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Abstract. This paper observes what effect, if any, weather events exert on congestion prices in energy markets. Millions of dollars are traded daily in these markets, and with the knowledge of how weather events affect electricity prices, traders can make more informed decisions on when to act. I have 7 years of panel data at the zonal level of the New England Independent System Operator market to contrast with National Oceanic and Atmospheric Administration weather data from surface meteorological stations. I utilized an ordinary least squares model controlling for season by year, day of week, and zonal fixed effects along with various demand side controls to test for the effect of weather events on average zonal daily real time congestion prices. My results suggest that in the New England Independent System Operator market, on average, hail decreases congestion pricing, sleet and tornadoes increase congestion pricing, days following tornadoes and freezing rain have higher congestion pricing, and days following thunderstorms have lower congestion pricing.

Keywords and phrases. Congestion, Locational Marginal Prices, Weather Events, Independent System Operator - New England
Introduction.

Weather events, such as freezing rain, sleet, and tornados, can act as significant shocks to the electricity market. Prior to the adoption of independent system operator markets the effect of weather events among regions were more difficult to study due to an imbalance of rules in response to constraints in generation or transmission, and lack of competition in electricity generation. The creation of the New England Independent System Operator (NEISO) market homogenized the response to constraints and unexpected demand for electricity, and encouraged competition through financial incentives. As a result, it is less difficult to study the effect of supply shocks such as weather events on electricity pricing within an independent system operator (ISO).

The question I answer in my paper, is: how does the presence of weather events such as tornados, freezing rain, sleet, thunderstorms, and hail affect congestion in the New England Independent System Operator market? I use a fixed-effects ordinary least squares model over 7 years of panel data from 2008 to 2014 to answer my question. My findings suggest that when controlling for temperature, load, season by year fixed effects, day of week fixed effects, and zonal fixed effects, weather events do significantly impact congestion. Specifically, on average, presence of sleet or tornados increases average daily zonal congestion, presence of hail decreases average daily zonal congestion, presence of freezing rain on day t-1 increases average daily zonal congestion on day t, and presence of a thunderstorm on day t-1 decreases average daily zonal congestion on day t.
Millions of dollars in both speculative and hedging trades are transacted in the New England Independent System Operator market daily. By understanding the impact of weather events on congestion pricing at the daily specification, traders can make more informed trades on both the day ahead and real time markets. Specifically for the day ahead market, the results of my research paired with reliable weather forecasting could lead to more accurate predictions of contingencies. Therefore, the spread between the day ahead and real time markets in ISO-NE would shrink, and would increase the reliability of electricity generation for the region.

**Literature Review.**

The objective of this literature review is to better understand how to approach the challenges associated with analyzing the effect of weather events on congestion pricing. The first obstacle is defining ‘weather events’ under the context of energy markets. The second difficulty is selecting appropriate demand-side controls for a model that isolate the impact of weather events on energy generation and transmission. Third, weather events and demand for power vary heavily by time of year, day of week, and geolocation. Therefore, seasonality, intra-week, and locational differences should be accounted for.

There is expanding research on weather events causing harm to the power grid. A recent study by the Lawrence Berkeley National Laboratory (Mills, 2012) cited by the Congressional Research Service (Campbell, 2012) suggests damaging winds, lightning, and ice storms are increasingly contributing to constraints on the power grid.\(^1\)\(^2\) As such, the model used in this

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paper includes weather types suggested by LBNL and CRS research, as well as other weather
types reported by the National Climatic Data Center (NCDC) that are found to be significant.

Selecting controls for weather analysis in power markets is a daunting task. Hines, Apt, and Talukdar (2008) show a significant portion of power outages and constraints are not caused by weather events. In order to isolate the impact of weather events on congestion pricing, it will be important to control for electricity demand, or load (Valor et al. 2001). Although load and temperature are correlated, temperature will also be included to account for any variation in congestion due to temperature (Kaffine et al. 2012).

The next issue involves accounting for seasonality. Electricity market analysis is susceptible to seasonal and intra-week trends, mostly between weekdays and weekends. In order to capture trends over time, the model in this paper uses a variation of the fixed-effects treatment used by Kaffine, McBee, and Lieskovsky (2012).

Another difficulty present in answering my question lies in the geographical heterogeneity of the data. Different ISOs span across multiple regions of the country. It is much more likely, for instance, for a winter storm to impact New England or Michigan than it is for California. However, if a winter storm were to strike California, the effect on electricity pricing would be much greater than a blizzard striking New England or Michigan (Yost-Bremm, 2014).

