events, like hurricanes, floods, etc., on the truckload (TL) spot market.

The freight spot market is dynamic. Dynamic changes in spot market rates have been recently observed due to the “tightening” of the market. Spot market fluctuations are often a result of general socio-economic factors within the U.S., an example of this can be seen from the Recession of 2008. The Recession saw the previous peak of the tight market trend towards an oversaturation of the market that would last until 2010 (Pickett, 2018). Socio-economic events are generally expected to cause spot rate fluctuations, but other unseen forces could be just as effective in manipulating the market. These unexpected occurrences will be called “special events” because their presence in the physical realm is potentially affecting the economic market. The special events' appearance and effects drastically fluctuate based upon their severity, which is usually determined by how it changes the infrastructure, local populace, and economy of the region in which it appears. The most recognizable special events are natural disasters,

like those reviewed earlier but the harvest season, Amazon Prime Day, 9/11, and Black Friday are other events that could be included due to their potential impact on the market. No two special events are the same, and each would have differing effects on the economy that are based upon that event's severity and location. Natural disasters are simple to recognize, but due to the specific nature of most economic and market-based data sets prevalent in the freight spot market, they are not easily correlated with price fluctuations. Correlations between the spot market and natural disasters are tenuous because of the disaster's regionalization, and the macro scale of economies.

In order to better understand transportation spot markets, forecasting models such as multiple regression and ARIMA are being used to "predict the future" (Bai, 2018). These forecasting models, along with others, attempt to estimate future market prices by aggregating different fields of data to return an estimation that will potentially be the future price of the shipping rate within a certain range of error. This research attempts to correlate changes in the transportation spot market with occurrences of random special events and identify predictable patterns in the associated spot market rate costs.

Special events are as varied as the freight market dynamics that they potentially affect. Such special events like natural phenomena, and holidays take their toll on the responsiveness of the freight industry during such events. The natural events are often unplanned and may come as a disaster or uncontrolled change in an ecosystem. The planned events, e.g. Black Friday or Amazon Prime Day, are accompanied by increased human activities with great impact on logistics infrastructures. Our research provides insight into how the freight market should respond to the short-term supply/demand imbalance caused by these unpredictable special events.

Currently, there is a gap in knowledge regarding the relationship between spot market rate price fluctuations and special events. Determination of how the FEMA data should be used to represent the special is evident in the limitation presented by the surrogacy issues. This issue primarily revolves around determining whether the acquired event data should be related to a binary instance or can be expressed

explicitly, e.g. wind velocity. The use of surrogate data sets to represent the special event should be relatable to our corporate sponsor's data source using MySQL and Python. Upon completion of data aggregation, the resultant data is mappable and synthesizable through the use of multivariable linear regression. Sources of data include those available in public spaces relating to natural events, information from disaster management agencies, and first responders' records of events. Such information may include period, locale, duration and relevant announcements relating to the occurrence of events like hurricanes, tornadoes, floods and other adverse weather reports.

In order to provide answers to the research questions, metrics relating to price and volume are used to estimate the effect of these special events. The synthesized data provides opportunities to visualize and map the trends shown by the metric-special event correlation through the utilization of "heat maps." These trends are focused on the influences of special events on spot market rates and provide a glimpse into their realistic forecast by showing predictable patterns in their costs. The remainder of this report is organized as follows: chapter 2 is the literature review, chapter 3 is the methodology, chapter 4 contains the results, and chapter 5 is the conclusion, the appendix contains the compilation of all models.

2.0 LITERATURE REVIEW

While building a background within the field of freight transportation, the vast amount of resources within the field helped to shape the process through which the analysis of our corporate partner's data was synthesized. The following topics were used to not only further personal understanding, but also further develop the idea of a spatial-temporal regression model.

2.1 Truckload Rates

Trucking is the most prevalent mode of freight movement in the United States, collecting \$641 billion in revenues in 2012, compared to \$80.5 billion by rail the same year (A.T. Kearney, 2018). Historically, freight rates have revolved around two key factors, distance and time. Rate estimation errors can be reasonably projected by using external explanatory variables that are separate from the primary variable if the two variables have similar absolute error values (Ballou, 1991). By recognizing that external factors can be accounted for through error projections, organizations can produce strategic plans with more reliable rate estimates. The external factors that produce the "more reliable rate estimates" are being extrapolated upon and will be the special events that are guiding our research.

These reliable rate estimates are the primary decision factor for the acceptance of a load by the carrier. After a load is accepted by a carrier, the shipper may incur cost penalties when negative patterns, such as late loads and over-weight loads, cause the carrier to deviate from their norm (Caldwell & Fisher, 2008). With optimization of transportation forecasting, reduction of time between tenders, and the management of expensive outlier costs, a shipper will notice a reduction in load costs. This reduction of load costs helps to ensure that rate estimates remain constant for consistent loads.

2.2 Sectors of Influence Truckload Rates

The influence of the United States government has created modest changes in the transportation industry due to increasing regulations that limit the influence of the private sector. In the midst of this struggle are infrastructure quarrels that become mired between private sector wants and public sector necessities. This battle "inhibits revenue-generating projects for both entities and stifles the development

of a deterministic market (Eisenack, Stecker, Reckien, & Hoffmann, 2012).” Fortunately, the United States’s deterministic market includes an adaptive system management approach focused on the ever-changing nature of risk. The market uses transportation as a predetermined smoothing mechanism. By updating the infrastructure used by the freight movement industry, it provides adaptation opportunities that are pre-built into the system and account for fluctuations provided by significant events, such as natural disasters or above-average traffic density (Meyer & Weigel, 2011). The inter-relationship between the public and private sectors and their effect on the marketplace could potentially skew the truckload rates being researched.

2.3 Regression Models

Regression modeling is prevalent within the academic sphere because it recognizes pattern-fit between defined data points and externally applied variables. Through regression, correlations between the variables and defined data are presented through multiple outputs which are synthesized holistically (Kleinbaum, Kupper, Nizam, & Rosenberg, 2013). Linear regression is a form of regression that has been used to provide short term and mid-term forecasts resulting from future forecast values and their error when combined with forecast accuracy results (Yang, 2015). Freight transportation demand (FTD) is an associate factor that determines spot market pricing, as it is based on the availability of capacity within the market. This capacity’s regionality created discrepancies when Yang (2015) attempted to fit a multiple linear regression, a nonlinear regression, and a simple linear regression with real freight volume in Shanghai. The utilization of a multiple linear regression model will be used to determine the temporal-spatial correlations within the datasets. A multivariable linear regression (MLR) will make it possible to differentiate the distance and time variables, providing outputs on the individual effect of each variable and the associated data prediction

2.4 Forecasting Models

The freight community is deeply interested in forecasting spot market rates. The development of forecasting models based on the recognition that the spot market is volatile has relatively new roots.

Traditional forecasting models are unable to accurately predict rate changes, remaining uncorrelatable even with the addition of historic contract rates and volumes. As an example, a discrete-time non-linear system was developed to determine the equivalency of fit when provided real data (Chen, Billings, & Grant, 1990). Budak, Ustundag, and Guloglu (2017) continue the forecasting research through a mixture of artificial neural networks (ANN) and a quantile regression model to help determine the route-based approach that accurately determines pricing models. The ANNs and quantile regression model were able to determine risk and price fluctuations but they could not recognize small variations in data that suddenly changed from government changes, economic instability or other external factors (Budak, Ustundag, & Guloglu, 2017). The most accurate spot forecasts remain constrained to a seven-day time window through the use of a NARX model (Bai, 2018). While long-term forecasting remains beyond-reach, it is not deterring organizations from developing long-term contracts. Long-term service contracts provide shippers and carriers the ability to pre-determine responsibilities and rates for shipments without the worry of utilizing spot market rates. But the procurement of long-term contracts removes the possibility of marketplace changes, which can potentially negatively affect the shipper, the carrier, or both. While the volatility of the spot market presents its own faults, it does closely mirror the market and can provide shippers and carriers positive revenue due to a spatial-temporal match through a double-auction system. In this system, a shipper's demand moves with the minimum freight prices which incorporate systemic and stochastic components as well as other external factors (Garrido, 2007). The minimum freight prices associated with shipper demand provides an alternative method to forecasting in the determination of spot market rates. While the scope of this research does not cover forecasting, it is important to recognize the potential models that attempt to estimate future rates in order to better understand historic rate determinations.