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Additionally, the literature suggests that the results of my study would be vastly different in separate ISOs. As suggested by Yost-Bremm, this is partially because each ISO abides by its own rule set, and also because each ISO has varying geographical factors. Therefore, I analyze ISO-NE, for small size and geographic homogeneity in relation to the other ISOs.

Although useful, the literature on ISO markets is far from comprehensive. Mostly deregulated energy markets are relatively new, and there is much room for expansive research on these markets. Analyzing the literature referenced here has been insightful in revealing classification of weather events, controlling for demand-side factors of electricity markets, how to approach seasonal and intra-week trends, and region selection.

**Congestion.**

Congestion is a component of locational marginal pricing (LMP). LMP is equal to the sum of the cost of electricity as determined by the ISO, heat loss along wires, and congestion. Congestion is equal to the marginal cost of power caused by a constraint on the market. For example, if load point A required 500 MW, and could purchase 200 MW from generator B for $20/MW, 300 MW from generator C for $50/MW, and 300 MW from generator D for $30/MW, load point A would meet demand from generators B and D. However, if there was a transmission capacity constraint on line DA that limited the line to 200 MW, load point A would need to obtain the final 100 MW from generator C for $50/MW. The congestion price in this situation is the marginal cost difference of obtaining the final MW of power with and without the constraint.\(^7\) \( ($50/MW - $30/MW) = $20/MW\)

\(^7\) See Figure 1
Data.

My data covers 7 years of the New England Independent System Operator market information, from January 2008 through December 2014. The advantage of selecting data from this time period is it follows a major boom in market participation. Between 2006 and 2008 there was an increase from 250 market participants to over 400. However, between 2008 to 2014 there was only an increase from 400 market participants to just over 450. Intuitively, market response to constraints should be more reliable with more participants. Therefore, by excluding observations before 2008, the capacity of the market to respond to constraints should be somewhat more homogenous across years.

The potential downside to selecting data from 2008 to 2014 is accounting for market changes to the day ahead market implemented in 2010 and 2013. In 2010, the New England Independent System Operator market began accounting for supply obligations through forward capacity auctions. Forward capacity auctions allow traders to more easily account for contingencies in the day ahead market, which could potentially allow for better preparation for transmission or outage constraints. In 2013, the New England Independent System Operator implemented strategic planning changes to the day ahead energy market, improving the efficiency of switching between natural gas and different methods of generation such as coal and renewables, which might reduce congestion. However, I include data from 2008 to 2014 because the results suggest that seasonal and yearly trends of average daily zonal congestion lack significance, and I did not want to exclude observations of weather events from 2008 to 2009.

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8 See Figure 3 for a map of the NEISO zones.
I gathered my electricity market data from Yes Energy, specifically average daily zonal congestion pricing and average daily zonal load for each of the 8 zones within the New England Independent System Operator market. Average daily zonal congestion pricing is the aggregation of nodal congestion within an individual zone divided by the number of nodes in that zone. Average daily zonal congestion pricing is calculated in dollars per megawatt hour. Average daily zonal congestion was converted from $/MWh to $/GWh for readability of results. Average daily zonal load is the aggregation of energy demand from all nodes within a zone, divided by the number of nodes within that zone. Table 2 displays the min, max, mean, and standard deviation of congestion by each zone. Average daily zonal load is calculated in megawatt hours.

My weather data was retrieved from the National Climatic Data Center, which includes maximum daily temperatures, and the weather types freezing rain, hail, high or damaging winds, sleet, thunderstorms, and tornados from every weather station in Massachusetts, New Hampshire, Vermont, Maine, Connecticut, and Rhode Island. Maximum daily temperature was

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9 I selected average daily zonal congestion pricing as my dependent variable because it is the component of locational marginal pricing (LMP) I intuitively suspect weather events affect. Although LMP represents the total cost of electricity at a given node, LMP is equal to the summation of electricity cost determined by the independent system operator, heat loss along lines, and congestion pricing. Therefore, using locational marginal pricing as the dependent variable would make interpreting the coefficients on weather events much less clear, because the coefficients on weather events would be describing not just the effect of weather events on introducing constraints into the market, but also on loss along lines as well as the cost of electricity as set by the independent system operator.

10 See table 2 for summary statistics of congestion price by zone.

11 I include average daily market load as a control because load represents the demand for energy within a given zone. Accounting for daily zonal electricity demand should isolate the interpretation of the effect of weather events to the supply-side impact of the weather event, either through affecting electricity generation or transmission.

12 Congestion varies heavily by zone, with extremely large standard deviations. This provides evidence to how volatile energy markets can be.

13 Controlling for temperature shows the distinct effect that freezing rain or sleet has on congestion, rather than the effect of colder weather on congestion associated with freezing rain or sleet.

14 High or damaging winds are classified as those exceeding 50-60mph.
recorded in tenths of degrees celsius, and was converted to kelvin. The weather types were stored as binary indicators, 0 if they did not occur or 1 if they did. Over the 7 year span across the New England Independent System Operator region, freezing rain occurred 5 times, hail occurred 369 times, high or damaging winds occurred 91 times, sleet occurred 77 times, thunderstorms occurred 610 times, and tornadoes occurred 3 times. No weather events occurred on December 31, 2014, therefore there are as many same-day observations as there are lagged.

In order to combine the energy and weather data, I appoint weather station values given in the most population-dense areas inside each zone to congestion and load values within every zone, and merge by date. Then, I generate 1-day lagged observations, with weather events occurring at time \( t - 1 \) in order to test for a delayed effect of weather events on average daily zonal congestion pricing. My resulting dataset includes 20,358 observations, for around 2545 days per zone.

**Methodology.**

In order to test for the effect of weather events on electricity pricing, I utilize an ordinary least squares model with maximum daily zonal congestion pricing as the independent variable and the weather shocks as the dependent variables.

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15 I first divided the tenths of degrees celsius by 10, then added 273.15 to convert to kelvin. Following the conversion, some observations were zero or negative (because they had been recorded as -9999), and were therefore dropped. It was important to convert to kelvin in order to keep all of my observations positive.

16 Norwich for Connecticut, Waterville for Maine, Bedford Hanscom Airbase for N.E. Massachusetts Boston, Manchester Airport for New Hampshire, Providence for Rhode Island, Middleboro for S.E. Massachusetts, Montpelier for Vermont, and Westfield for Western Central Massachusetts. Limiting the number of stations shortened my number of observed days from over 500,000 to 20,358.

17 It should be noted that there are no lagged observations for January 1, 2008 for each zone, because I lack weather type data for December 31, 2007. These observations are missing.

18 Variation in days per zone is attributed to incomplete weather data. Some dates had missing observations, and were omitted when the energy and weather datasets were merged.

19 I chose an ordinary least squares method over an autoregressive method because it more closely answers what the weather-related idiosyncratic supply-side and demand-side shocks are. Similarly, intuition suggests that a supply-side
My conceptual framework is

\[ P_{zt} = \sum_{i=1}^{n} \gamma_i W_{i,zt} + \varepsilon_{zt} \]  

(1)

where \( P_{zt} \) is average daily zonal congestion price at zone \( z \) and time \( t \), \( W_{i,zt} \) represents the summation of various binary indicators \( i \), where \( i \) discerns the weather type between freezing rain, hail, thunderstorms, tornadoes, sleet, and high or damaging winds in zone \( z \) at time \( t \), and \( \varepsilon_{zt} \) is the error term for zone \( z \) at time \( t \).

It is likely that weather events have a lagged effect on congestion pricing. For instance, freezing rain occurring at time \( t-1 \) might damage wires and add a transmission constraint to the market at time \( t \). In order to test for a lagged effect of weather events on congestion pricing, I include 1-day lagged weather event data in my regression.

\[ P_{zt} = \sum_{i=1}^{n} \gamma_i W_{i,zt} + \sum_{i=1}^{n} \delta_i W_{i,zt-1} + \varepsilon_{zt} \]  

(2)

\( W_{i,zt-1} \) is the summation of various binary indicators \( i \), where \( i \) discerns the weather type between freezing rain, hail, thunderstorms, tornadoes, sleet, and high or damaging winds in zone \( z \) at time \( t-1 \). Introducing 1-day lagged weather event data displays whether or not weather events significantly impact the following day's average zonal congestion pricing.

Three major foreseeable issues with my model are endogeneity through omitted variable bias and seasonality of both weather and electricity markets, potential autocorrelation, and a cointegrated unit-root. I use the Dickey-Fuller test which observes no presence of unit-root.\(^{20}\) In shock such as freezing rain does not increase the future likelihood of further supply-side shocks. Additionally, it would be easier to control for serial correlation than deal with varying lags.