2.5 Weather Impacts on Transportation

Transportation infrastructure and traffic patterns are being affected by recent changes in global weather patterns. Affected areas are beginning to track and record how weather is beginning to constrain the regional modes of transportation. The transference of geography-based weather analytics that revolve around urban centers shows a marked decrease in traffic flow even after minor weather events. Minor

weather events such as thunderstorms, snow-showers, and rain-showers provide common examples of minor changes in traffic patterns through a local system. Although decreased traffic flow would normally positively affect the movement of freight, we see delays due to outdated infrastructure models that are based on historical weather forecasts (Suarez, Anderson, Mahal, & Lakshmanan, 2005). These delays are compounded when the severity of the weather event increases. Natural disasters have the ability to leave lasting impacts that affect the freight community multi-dimensionally through deep-tier impacts on sellers and damages to public infrastructure. These freight disruptions could be avoided by improving “vulnerability assessment and disaster management” while concurrently developing disaster preparedness plans for freight movement (Chu, 2016). These preparations are starting to be conducted by disaster organizations such as FEMA (Chu, 2016). The impacts of weather and natural disasters on spot market rates are a major focus of this project and understanding how the natural world affects infrastructure can help to provide reasons for why rates increase during these events.

2.6 Impacts of planned events on transportation

Apart from weather incidents, which are unplanned, transportation and freight activities are largely affected by planned social events. Notable events in the United States include Thanksgiving night, Black Friday, Cyber Monday, the Christmas season, and school resumption. According to a 2016 survey by the National Retail Federation (NRF), “137.4M consumers plan to shop Thanksgiving weekend”. David Berk in his article, (“How Black Friday Impacts the Trucking Business,” 2016), noted that consumers spend in excess of \$2B in 2014 over the Thanksgiving weekend. The spike in sales cuts across traditional stores and online stores in the retail business. As sales spike, there is an increase in the volume of freight requirements throughout the region, creating a potential for freight prices to increase in correlation with volume increases.

In the United States, there are known periods when sales will spike. The largest period of freight volume is from September through to December, which is created by an increase in inventory stock up by retailers, leading to more demand on the supply chain. During this period, the effect is equally apparent from raw material supplies to the manufacturing plants (upstream) and from the manufacturing plants to

the retailers (downstream). Although the upstream segment experiences the inventory push in a longer time horizon (say months), the downstream build up is in a matter of weeks. One notable impact of this change in dynamics is more volume for the carriers and the trucking companies to handle, creating the potential for increased profits.

2.7 US Freight Market

The United States transportation sector is a significant portion of the country's overall GDP and workforce. Gross tonnage is being transported through a sector that has over 700 thousand representative firms is being fueled by a consumer-based market that consistently wants more. This large sector based around vehicular movement is dependent on the public infrastructure and its ability to recognize potential areas of stress and compensate for them. It becomes imperative to provide an exchange place for goods and services that follows current trends based on consumer needs and the market. The freight spot market developed from this need and it has the potential to be fluctuated by events that are not common. These uncommon events, or special events, create discord in the system and change the way shippers, carriers and brokers interact. There is a gap in the process, fueled by a common thread of uncertainty around the scope of how "special events" affect the system. An ability to bridge the gap is available through the incorporation of forecast modeling into a set of aggregate data that spans a time-period where these special events occurred. By using data and correlating it to the occurrence of "special events," there can be a reconciliation between the abnormal trends in spot market forecasts and the expected trend when incorporating a special event.

3.0 METHODOLOGY

3.1 Project Scope

Our project evaluates the impact of special events on the truckload freight market in the United States. Using historical data, we built a model that can be used to measure the impacts created by special events on market rates. Full truckload (FTL) service is a mode of land transportation in which the truck carries the dedicated shipment from point A to point B. FTL services are popular with shippers who want to have control of their transportation scheduling. The shipper is the entity that owns or is responsible for the freight. Using the FTL service gives the shipper flexibility to determine when the trucking service is executed. The study did not incorporate multi-lane shipments, this exclusion removes the cost of labor required for load exchanges stops in between points, stabilizing the costs per route.

The impact of special events on FTL services is reflected in how much it costs to acquire the service. The scope of our project is limited to spot market rates. Spot market rates are instantaneous rates obtained from the carrier at the time of the request. The rates are based on distance to be traveled, premised on FTL. This implies that the rates are independent of the weight of the freight to be transported. However, whenever there is a special event, the quoted spot market rates change. The project builds a predictive model using historical broker transaction data to evaluate how the spot market rates change in response to special events. A broker is the contracted agent who acquires shipment services on behalf of a shipper. The broker will default to spot market rates whenever there are no contracted rates for the routes under consideration.

3.2 Identifying the relevant metrics

The US freight market is characterized by metrics, which may include distance traveled per truck, volume of freight per period, average costs per mile traveled, load rejection rate, truck concentration, and availability. However, the metrics may experience deviations when there is a special event. Special events that affect the freight market are either planned or unplanned. As discussed in the introduction, unplanned events are dynamic, and are forecasted based on available weather reports. These two categories of events

affect the freight market's response in terms of costs. These events may lead to unpredictable impacts as a result of increased activities either around the location of occurrence or in adjacent regions. As mentioned earlier, we will build a predictive model able to forecast the change in spot market rates whenever there is a special event. The model will use relevant metrics as the independent variable.

3.3 Creating the network

The US freight market has infrastructural attributes that can be used to characterize the point-to-point connection between two or more regions. This point-to-point connection is referred to as a lane. The intersections of lanes with points, referred to as nodes, comprise the basic structure of a freight network. Freight networks are delineated by their design needs and are split into three types: physical, operational, and strategic. We used our corporate partner's existing operational network as the optimal method to determine wide-ranging disruptions amidst geographically dispersed regions. Data aggregation inside single lane networks provides the ability to generalize regionality and bypass the potential individual variables inherent in describing multi-lanes. Furthermore, the ability to generalize locations with the singular lane/double node combination incurs less deviation when determining factors such as distance, freight weight, cost, and truck availability. As lane utilization stabilizes, it becomes possible to recognize trends that cause the lane average to fluctuate in terms of volume and cost-per-mile. Fluctuations in the key performance indicators provide a lens through which special events can be recognized as deviations from the norm.

3.4 Analyzing the data

Our research used transactional data from logistics operations and records of special events to develop a spatial-temporal regression model. The data is used as a representative sample of FTL operations in the United States. The special event logs were obtained from the Federal Emergency Management Agency (FEMA) operations. After reviewing the FEMA data, we focused the numerous data logs of previous natural disasters by selecting only four FEMA declared disasters. These disasters were chosen according to two primary factors: disruption cost and pre-event warning. The pre-event warning was

chosen due to the ability for potentially affected regions to prepare for the special event, providing the highest potential to see change saturate from the social sphere and affect the economic realm. Disruption cost plays an enormous role in recovery operations and can be a semi-tangible determinant of impact. After determining which events we would pursue, corollary data within the corporate sponsor's dataset was located. The third party service provider's data needed to be grouped into relatable tables using distance and trailer type as the delineating factors. Those two factors were used to create four tables, the largest being long haul (greater than 250 miles), dry van (base 53' trailer). The largest table was also determined to be the most viable for further analysis due to its high volumes and consistent cost per mile rates. As the analysis expands, trend recognition along relevant metrics will be used to develop a model that describes the changing parameters based on geodata and time lapse.

3.5 Data cleaning

Building a good model requires data consistencies. A given dataset is considered consistent if it is void of missing values or unexplainable outliers which may create misleading information. Before modeling, the dataset was cleaned and made consistent using appropriate data re-engineering methodologies. Working with the original dataset provided by the partner, a preliminary analysis of the data was conducted to determine if there were any underlying patterns that could be established. Further study of the entries showed inconsistencies in zip code representations, non-standardization of region nomenclature, negative prices, and distances of zero in some cases, these were categorized as bad data. After further engagements with the sponsor and MIT's team, it was agreed on variables that were not significant for the analysis and could be removed in addition to the identified bad data. Information such as whether a load was hot or not (indicating urgency), hazmat conditions, Free-On-Board (FOB) designation and trips with multiple stops were removed from the working data.

After the removal of this extraneous data, the newly cleaned data was broken into four new tables. To more easily conduct analysis within homogenous groups, the new tables differentiated between dry trailers and refrigerated trailers. The working data was further divided into short haul or long haul using the

250-mile industry standard as a benchmark. Travel distances of up to 250 miles were classified as short haul. The classification was based on the possibility of same-day return trips without violating the maximum travel time allowed for drivers by law. Trips above 250 miles most likely take more than a day so pricing will be different from same-day return trips. Further solidifying the decision to split the data, cost standard deviations declined among each of the groups when compared to the cost standard deviation of the singular table. The standard deviation reductions provided evidence that the data cleaning and consolidation had been successful. With the newly cleaned data, the results would have fewer errors and provide a better understanding of how our tests for special events affected the aggregated data sets.

3.6 Data synthesis

With a general idea of the temporal-spatial regression model, and a cleaned data set that measured in excess of 6.98 million data points, the team began conducting further analysis. In order to recognize temporal changes, the date-based data points needed to be aggregated into larger units that could present a calmer representation of the experienced average. Sequential remediation along the temporal axis and the data points' necessity for aggregation led to a MySQL query that associated all of the data points with their "load dates" week number and year. Another MySQL query was then used to correlate all of the data within each cluster and sort it according to week. Weekly clustering allows seasonality and temporal trends to appear while also providing the ability to incorporate binary designators to the generalized time of when the special events occurred. The emergence of trends in relation to the binary special event designators along the temporal sphere would provide the potential for synthesis of the outliers to occur.

Next, the spatial data points were grouped within associated geographic regions. The partner service provider had previously generated a cluster map that had regional groups within a system of 136 distinct clusters. The cluster references were used to aggregate the volume and cost for the trips. To provide a reference point for each cluster, a centroidal value for the cluster based on density was created. This value was then used to assign a tangible physical location to the partner's proprietary clustering system which acted as the aforementioned reference point. Cluster density was determined by the relational load volume

of each zip-code within the region. The zip code with the highest volume was used as the centroid for the cluster. Python was used to find the longitude and latitude of each cluster and determine their corresponding distances, in miles, with the Great Circle formula, creating a distance map in the process. The circuitry factor, inherent in the formula, adjusts for the actual travel distances based on connectivity of the road network for the region under consideration and is shown by the mirrored results of a distance map.

With the distance and transaction cost known, cost per mile became a viable metric of interest that could be leveraged to capture and measure spot market behavior. The aggregate volumes and costs per mile were calculated by averaging the values of the individual locations within the region over the years of interest. Given that the average volume and cost per mile were calculated for each region, the spatial characteristics of the outbound and inbound costs and volumes were readily definable within the same region. The time effect of the costs and volume metrics were evaluated on a per week basis to synthesize the models in order to discern any possible patterns from the weeks before and after the incident. Any dissipation of the effects of costs and volumes over time were also tracked so as to more effectively define the temporal behavior of the model.

“Special events,” while physically observable, are relatively ambiguous when transferred into the database space. The many characteristics that represent hurricanes, like wind velocity and rainfall, are easily quantifiable and incorporated into singular datasets, but there is little more than binary designators when attempting to depict the whole. FEMA’s dataset provided the temporal-spatial information required to binarize impact areas. While defining the spatial characteristics, the service provider’s cluster map, cluster region/number sheet, and Google had to be used in order to transform FEMA’s County/State characteristic into the service provider’s cluster characteristic. A binary matrix was created from the temporal-spatial relationships with regards to disaster occurrences in the United States within the eighteen-week timespan surrounding Hurricane Harvey. Hurricane Harvey was chosen to determine if there exists any correlation between the event that happened and the observed effects for two reasons. First, the Hurricane affected the Texas area which happened to have sizable traffic that can be used as a representative

sample for the evaluation of the impact of the event on the cost of freight. Second, there was a significant change in the volume of freight to and from the Texas area during around the occurrence period compared to similar Hurricanes that affected a different part of the country

After the development of the temporal-spatial and binary matrices, data normalization was required in order to create a desirable model with less noise, yet representative of the reality. The first step to normalization came in the form of yearly splits, separating data for 2012 through 2018. After splitting, the 2012-2016 datasets were averaged together and used as the baseline for the normalization. Next, a comparison of the normalized data for costs and volumes between the years of 2012 to 2016 was used to determine the amount of change over the course of a special event. Using the 2012 to 2016 data, we developed a regression model from the training datasets using time and distance as the independent variables. Datasets for 2017 and 2018 were then used as the testing data for the model derived from the training data. The test was done by comparing the data of 2017 and 2018 against their arithmetic means to determine the ratio of comparison. The comparison ratio provided a normalized view of the dataset without removing outliers. This method was used to determine the outbound cost per mile, outbound volume and inbound volume of all the data within the long-haul dry van dataset. Normalization of the data throughout all the distinct tables helps to keep a stable universality when comparing the otherwise distinct data, paving the way for easier trend recognition.

3.7 Modeling

After the data normalization, the next step was to extract the correct data within the determined timespan and throughout the entire cluster range. An initial range of eighteen-weeks was determined to be used as the baseline, as it would provide visibility on any changes occurring amidst the key performance indicators, both five weeks before and twelve weeks after the event. A subsequent test was conducted utilizing only the data from the event's occurrence up to twelve weeks post-event. After the appropriate data had been collected from three separate consolidated matrixes of cost-per-mile, inbound volume, and outbound volume, it was input into an Excel sheet that was used to conduct the regression technique. The

d represents distance, and t represents time, with each β acting as a representative for the corresponding coefficient.

$$Y = \beta_0 + \beta_1d + \beta_2d^2 + \beta_3t + \beta_4t^2 + \beta_5td \dots \dots \dots \text{Eq. 1}$$

In later testing, a binary dummy variable was included within the equation and tested with the same multivariable regression technique as previously described, with e representing the binary variable. The e is used to represent any special event determined from the FEMA database that was input into the binary map.

$$Y = \beta_0 + \beta_1d + \beta_2d^2 + \beta_3t + \beta_4t^2 + \beta_5td + \beta_6e \dots \dots \dots \text{Eq. 2}$$

The equation would later be modified to remove the last two β terms due to near zero coefficients.

$$Y = \beta_0 + \beta_1d + \beta_2d^2 + \beta_3t + \beta_4t^2 \dots \dots \dots \text{Eq. 3}$$

The multivariable linear regression's (MLR) results were then used to generate a heat map that represents the temporal-spatial relationship as presented through the regression equation. Distance buckets with 100-mile intervals were used along a row, these generalized evenly spaced clusters and reduced the table width. Time intervals in relation to the event's occurrence populated columns from -5 to 12 or 0 to 12 depending on the model. A secondary matrix is used when involving the binary designators, it follows the same layout as the model heat-map explained above. Once the rows and columns are created, a pivot table should be used to populate the actual data into a heat map. This heat map is used to recognize any visually apparent trends between the models. After the "actual" heat map is created, the regression equation is input into the first cell within the matrix, and it uses the summary output results to auto-populate the rest of the map. Each key performance indicator will have two maps, one is created from the actual data, and the other is built from the results of the regression model. This process was conducted for Hurricanes Harvey, Matthew, Florence and Irma, and it has the potential for future repeatability. The heat maps were then used to determine the relationship between the freight spot market and special events.

4.0 RESULTS

4.1 Initial results from regression

The following analysis is derived from the initial regression model, the model used Hurricane Harvey as the special event due to its pre-event warnings and high disruption cost. As the model developed around the key performance indicators of cost per mile and volume, the associated indices changed with regards to their temporal-spatial relationship to the event. Unfortunately, the regression model's independent variables explained only a small percentage of the forecast, as indicated by the low adjusted R^2 value found in the summary statistics. The test was conducted utilizing outbound cost-per-mile, and outbound and inbound volumes. These tests eventually resulted in the second highest adjusted R^2 value of all testing, 0.139 (Table 4: Outbound volume regression summary statistics for Harvey (unconstrained)).

Table 5 and Table 6 show the heatmaps generated from the regression model and actual volumes from transactional data respectively. The tables contain volume indexes in two dimensions given as $V_{d,t}$, where d represents the distance from the centroid of the event to the point of measurement in buckets of 100 miles; and t is the time in weeks from the date event occurred at the centroid. Similar heatmaps were developed for cost per mile (CPM) indexes from the corresponding regression models as shown in the appendix.