\(^{20}\) Presence of unit-root suggests that the data is non-stationary, that the data evolves through time. One of the assumptions of an ordinary least squares regression is that the data must be stationary. Therefore, if there is unit-root present, the coefficients in my regression would be uninterpretable. The null hypothesis of the Dickey-Fuller test is
order to reduce omitted variable bias, I account for average daily zonal market load, temperature, and temperature squared.

\[ P_{z,t} = \sum_{i=1}^{n} \gamma_i W_{i,z,t} + \sum_{i=1}^{n} \delta_i W_{i,z,t-1} + \beta_1 L_{z,t} + \beta_2 T_{z,t} + \beta_3 T_{z,t}^2 + \varepsilon_{z,t} \]  \hspace{1cm} (3)

\( L_{z,t} \) represents maximum daily zonal market load for zone \( z \) and time \( t \), and \( T_{z,t} \) is temperature at zone \( z \) and time \( t \). After controlling for load and temperature, I am left with the effect of weather events on maximum daily zonal congestion pricing independent of market load and temperature, both factors that can influence demand for electricity.\(^{21}\)

Seasonality is an issue when analyzing both weather data as well as electricity markets. For example, weather types such as thunderstorms and sleet vary by season, and market load is much lower during the spring and the fall. Controlling for seasonality allows me to observe the effect of weather events on congestion pricing independent of unobservable factors or seasonal trends that might be correlated with congestion in electricity markets. I seasonally de-mean my data using a fixed effect treatment, including season by year, and day of week terms.

\[ P_{zt} = \sum_{i=1}^{n} \gamma_i W_{i,z,t} + \sum_{i=1}^{n} \delta_i W_{i,z,t-1} + \beta_1 L_{z,t} + \beta_2 T_{z,t} + \beta_3 T_{z,t}^2 + \lambda_{sy} + \mu_{dow} + \varepsilon_{z,t} \]  \hspace{1cm} (4)

\( \lambda_{sy} \) represents a season by year indicator, and \( \mu_{dow} \) indicates the day of week. These fixed-effects de-mean the the season by year and day of week. As a result, this model captures that the data is non-stationary. The alternative hypothesis of the Dickey-Fuller test is that the data is stationary. The results of my Dickey-Fuller test allow me to reject the null hypothesis of non-stationary data, in favor of the alternative. Therefore, my data does not have a unit-root problem.

\(^{21}\) Load represents market demand for electricity. Intuitively, temperature should be a driving component for electricity load because when it is hotter, there is an increased demand for people to turn on air conditioners, and when it is colder, there is an increased demand for people to turn on heaters. Therefore, I am controlling for what I suspect to drive the demand side of congestion, hoping to further isolate the supply side effect of weather events, or how weather events might introduce constraints into the market by limiting generation or transmission of power. For example, by controlling for temperature, the effect of freezing rain on congestion pricing would not be explained by both the damage to the wires and low temperature, but only by the constraint imposed by wire damage.
the isolated effect of weather events on maximum daily zonal congestion pricing, independent of market demand factors temperature and load, as well as seasonal, yearly, and day of week influences.

In order to control for unobservable factors within each zone that might impact congestion, I include zonal fixed effects.

\[
P_{zt} = \sum_{i=1}^{n} \gamma_i W_{i,z,t} + \sum_{i=1}^{n} \delta_i W_{i,z,t-1} + \beta_1 L_{z,t} + \beta_2 T_{z,t} + \beta_3 T_{z,t}^2 + \lambda_{sy} + \mu_{dow} + \kappa_{z} + \epsilon_{z,t}
\]

\(\kappa_z\) represents a zonal indicator. This model explains the effect of weather events on average daily zonal congestion pricing independent of intra-zonal factors that might be correlated with congestion in electricity markets. To control for serial correlation within zones I cluster by zone.\(^{22}\)

In model (5), \(\gamma_i\) explains the impact of weather type \(i\) in zone \(z\) at time \(t\), and \(\delta_i\) shows the impact of weather type \(i\) in zone \(z\) occurring at time \(t-1\) on average daily zonal congestion pricing in the real time market at time \(t\) after controlling for temperature, load, seasonal, within-week, and intra-zonal variation. Intuitively, a positive \(\gamma_i\) can suggest 1 of 2 situations:

1. on average, weather type \(i\) damages electricity transmission and/or generation, and/or introduces constraints on the market, and these damages caused by weather type \(i\) are under-estimated in the day-ahead market.

\(^{22}\) The data is unlikely to be independent across observations due to intra-zonal factors. By clustering my data by zone, I control for serial correlation of the data.
2 - weather type \( i \) on average helps electricity transmission and/or generation and/or alleviates constraints, however the day-ahead market overestimates the benefit to the market caused by weather type \( i \).