Table 7: Outbound volume model heat map for Harvey (unconstrained)

		Distance, d (Miles)																		
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
Time, t (Weeks)	0	0.79	0.85	0.90	0.94	0.97	0.99	1.01	1.01	1.01	1.00	0.98	0.95	0.91	0.86	0.81	0.74	0.67	0.58	0.49
	1	0.78	0.84	0.89	0.93	0.96	0.99	1.00	1.01	1.00	0.99	0.97	0.94	0.90	0.85	0.79	0.73	0.65	0.57	0.48
	2	0.79	0.85	0.90	0.94	0.97	0.99	1.01	1.01	1.01	0.99	0.97	0.94	0.90	0.85	0.79	0.73	0.65	0.57	0.47
	3	0.81	0.86	0.91	0.95	0.98	1.00	1.02	1.02	1.02	1.00	0.98	0.95	0.91	0.86	0.80	0.73	0.66	0.57	0.48
	4	0.83	0.89	0.94	0.98	1.01	1.03	1.04	1.04	1.04	1.02	1.00	0.97	0.93	0.88	0.82	0.75	0.68	0.59	0.50
	5	0.87	0.92	0.97	1.01	1.04	1.06	1.07	1.08	1.07	1.05	1.03	1.00	0.96	0.91	0.85	0.78	0.70	0.62	0.52
	6	0.91	0.97	1.01	1.05	1.08	1.10	1.11	1.12	1.11	1.09	1.07	1.04	1.00	0.94	0.88	0.82	0.74	0.65	0.56
	7	0.97	1.02	1.07	1.11	1.13	1.15	1.16	1.17	1.16	1.14	1.12	1.09	1.04	0.99	0.93	0.86	0.78	0.70	0.60
	8	1.03	1.08	1.13	1.17	1.20	1.22	1.23	1.23	1.22	1.20	1.18	1.14	1.10	1.05	0.99	0.92	0.84	0.75	0.65
	9	1.10	1.16	1.20	1.24	1.27	1.29	1.30	1.30	1.29	1.27	1.25	1.21	1.17	1.12	1.05	0.98	0.90	0.82	0.72
	10	1.19	1.24	1.28	1.32	1.35	1.37	1.38	1.38	1.37	1.35	1.32	1.29	1.24	1.19	1.13	1.06	0.98	0.89	0.79
	11	1.28	1.33	1.38	1.41	1.44	1.46	1.46	1.46	1.46	1.44	1.41	1.37	1.33	1.28	1.21	1.14	1.06	0.97	0.87
	12	1.38	1.43	1.48	1.51	1.54	1.56	1.56	1.56	1.55	1.53	1.51	1.47	1.43	1.37	1.31	1.24	1.16	1.07	0.97

Table 8: Outbound actual volume heat map for Harvey (unconstrained)
Distance, d (Miles)

OUTBOUND	0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
0	1.16	0.93	1.19	1.31	1.00	1.30	1.37	1.51	1.22	1.32	1.37	0.84	1.06	1.03	0.86	0.63	0.61	0.35	0.44
1	0.84	0.80	1.02	1.00	1.05	0.96	0.95	1.19	0.91	1.09	1.23	0.54	0.80	0.93	0.64	0.44	1.02	0.58	0.53
2	1.13	0.25	0.90	0.93	0.93	0.82	0.68	0.61	0.73	0.72	0.86	0.59	0.47	0.85	0.86	0.58	0.57	0.43	0.29
3	1.13	0.49	0.60	0.72	0.86	0.41	0.75	0.79	0.95	0.79	0.56	0.96	0.78	0.49	0.86	0.55	0.57	0.90	0.20
4	0.27	0.51	0.60	0.91	0.66	0.78	0.89	1.16	0.90	0.75	0.80	1.10	0.97	0.60	1.05	0.61	0.89	0.83	0.37
5	0.55	1.04	1.03	1.41	0.87	0.98	1.13	1.19	1.27	1.09	1.06	1.27	0.81	0.90	0.80	0.62	0.78	0.23	0.63
6	0.52	1.02	1.23	1.60	0.87	1.17	1.22	1.03	0.98	1.17	1.36	1.04	0.95	1.02	1.04	0.77	1.39	0.58	0.46
7	1.26	0.99	1.15	1.53	1.40	1.41	1.25	1.40	1.29	1.22	1.33	1.07	0.97	1.49	1.12	0.91	0.93	0.29	0.48
8	0.95	0.96	1.21	1.60	1.22	1.27	1.27	1.32	1.33	1.36	1.40	1.13	1.43	1.11	1.26	0.72	1.02	0.36	0.62
9	1.49	1.87	1.00	1.97	1.23	1.39	1.06	1.06	1.09	1.05	1.12	0.82	0.66	1.33	0.76	0.74	0.55	0.45	0.57
10	1.20	0.94	1.19	1.43	1.50	1.44	1.49	2.13	1.66	1.31	1.38	1.14	1.23	1.32	1.44	0.83	1.11	1.50	0.54
11	1.33	1.21	1.42	1.50	1.26	1.65	1.47	1.32	1.53	1.29	1.39	1.12	1.39	1.17	1.31	1.03	1.08	2.22	0.54
12	1.09	1.25	1.42	1.31	1.39	1.35	1.55	1.54	1.52	1.46	1.47	1.17	1.23	1.29	1.48	1.10	1.08	2.56	0.63

The results of our analysis show that the outbound volume provided the highest correlation between the dependent and multiple independent variables 75% (6 out of 8 models or events) of the time when compared to the inbound and cost per mile tests for the same model. This trend continued throughout the testing of Hurricanes Irma and Matthew as each regressed outbound volume was slightly better than the inbound models in terms of the values of adjusted R². Hurricane Florence’s results were relatively unexpected as the inbound volumes were higher than outbound. An interesting result of the models that had $d*t$ included was an extremely low coefficient that never exceeded 1.03×10^{-6} (Table 14: Irma inbound volume regression summary output).

4.2 Effect of binary designator for events

The binary designator’s effect on the models was determined through two stages of tests. The first stage included using only distance and time as the independent variables in order to discern the baseline correlations. The second stage of analysis incorporated the binary designator as the surrogate for a special event’s occurrence within a cluster. The designator utilized the FEMA dataset to determine any natural disasters that occurred throughout the United States within the associated timeframe and their affected clusters. These affected clusters, now with associated binary variables that were relational through time, could show the effects of special events nationally as it related to the timeframe of our primary special event. The results showed a slight change (0.003-outbound, 0.0004-inbound) in the R² value of the inbound and outbound volume of the Harvey model as shown in tables 15 and 16. The introduction of the binary

designator did not provide consistent results in regards to an improved R^2 value when used in the Harvey and Florence models. Potential future research should include a variability smoothing addition to the regression equation with the binary addition. As seen in the attached modeled heat maps, there is a noticeable and abrupt color distinction within the map resulting from the binary designator. If variable smoothing were used, it might be able to redefine the model's pattern and produce fluctuations that better correlate to the actual map.

4.3 Results from constrained regression

Given that the first sets of models were built considering the shipment nationwide, a constrained model was created to narrow the loads to only include freight movements that directly related to the cluster affected by the special event. The constrained model did not include the binary designator because of the previously inconsistent results within the Harvey models. Hurricane Harvey was the only disaster tested due to its comparatively high freight rates, both into and out of the cluster. An attempt to repeat the experiment with Florence was determined to be ill-advised because of its lack of direct freight relationships with the other clusters. Irma could be a potential candidate for future testing due to its cluster's region which includes the Port of Jacksonville. Although there was no significant improvement in the R^2 values for the new model, there were slight changes between the two different tests done within the constrained model. The region associated with Harvey (C133) that was used in the constrained model, had a relatively high number of data points with over 23-thousand when compared with Florence's (C113) 4.7-thousand. Yet, there were plenty of clusters whose aggregated data was missing which resulted in unusable data when input into the regression table. Of the 136 available clusters, only 22 had reliable data within the associated model. This led to sorting the data between two tables, one included values of zero for the "ghost regions," and the other removed the zero values. The inclusion of the ghost regions resulted in an almost 7% better R^2 value, but this change did not result in the R^2 surpassing the 0.15 mark. Constraining the data should have presented a more precise picture as to the effects of special events on spot market rates. Through limitation, any relational trends between the spot market pricing and the C133 cluster should have materialized through demand fluctuations that are expected post-event. The fact that there was no

major relational change when restricted to a single afflicted area provides even greater support against the initial hypothesis that special events directly affect the freight spot market.

4.4 Review of results

The results showed that clusters, when considered in isolation during the time of a special event, received a noticeable increase in volume and cost per mile going into the cluster location while outbound metrics were reduced. While this trend was recognizable in the “actual heat maps,” the model correlation was not strong enough to definitively confirm the reality-model relationship. This might be associated with the movement of relief materials into the area, population changes, and numerous other factors that were not incorporated into the model that would lead to more inbound freight loads. While the reverse is the case for outbound, which has a negative coefficient as shown in the model, it did have a consistently higher correlation within the model. The relationship between outbound trucking and the model is due in-part to the natural relationship between economic visibility within non-affected sectors. Due to the model’s national view, outbound volume and cost per mile can not be localized and will be aggregated across all the distances that are more than 250 miles away from Houston. Distance delineation within the bounds of the long-haul parameter created radius buckets of 100-mile intervals from the affected cluster as the center. The potential for an incomplete relationship within the bucketing system due to the long-haul distance being greater than the first 100-mile bucket would could have potentially skewed the data, but this would have been negligible as the cluster centroid distance relationships were sometimes below the 250-mile threshold, creating local distance buckets. Results showed that distances above 2,000 miles have indices average based on LA volume associated with Ohio’s volume. This aggregation of volumes had the potential to skew spatial results and a weighting scheme will need to be included in the future.

This spatial bucketing approach provides visibility of outbound freight everywhere, except for the affected cluster. Normally, if there was no direct impact from a special event in a region, there would be no change to the region’s freight output. No change in freight output would have provided an expectedly higher correlation value when the cost per mile was regressed against the distance, but the R^2 never

surpassed 0.15. With no correlation on either end of the spectrum, neither inbound nor outbound, the possibility of an undefined feature that crosses the boundaries of all three of the key performance metrics gains further plausibility. This hidden feature, or features, that can significantly affect the freight spot market are the indistinguishable markings of special events. Our temporal world has become susceptible to these intangible watermarks, and as humanity continues to react to the ephemeral, there will always be a socio-economic response to these “special events.”

5.0 CONCLUSION

After the completion of multiple models for four different hurricanes which were tested against cost-per-mile and volume provided by the corporate sponsor, the analysis shows that the methods used were not sufficient to determine a correlation between the trucking spot market and special events. These initial findings are contrary to the general expectation that when something occurs, the socio-economics within the afflicted region will affect the supply and demand requirements of the nation. It is still possible that this idea is true, as future tests could utilize machine learning and other non-linear techniques to find a solution that linear regression is too rigid to recognize. Special events that are pre-planned could provide more data to train the non-linear models that could coincide with the unplanned binary map already developed. The trucking industry runs off seasonality, and special events are already involved in decision-making as a result. When a randomly occurring special event happens and affects a region, the size of the United States and its cross-national interdependence remains largely unaffected as shown by Table 11. While it was discovered that FEMA pays \$1.33 more per mile than the average spot market load, the relatively small and dispersed volume of these loads doesn't offset the weekly regional average. Post-Harvey, Cluster C133 did not see an increase in inbound freight from any other region, relying on only eleven regions to bring the supplies it needed to rebuild. Potential future research on this subject could include machine learning techniques such as random forest or a neural network. It is important to note that this is just an initial step towards determining any temporal-spatial relationships inherent within the United States' trucking spot market and it can be further extrapolated into broader social and/or economic studies.

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Table 4: Outbound volume regression summary statistics for Harvey (unconstrained)

Regression Statistics	
Multiple R	0.377389505
R Square	0.142422838
Adjusted R Square	0.139989305
Standard Error	0.564493778
Observations	1768

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.785665381	0.089856952	8.743512442	5.16734E-18	0.60942793	0.961902832	0.60942793	0.961902832
DIST	0.0006384	0.000144924	4.405055661	1.12118E-05	0.000354158	0.000922642	0.000354158	0.000922642
TIME	-0.007837948	0.016110885	-0.486500163	0.626673094	-0.039436407	0.023760511	-0.039436407	0.023760511
D^2	-4.45897E-07	6.56388E-08	-6.793201451	1.49498E-11	-5.74635E-07	-3.17159E-07	-5.74635E-07	-3.17159E-07
T^2	0.004785142	0.001081827	4.423205655	1.03192E-05	0.002663343	0.00690694	0.002663343	0.00690694
D*T	-5.47318E-06	8.74417E-06	-0.625923781	0.531446003	-2.26232E-05	1.16769E-05	-2.26232E-05	1.16769E-05

Table 5: Outbound volume model heat map for Harvey (unconstrained)

		Distance, d (Miles)																		
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
Time, t (Weeks)	0	0.79	0.85	0.90	0.94	0.97	0.99	1.01	1.01	1.01	1.00	0.98	0.95	0.91	0.86	0.81	0.74	0.67	0.58	0.49
	1	0.78	0.84	0.89	0.93	0.96	0.99	1.00	1.01	1.00	0.99	0.97	0.94	0.90	0.85	0.79	0.73	0.65	0.57	0.48
	2	0.79	0.85	0.90	0.94	0.97	0.99	1.01	1.01	1.01	0.99	0.97	0.94	0.90	0.85	0.79	0.73	0.65	0.57	0.47
	3	0.81	0.86	0.91	0.95	0.98	1.00	1.02	1.02	1.02	1.00	0.98	0.95	0.91	0.86	0.80	0.73	0.66	0.57	0.48
	4	0.83	0.89	0.94	0.98	1.01	1.03	1.04	1.04	1.04	1.02	1.00	0.97	0.93	0.88	0.82	0.75	0.68	0.59	0.50
	5	0.87	0.92	0.97	1.01	1.04	1.06	1.07	1.08	1.07	1.05	1.03	1.00	0.96	0.91	0.85	0.78	0.70	0.62	0.52
	6	0.91	0.97	1.01	1.05	1.08	1.10	1.11	1.12	1.11	1.09	1.07	1.04	1.00	0.94	0.88	0.82	0.74	0.65	0.56
	7	0.97	1.02	1.07	1.11	1.13	1.15	1.16	1.17	1.16	1.14	1.12	1.09	1.04	0.99	0.93	0.86	0.78	0.70	0.60
	8	1.03	1.08	1.13	1.17	1.20	1.22	1.23	1.23	1.22	1.20	1.18	1.14	1.10	1.05	0.99	0.92	0.84	0.75	0.65
	9	1.10	1.16	1.20	1.24	1.27	1.29	1.30	1.30	1.29	1.27	1.25	1.21	1.17	1.12	1.05	0.98	0.90	0.82	0.72
	10	1.19	1.24	1.28	1.32	1.35	1.37	1.38	1.38	1.37	1.35	1.32	1.29	1.24	1.19	1.13	1.06	0.98	0.89	0.79
	11	1.28	1.33	1.38	1.41	1.44	1.46	1.46	1.46	1.46	1.44	1.41	1.37	1.33	1.28	1.21	1.14	1.06	0.97	0.87
	12	1.38	1.43	1.48	1.51	1.54	1.56	1.56	1.56	1.55	1.53	1.51	1.47	1.43	1.37	1.31	1.24	1.16	1.07	0.97

Table 6: Outbound actual volume heat map for Harvey (unconstrained)

		Distance, d (Miles)																		
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
Time, t (Weeks)	0	1.16	0.93	1.19	1.31	1.00	1.30	1.37	1.51	1.22	1.32	1.37	0.84	1.06	1.03	0.86	0.63	0.61	0.35	0.44
	1	0.84	0.80	1.02	1.00	1.05	0.96	0.95	1.19	0.91	1.09	1.23	0.54	0.80	0.93	0.64	0.44	1.02	0.58	0.53
	2	1.13	0.25	0.90	0.93	0.93	0.82	0.68	0.61	0.73	0.72	0.86	0.59	0.47	0.85	0.86	0.58	0.57	0.43	0.29
	3	1.13	0.49	0.60	0.72	0.86	0.41	0.75	0.79	0.95	0.79	0.56	0.96	0.78	0.49	0.86	0.55	0.57	0.90	0.20
	4	0.27	0.51	0.60	0.91	0.66	0.78	0.89	1.16	0.90	0.75	0.80	1.10	0.97	0.60	1.05	0.61	0.89	0.83	0.37
	5	0.55	1.04	1.03	1.41	0.87	0.98	1.13	1.19	1.27	1.09	1.06	1.27	0.81	0.90	0.80	0.62	0.78	0.23	0.63
	6	0.52	1.02	1.23	1.60	0.87	1.17	1.22	1.03	0.98	1.17	1.36	1.04	0.95	1.02	1.04	0.77	1.39	0.58	0.46
	7	1.26	0.99	1.15	1.53	1.40	1.41	1.25	1.40	1.29	1.22	1.33	1.07	0.97	1.49	1.12	0.91	0.93	0.29	0.48
	8	0.95	0.96	1.21	1.60	1.22	1.27	1.27	1.32	1.33	1.36	1.40	1.13	1.43	1.11	1.26	0.72	1.02	0.36	0.62
	9	1.49	1.87	1.00	1.97	1.23	1.39	1.06	1.06	1.09	1.05	1.12	0.82	0.66	1.33	0.76	0.74	0.55	0.45	0.57
	10	1.20	0.94	1.19	1.43	1.50	1.44	1.49	2.13	1.66	1.31	1.38	1.14	1.23	1.32	1.44	0.83	1.11	1.50	0.54
	11	1.33	1.21	1.42	1.50	1.26	1.65	1.47	1.32	1.53	1.29	1.39	1.12	1.39	1.17	1.31	1.03	1.08	2.22	0.54
	12	1.09	1.25	1.42	1.31	1.39	1.35	1.55	1.54	1.52	1.46	1.47	1.17	1.23	1.29	1.48	1.10	1.08	2.56	0.63