Situation 1 is the more likely explanation for a positive \( \gamma_i \).

Similarly, a negative \( \gamma_i \) could signify 1 of 2 things:

3 - on average, weather type \( i \) unexpectedly benefits electricity transmission and/or generation and/or alleviates constraints on the market, however the day-ahead market underestimates the benefit to the market caused by weather type \( i \).

4 - weather type \( i \) on average damages electricity transmission and/or generation and/or introduces constraints to the market, although the day-ahead market overestimates the damages to the market caused by weather type \( i \).

Situation 3 is the more likely explanation for a negative \( \gamma_i \).

**Results.**

The estimates of the impact of weather events on average daily zonal congestion pricing in the New England Independent System Operator market are displayed in Table 1. The coefficients of Table 1 can be interpreted as the dollar change on average daily zonal congestion pricing in gigawatts per hour (GWh). The first column in Table 1 reports equation 2, the initial regression of weather types and corresponding 1-day lags against average daily zonal congestion. The second column in table 1 reports equation 3, the effect of weather types and corresponding 1-day lags against average daily zonal congestion controlling for load and temperature. The third column in table 1 reports the preferred model, equation 5, the effect of weather types and corresponding 1-day lags against average daily zonal congestion including load and temperature.
controls, zone fixed effects, season by year fixed effects, and day of week fixed effects. The standard errors for each column were clustered by zone to account for intra-zonal correlation of errors.

The results of my model in Table 1 suggest a small, yet significant effect of weather events on average daily zonal congestion pricing in the NEISO market. On average, hail decreases mean daily zonal congestion pricing by $0.029/GWh, sleet increases mean daily zonal congestion pricing by $0.054/GWh, and a tornado increases mean daily congestion pricing by $0.048/GWh. The coefficients of hail and sleet are significant with a p-value <.01, and the coefficient of tornadoes is significant with a p-value <.05. On average, freezing rain incurs a 1-day lagged increase on mean daily zonal congestion pricing by $0.014/GWh, a tornado incurs a 1-day lagged increase on mean daily zonal congestion pricing by $0.029/GWh, and a thunderstorm incurs a 1-day lagged decrease on mean daily zonal congestion pricing by $0.006/GWh. The coefficients on lagged freezing rain and thunderstorms are significant with a p-value <.05, and the coefficient on lagged tornadoes is significant with a p-value <.10. The coefficients on weather events were relatively robust to changes to the model.

Initially, one might not expect hail to decrease congestion pricing. However, there are many possible explanations for why hail might decrease congestion. Unlike freezing rain, hail is unlikely to damage power lines and restrict energy transmission. Instead, due to vehicle damage or the threat of vehicle damage, hail is likely to disincentivize people from driving, which reasonably explains the negative correlation between hail and average daily zonal load.

23 Significant coefficients were bolded for increased readability.
24 A correlation test between hail and average daily zonal load showed a negative correlation between the two at the 99.9% confidence level. The issue of multicollinearity was considered for my model, however the coefficient of
Additionally, 85.9% instances of hail captured between 2008 and 2014 in the NEISO region occurred in non-winter months where congestion is typically lower. However, I control for both load and seasonality in the primary regression, which discredits those theories. One potential explanation for why hail significantly lowers congestion pricing is the poor predictability of hail in the day-ahead market. Due to the contingent nature of hail, it is possible that the day-ahead market will prepare for a day without hail, and over-generate electricity.25

The results suggest that days following thunderstorms experience lower congestion than other days. One potential explanation for why thunderstorms exert a negative lagged effect on congestion pricing is due to the life cycle of thunderstorms. A thunderstorm dissipates once their updraft dies out, either due to insufficient surface heating or when a downdraft in precipitation interacts with the updraft. The passage of a thunderstorm is typically followed by clear and cool weather which results in lower temperatures and load. Thunderstorms tend to occur during warmer months. The NCDC data shows 86.3% of thunderstorms in the NEISO region between 2008 and 2014 happened between April and November, historically the warmest 6 months. However, I control for temperature and load in my primary regression, which suggests that although more comfortable temperatures following thunderstorms might contribute to a decrease in congestion, there is likely a positive supply-side shock associated with days following thunderstorms. Solar generation, especially in Massachusetts, has grown in market share since 2008. In 2013, NEISO had a photovoltaic capacity of nearly 500 MW/h, 360MW/h of which is

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25 Following this, it would be interesting to observe how weather expectations affect generation and generation patterns by fuel type.
According to the Solar Energy Industries Association, by 2016 Massachusetts will install an additional 1100 MW/h of photovoltaic generation capacity. Clear weather following thunderstorms is likely to improve photovoltaic generation, and could help explain the negative coefficient for days following thunderstorms.