Table 7: Outbound cost per mile regression summary statistics for Harvey (unconstrained)

Regression Statistics	
Multiple R	0.226432
R Square	0.051271
Adjusted R Square	0.04933
Standard Error	0.313764
Observations	2449

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Constant	1.046006	0.032988	31.70844	4.2E-185	0.981318	1.110694	0.981318	1.110694
Distance, d	0.000289	0.0000647	4.466416	0.0000832	0.000162	0.000416	0.000162	0.000416
Distance sq, d ²	0.010437	0.003741	2.789858	0.005314	0.003101	0.017773	0.003101	0.017773
Time, t	-0.00000019	0.000000031	-5.97596	2.62E-09	-0.00000025	-0.00000012	-0.00000025	-0.00000012
Time sq, t ²	-0.00168	0.000264	-6.35066	2.55E-10	-0.0022	-0.00116	-0.0022	-0.00116
d*t	0.00000856	0.00000298	2.877683	0.004041	0.00000273	0.0000144	0.00000273	0.0000144

Table 8: Outbound cost per mile model heat map for Harvey (unconstrained)

		Distance, d (Miles)																		
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
Time, t (Weeks)	0	1.05	1.07	1.10	1.12	1.13	1.14	1.15	1.16	1.16	1.15	1.15	1.13	1.12	1.10	1.08	1.05	1.02	0.99	0.95
	1	1.05	1.08	1.11	1.13	1.14	1.16	1.16	1.17	1.17	1.17	1.16	1.15	1.14	1.12	1.10	1.07	1.04	1.01	0.97
	2	1.06	1.09	1.12	1.14	1.16	1.17	1.18	1.18	1.19	1.19	1.18	1.17	1.16	1.14	1.12	1.10	1.07	1.03	1.00
	3	1.07	1.10	1.13	1.15	1.17	1.18	1.19	1.20	1.20	1.20	1.20	1.19	1.18	1.16	1.14	1.12	1.09	1.06	1.02
	4	1.08	1.11	1.14	1.16	1.18	1.20	1.21	1.21	1.22	1.22	1.21	1.21	1.20	1.18	1.16	1.14	1.11	1.08	1.05
	5	1.09	1.12	1.15	1.17	1.19	1.21	1.22	1.23	1.23	1.23	1.23	1.22	1.21	1.20	1.18	1.16	1.13	1.10	1.07
	6	1.10	1.13	1.16	1.18	1.20	1.22	1.23	1.24	1.25	1.25	1.25	1.24	1.23	1.22	1.20	1.18	1.16	1.13	1.10
	7	1.11	1.14	1.17	1.19	1.22	1.23	1.25	1.26	1.26	1.27	1.27	1.26	1.25	1.24	1.22	1.20	1.18	1.15	1.12
	8	1.12	1.15	1.18	1.21	1.23	1.25	1.26	1.27	1.28	1.28	1.28	1.28	1.27	1.26	1.24	1.22	1.20	1.17	1.14
	9	1.12	1.16	1.19	1.22	1.24	1.26	1.28	1.29	1.30	1.30	1.30	1.30	1.29	1.28	1.26	1.25	1.22	1.20	1.17
	10	1.13	1.17	1.20	1.23	1.25	1.27	1.29	1.30	1.31	1.32	1.32	1.32	1.32	1.31	1.30	1.29	1.27	1.25	1.22
	11	1.14	1.18	1.21	1.24	1.27	1.29	1.30	1.32	1.33	1.33	1.34	1.33	1.33	1.32	1.31	1.29	1.27	1.24	1.22
	12	1.15	1.19	1.22	1.25	1.28	1.30	1.32	1.33	1.34	1.35	1.35	1.35	1.35	1.34	1.33	1.31	1.29	1.27	1.24

Table 9: Outbound actual cost per mile heat map for Harvey (unconstrained)

		Distance, d (Miles)																		
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
Time, t (Weeks)	0	1.06	0.97	1.06	1.00	1.17	1.09	1.04	1.12	1.07	1.04	0.98	1.28	1.03	1.00	0.94	1.00	0.88	2.12	0.65
	1	1.29	1.06	1.18	1.30	1.38	1.11	1.17	1.22	0.99	1.08	1.05	1.23	1.05	1.09	0.96	1.04	1.05	1.04	0.83
	2	1.22	1.11	1.17	1.07	1.33	1.18	1.10	1.19	1.12	1.04	1.11	1.23	1.10	1.18	1.06	1.06	0.99	2.60	0.61
	3	1.12	1.24	1.17	1.11	1.35	1.22	1.21	1.30	1.08	1.12	1.10	1.26	1.13	1.17	1.06	1.20	1.05	1.50	0.59
	4	1.19	1.09	1.13	1.02	1.40	1.32	1.13	1.26	1.20	1.24	1.21	1.44	1.21	1.25	1.05	1.34	1.02	1.14	0.70
	5	1.14	1.24	1.19	0.96	1.38	1.34	1.14	1.15	1.24	1.21	1.27	1.43	1.23	1.36	1.15	1.33	1.09	1.35	0.80
	6	1.09	1.32	1.14	1.06	1.29	1.32	1.27	1.25	1.20	1.21	1.24	1.33	1.34	1.33	1.29	1.41	1.20	1.08	0.64
	7	1.14	1.15	1.08	1.09	1.21	1.27	0.99	1.23	1.24	1.19	1.13	1.38	1.26	1.34	1.13	1.21	1.04	1.59	1.35
	8	1.04	1.22	1.13	0.98	1.18	1.24	1.14	1.28	1.24	1.03	1.09	1.30	1.14	1.40	1.27	1.19	1.00	0.87	1.24
	9	1.06	1.12	1.16	1.04	1.16	1.13	1.05	1.04	0.99	1.00	1.06	1.19	1.10	1.22	1.23	1.06	0.97	1.18	0.61
	10	1.11	1.13	1.11	1.01	1.21	1.14	1.08	1.38	1.15	1.17	1.07	1.23	1.06	1.23	0.97	1.13	0.89	1.09	0.70
	11	1.14	1.17	1.14	0.90	1.17	1.10	0.98	1.06	0.97	1.10	1.05	1.31	1.13	1.18	1.19	1.28	0.93	1.54	1.63
	12	1.08	1.01	1.14	0.97	1.23	1.07	1.20	0.93	1.01	1.10	1.05	1.18	1.18	1.25	1.13	1.33	0.91	1.48	0.56

Table 10: Harvey constrained inbound volume regression summary statistics for Harvey

Regression Statistics	
Multiple R	0.211038194
R Square	0.044537119
Adjusted R Square	0.042188583
Standard Error	0.693711244
Observations	2448

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	0.917798881	0.074147323	12.37804479	3.56177E-34	0.772400704	1.063197057	0.772400704	1.063197057
DIST	0.000538348	0.000143779	3.744271929	0.0001851	0.000256406	0.000820289	0.000256406	0.000820289
TIME	-0.033794268	0.008273377	-4.084700647	4.5556E-05	-0.050017833	-0.017570703	-0.050017833	-0.017570703
D^2	-3.33702E-07	6.87314E-08	-4.855158011	1.27892E-06	-4.6848E-07	-1.98924E-07	-4.6848E-07	-1.98924E-07
T^2	0.002335733	0.00058959	3.961623072	7.65755E-05	0.001179585	0.003491882	0.001179585	0.003491882
D*T	-3.0002E-06	6.5894E-06	-0.455307476	0.648928543	-1.59216E-05	9.92119E-06	-1.59216E-05	9.92119E-06
DISASTER	0.026130846	0.093332461	0.279975969	0.779519664	-0.156888165	0.209149858	-0.156888165	0.209149858

Table 11: Harvey constrained inbound volume model heat map

		Distance, d (Miles)																		
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
Time, t (Weeks)	0	0.94	0.99	1.04	1.08	1.11	1.10	1.12	1.13	1.13	1.12	1.13	1.08	1.05	1.02	1.00	0.92	0.87	0.81	
	1	0.91	0.96	1.01	1.04	1.07	1.07	1.09	1.10	1.10	1.12	1.09	1.07	1.05	1.02	0.98	0.94	0.89	0.83	0.77
	2	0.89	0.94	0.98	1.02	1.05	1.04	1.06	1.07	1.07	1.07	1.06	1.04	1.02	0.99	0.95	0.91	0.86	0.80	0.74
	3	0.86	0.91	0.96	0.99	1.02	1.04	1.06	1.07	1.07	1.07	1.03	1.02	0.99	0.96	0.92	0.88	0.83	0.77	0.71
	4	0.82	0.87	0.91	0.95	0.98	1.03	1.04	1.05	1.05	1.05	1.01	1.00	0.97	0.94	0.90	0.86	0.81	0.75	0.69
	5	0.81	0.86	0.90	0.93	0.96	1.01	1.03	1.04	1.04	1.03	1.00	0.98	0.95	0.92	0.89	0.84	0.79	0.73	0.67
	6	0.80	0.85	0.89	0.93	0.95	0.98	0.99	1.00	1.00	1.02	0.99	0.97	0.94	0.91	0.87	0.83	0.78	0.72	0.65
	7	0.80	0.84	0.89	0.92	0.95	0.97	0.99	0.99	1.00	0.99	0.98	0.96	0.94	0.90	0.87	0.82	0.77	0.71	0.65
	8	0.80	0.85	0.89	0.92	0.95	0.97	0.99	0.99	0.99	0.99	0.98	0.96	0.93	0.90	0.86	0.82	0.77	0.71	0.64
	9	0.80	0.85	0.89	0.93	0.95	0.98	0.99	1.00	1.00	0.99	0.98	0.96	0.94	0.90	0.86	0.82	0.77	0.71	0.64
	10	0.81	0.86	0.90	0.94	0.96	0.98	1.00	1.01	1.01	1.00	0.99	0.97	0.94	0.91	0.87	0.83	0.77	0.71	0.65
	11	0.83	0.88	0.92	0.95	0.98	1.00	1.01	1.02	1.02	1.01	1.00	0.98	0.95	0.92	0.88	0.84	0.78	0.72	0.66
	12	0.85	0.90	0.94	0.97	1.00	1.02	1.03	1.04	1.04	1.03	1.02	1.00	0.97	0.94	0.90	0.85	0.80	0.74	0.67

Table 12: Harvey constrained outbound volume regression summary statistics for Harvey

Regression Statistics	
Multiple R	0.386444127
R Square	0.149339063
Adjusted R Square	0.147248131
Standard Error	0.569470679
Observations	2448

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	1.00691514	0.0608679	16.543	2.40874E-58	0.887557123	1.126273157	0.887557123	1.126273157
DIST	0.000550054	0.0001180	4.660	3.32667E-06	0.000318607	0.000781502	0.000318607	0.000781502
TIME	-0.053093409	0.0067917	-7.817	7.94961E-15	-0.066411406	-0.039775411	-0.066411406	-0.039775411
D^2	-4.57041E-07	0.0000001	-8.100	8.55897E-16	-5.67681E-07	-3.46401E-07	-5.67681E-07	-3.46401E-07
T^2	0.00677057	0.0004840	13.989	7.85006E-43	0.005821483	0.007719658	0.005821483	0.007719658
D*T	7.13802E-06	0.0000054	1.320	0.187095792	-3.46922E-06	1.77452E-05	-3.46922E-06	1.77452E-05
DISASTER	-0.26137785	0.0766170	-3.411	0.000656619	-0.411161898	-0.111136721	-0.411161898	-0.111136721

Table 13: Harvey constrained outbound volume model heat map
Distance, d (Miles)

OUTBOUND	0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1700	1800
0	0.75	0.80	0.84	0.87	0.89	1.17	1.17	1.17	1.15	1.13	1.10	0.80	1.01	0.95	0.88	0.54	0.72	0.62	0.52
1	0.70	0.75	0.79	0.83	0.85	1.12	1.13	1.13	1.11	0.83	1.06	1.02	0.97	0.91	0.84	0.77	0.68	0.59	0.48
2	0.67	0.72	0.76	0.79	0.82	1.10	1.10	1.10	1.09	1.07	1.04	1.00	0.95	0.89	0.82	0.75	0.66	0.57	0.46
3	0.65	0.70	0.74	0.78	0.80	0.82	0.83	0.82	0.81	0.79	1.02	0.98	0.94	0.88	0.81	0.74	0.65	0.56	0.46
4	0.90	0.96	1.00	1.04	1.06	0.82	0.82	0.82	0.81	0.79	1.02	0.99	0.94	0.88	0.82	0.74	0.66	0.57	0.46
5	0.91	0.96	1.01	1.05	1.07	0.83	0.84	0.84	0.83	0.81	1.04	1.00	0.96	0.90	0.83	0.76	0.68	0.59	0.48
6	0.93	0.99	1.03	1.07	1.10	1.11	1.12	1.12	1.11	0.83	1.07	1.03	0.99	0.93	0.87	0.79	0.71	0.62	0.52
7	0.97	1.02	1.07	1.11	1.13	1.15	1.16	1.16	1.15	1.14	1.11	1.07	1.03	0.97	0.91	0.84	0.76	0.67	0.57
8	1.02	1.07	1.12	1.16	1.19	1.20	1.22	1.22	1.21	1.19	1.17	1.13	1.09	1.03	0.97	0.90	0.82	0.73	0.63
9	1.08	1.13	1.18	1.22	1.25	1.27	1.28	1.28	1.28	1.26	1.23	1.20	1.16	1.10	1.04	0.97	0.89	0.80	0.70
10	1.15	1.21	1.26	1.30	1.33	1.35	1.36	1.36	1.36	1.34	1.32	1.28	1.24	1.19	1.13	1.06	0.98	0.89	0.79
11	1.24	1.30	1.35	1.39	1.42	1.44	1.45	1.46	1.45	1.44	1.41	1.38	1.34	1.29	1.23	1.16	1.08	0.99	0.89
12	1.34	1.40	1.45	1.49	1.53	1.55	1.56	1.57	1.56	1.55	1.52	1.49	1.45	1.40	1.34	1.27	1.19	1.10	1.01

Table 14: Irma inbound volume regression summary output

SUMMARY OUTPUT

<i>Regression Statistics</i>	
Multiple R	0.298513
R Square	0.08911
Adjusted R Square	0.087245
Standard Error	0.675922
Observations	2448

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	0.999509	0.05192229	19.2501	5.37E-77	0.8976931	1.1013257	0.89769314	1.10132572
DIST	0.000221	9.0856E-05	2.43612	0.014917	4.317E-05	0.0003995	4.3173E-05	0.0003995
TIME	-0.028997	0.00663493	-4.3704	1.29E-05	-0.042008	-0.0159866	-0.0420079	-0.01598661
D^2	-1.26E-07	3.5138E-08	-3.5927	0.000334	-1.95E-07	-5.734E-08	-1.951E-07	-5.7337E-08
T^2	-0.001443	0.00057011	-2.53078	0.011443	-0.002561	-0.0003249	-0.0025608	-0.00032487
D*T	1.03E-06	4.7595E-06	0.215752	0.829199	-8.31E-06	1.036E-05	-8.306E-06	1.036E-05

Table 15: Harvey inbound regression statistics (Base vs Binary)

<i>Regression Statistics</i>		INBOUND	<i>Regression Statistics</i>	
Multiple R	0.211038		Multiple R	0.2109655
R Square	0.044537		R Square	0.0445064
Adjusted R Square	0.042189		Adjusted R Square	0.0425501
Standard Error	0.693711		Standard Error	0.6935803
Observations	2448		Observations	2448

Table 16: Harvey outbound regression statistics (Base vs Binary)

<i>Regression Statistics</i>		OUTBOUND	<i>Regression Statistics</i>	
Multiple R	0.386444		Multiple R	0.3811604
R Square	0.149339		R Square	0.1452833
Adjusted R Square	0.147248		Adjusted R Square	0.1435332
Standard Error	0.569471		Standard Error	0.5707097
Observations	2448		Observations	2448

Table 17: Harvey constrained outbound regression statistics

<i>Regression Statistics</i>		OUTBOUND	<i>Regression Statistics</i>	
Multiple R	0.323647		Multiple R	0.22432
R Square	0.104747		R Square	0.050319
Adjusted R Square	0.102654		Adjusted R Square	0.038522
Standard Error	0.505243		Standard Error	0.776563
Observations	1716		Observations	327
With 0-values			With out 0-values	

Table 18: Outbound actual cost per mile for Matthew
Distance, d (Miles)

Row Labels	0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1800	1900	2000	2100	2200	2300
0	0.89	0.94	1.00	1.00	0.97	0.95	0.94	0.98	0.95	0.96	0.97	0.94	0.89	0.82	0.97	0.79	1.09	0.90	1.39	0.80	0.94	0.75	1.02
1	0.95	0.92	0.97	0.91	0.96	0.95	0.92	0.92	0.94	0.94	0.89	0.99	1.23	0.77	0.80	0.94	0.78	0.98	1.23	0.96	0.97	0.76	0.95
2	0.82	0.98	0.99	0.92	0.96	0.98	0.96	1.01	0.94	0.93	0.85	0.78	1.19	0.92	0.88	0.84	1.15	0.98	1.15	0.69	0.95	0.80	0.97
3	0.75	0.97	1.00	0.98	0.97	1.00	0.95	0.88	0.86	0.97	0.84	1.00	1.13	0.90	0.91	0.92	1.14	0.96	1.23	1.18	0.98	0.75	0.99
4	1.06	0.98	1.00	0.94	0.96	1.00	0.98	1.00	1.00	0.79	0.84	0.93	0.94	0.82	0.95	0.85	1.05	0.92	1.31	0.97	1.00	0.84	1.04
5	1.01	0.93	1.02	0.98	0.94	1.01	0.92	1.01	0.93	0.84	0.89	0.89	1.01	0.80	0.94	0.87	1.06	0.90	1.17	0.79	1.01	0.90	1.04
6	0.94	0.93	1.07	0.94	0.97	1.02	0.92	0.91	0.86	0.98	0.90	0.78	0.93	0.76	1.03	0.63	1.17	0.98	1.31	0.70	0.98	0.82	1.03
7	0.92	0.89	1.01	1.03	1.04	1.00	0.99	0.99	0.90	0.75	0.85	0.83	0.99	0.83	1.06	0.76	1.03	0.90	1.16	0.60	0.98	0.77	0.97
8	1.06	1.03	1.06	1.02	1.03	1.00	0.95	0.92	0.98	1.01	0.86	0.76	0.93	0.81	0.92	0.94	1.12	1.09	1.30	1.05	1.02	0.80	1.04
9	1.07	0.99	1.02	1.08	1.01	0.98	0.93	1.00	0.95	0.92	0.87	0.91	1.05	0.83	0.92	0.83	1.14	1.00	1.27	1.07	0.98	0.75	0.95
10	0.95	0.93	1.05	1.00	0.98	1.01	0.93	0.93	0.95	0.72	0.85	0.88	1.08	0.87	0.84	0.81	1.14	1.03	1.35	1.04	1.03	0.80	0.95
11	0.82	0.94	1.02	1.06	0.95	0.99	0.90	0.84	0.93	1.03	0.80	0.84	1.23	0.80	0.84	0.63	1.88	0.98	1.21	1.15	0.98	0.89	1.04
12	0.97	1.06	1.01	1.04	0.96	1.02	0.96	0.83	1.17	0.97	0.89	0.77	1.02	1.01	0.93	0.87	0.95	1.09	1.30	1.04	0.99	0.97	0.82

Table 19: Outbound model cost per mile for Matthew
Distance, d (Miles)

Row Labels	0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1600	1800	1900	2000	2100	2200	2300
0	1.02	1.01	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.92	0.92	0.91	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.93	0.94	0.94	0.95
1	1.02	1.01	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.92	0.92	0.91	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.93	0.94	0.95	0.96
2	1.02	1.01	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.93	0.92	0.92	0.91	0.91	0.91	0.91	0.91	0.92	0.92	0.93	0.94	0.95	0.96
3	1.03	1.01	1.00	0.98	0.97	0.96	0.95	0.94	0.93	0.93	0.92	0.92	0.91	0.91	0.91	0.91	0.91	0.92	0.93	0.93	0.94	0.95	0.96
4	1.03	1.01	1.00	0.98	0.97	0.96	0.95	0.94	0.93	0.93	0.92	0.92	0.92	0.91	0.91	0.91	0.92	0.92	0.93	0.93	0.94	0.95	0.96
5	1.03	1.01	1.00	0.99	0.97	0.96	0.95	0.94	0.94	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.92	0.93	0.93	0.94	0.94	0.95	0.96
6	1.03	1.01	1.00	0.99	0.98	0.96	0.95	0.95	0.94	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.93	0.93	0.94	0.94	0.95	0.96
7	1.03	1.02	1.00	0.99	0.98	0.97	0.96	0.95	0.94	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.92	0.93	0.93	0.94	0.95	0.96	0.96
8	1.03	1.02	1.00	0.99	0.98	0.97	0.96	0.95	0.94	0.94	0.93	0.93	0.92	0.92	0.92	0.92	0.92	0.93	0.93	0.94	0.95	0.96	0.97
9	1.04	1.02	1.01	0.99	0.98	0.97	0.96	0.95	0.94	0.94	0.93	0.93	0.93	0.92	0.92	0.92	0.92	0.93	0.94	0.94	0.95	0.96	0.97
10	1.04	1.02	1.01	1.00	0.98	0.97	0.96	0.95	0.95	0.94	0.93	0.93	0.93	0.93	0.92	0.93	0.93	0.93	0.94	0.95	0.95	0.96	0.97
11	1.04	1.03	1.01	1.00	0.99	0.97	0.96	0.96	0.95	0.94	0.94	0.93	0.93	0.93	0.93	0.93	0.93	0.94	0.94	0.95	0.96	0.96	0.97
12	1.04	1.03	1.01	1.00	0.99	0.98	0.97	0.96	0.95	0.94	0.94	0.94	0.93	0.93	0.93	0.93	0.93	0.94	0.94	0.95	0.96	0.97	0.98

Table 20: Outbound cost per mile summary regression statistics for Matthew

Regression Statistics	
Multiple R	0.127766
R Square	0.016324
Adjusted R Square	0.014092
Standard Error	0.208169
Observations	1768

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	1.021884	0.01946	52.5119	0	0.983717	1.060051	0.983717	1.060051
d	-0.00016	3.26E-05	-4.96923	7.37E-07	-0.00023	-9.8E-05	-0.00023	-9.8E-05
d2	5.76E-08	1.32E-08	4.377137	1.27E-05	3.18E-08	8.34E-08	3.18E-08	8.34E-08
t	0.001097	0.004967	0.220895	0.825199	-0.00864	0.010839	-0.00864	0.010839
t2	5.73E-05	0.000399	0.143539	0.885881	-0.00073	0.00084	-0.00073	0.00084

Table 21: Outbound volume actual and model for Florence

		Distance, d (Miles)																							
		Actual																							
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1700	1800	1900	2000	2100	2200	2300	2400
Time, t (Weeks)	0	458	41.6	184.8	141.333	104.667	207.5	117	158	160.667	107.455	145.6	184.4	137.2	0	0	56	932	68	0	152	254.286	178	149	406
	1	423	39.5	198.4	123.556	116.615	214	117.25	134	144	106.5	143.714	165.2	127.2	0	34.6667	64.6667	860	76.6667	0	94	283.143	142	123.5	409
	2	150	429.6	54.6667	76.9091	109.5	73.4286	42.7059	40	13.3333	131.667	48	56.6667	294	0	196.667	250.667	392	127.333	185	0	7.6	104	82.6667	70
		Model																							
		0	100	200	300	400	500	600	700	800	900	1000	1100	1200	1300	1400	1500	1700	1800	1900	2000	2100	2200	2300	2400
Time, t (Weeks)	0	199.96	187.63	176.46	166.47	157.64	149.99	143.51	138.20	134.05	131.08	129.28	128.65	129.19	130.90	133.79	137.84	149.45	157.02	165.75	175.65	186.73	198.97	212.39	226.98
	1	196.31	183.98	172.81	162.82	153.99	146.34	139.86	134.55	130.40	127.43	125.63	125.00	125.54	127.25	130.13	134.19	145.80	153.37	162.10	172.00	183.08	195.32	208.74	223.33
	2	149.28	136.94	125.78	115.78	106.96	99.31	92.82	87.51	83.37	80.40	78.60	77.97	78.51	80.22	83.10	87.15	98.77	106.33	115.06	124.97	136.04	148.29	161.71	176.29

Table 22: Outbound volume summary regressions statistics for Florence

<i>Regression Statistics</i>	
Multiple R	0.16848
R Square	0.028385
Adjusted R Square	0.018742
Standard Error	202.0495
Observations	408

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>	<i>Lower 95.0%</i>	<i>Upper 95.0%</i>
Intercept	199.9626	36.01661	5.551955	5.13E-08	129.1587	270.7665	129.1587	270.7665
DIST	-0.1292	0.064636	-1.99897	0.046283	-0.25627	-0.00214	-0.25627	-0.00214
TIME	18.04055	44.17437	0.408394	0.683201	-68.8004	104.8815	-68.8004	104.8815
D^2	5.85E-05	2.52E-05	2.321354	0.020766	8.96E-06	0.000108	8.96E-06	0.000108
T^2	-21.6916	21.22035	-1.02221	0.307297	-63.408	20.02485	-63.408	20.02485