The nature of sleet formation may contribute to the significant positive impact of sleet on congestion pricing. Sleet requires specific conditions to form, namely a shallow layer of warm air to melt snow as it is falling, followed by a cold layer of air to freeze the liquid before it hits the ground. Typically, sleet is seen during the winter following snowstorms as a thin layer of warm air is introduced. The data support this claim, as 75.3% of sleet observations between 2008 and 2014 in NEISO occurred on the same day as snowstorms or days immediately following snowstorms. Given large accumulation of sleet during snowstorms, power generation and transmission can be taken out. One example of sleet buildup following a snowstorm that affected the power grid was in Southeastern Massachusetts on February 9, 2013. A major snowstorm took out the Jordan and Auburn 345kv transmission lines in Southeastern Massachusetts leaving many homes and businesses without power. NEISO planned for, and was relying on the Jordan and Auburn 345kv line constraint to be lifted by February 11, 2013, however was delayed due to sleet accumulation: “efforts to reconnect homes could be affected, however, by further snow which was predicted to fall, gradually changing to sleet.” Because the constraint was expected to be lifted, the market did not adequately prepare for the power

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27 http://www.seia.org/research-resources/2014-top-10-solar-states
demand with the constraint in place, and congestion price spiked due to sleet on February 11, 2013, as shown in figure 2.\textsuperscript{30}

Tornadoes induce transmission constraints, which increases congestion pricing. One such example of this was in Western Central Massachusetts on June 1, 2011, where a tornado left over 50,000 homes without power after damaging power lines.\textsuperscript{31} The severity of damage caused by a tornado can take some time to repair, which explains the lagged significance of tornadoes. It makes sense that the lagged effect of tornadoes is smaller than the initial impact of tornadoes on congestion pricing. Intuitively, it takes time to repair the damaged power lines, and alleviate transmission constraints on the power grid. As the power lines are repaired, congestion should decrease. The coefficients on tornado and lagged tornadoes might not accurately portray the actual impact of tornadoes on congestion pricing, however, due a low sample size of 3.

Observations of freezing rain are limited. Between 2008 and 2014 in the NEISO region, only 5 instances of freezing rain were recorded. The literature agrees that freezing rain can damage power lines, however due to the small number of observations over the time period, freezing rain is not significant in my results. A greater sample size might show a significant effect of freezing rain on average daily zonal congestion pricing.

Conclusions.

In the preceding sections, I provided estimates for the effect of weather events such as hail, sleet, thunderstorms, freezing rain, and tornadoes on average daily zonal congestion pricing.

\textsuperscript{30} Figure 2 obtained from Yes Energy’s Transmission Outage tool. If you have any questions, please contact cory@yesenergy.com
for the New England Independent System Operator market. I used an ordinary least squares model controlling for load and temperature, with season by year, day of week, and zonal fixed effects. The results of my model suggest a small, yet significant effect of certain weather events on congestion pricing. In particular, on average sleet and tornadoes significantly increase congestion pricing, hail significantly decreases congestion pricing, days immediately following freezing rain and tornadoes have increased congestion pricing, and days immediately following thunderstorms have decreased congestion pricing.

This paper provides explanations for the directions of the coefficients on weather events in the model. Sleet that occurs directly after a winter storm can unexpectedly extend transmission constraints. The contingent nature of hail might lead to an overestimation in forecast load, which might decrease congestion pricing. Tornadoes damage power lines which take an extended time to repair, increasing congestion on the day of and following the tornado. Dry cool air masses that follow thunderstorms might improve photovoltaic generation, consequently increasing generation and causing congestion to drop on days after thunderstorms. Freezing rain can cause damage to power lines, which can inhibit transmission and increase congestion. However, the predictive capacity of the model in this paper has limitations.

The frequency of both tornadoes and freezing rain were low during 2008 through 2014. A likely consequence of a low sample is the coefficients on those values might be artificially small, as well as have higher p-values. With more observations, it is probable that we would be able to reject the null hypothesis that freezing rain has no effect on average daily zonal congestion pricing on the same day. Another limitation of the results in this paper is the results
only apply for the NEISO region. It is likely that due to geographic heterogeneity, weather events outside the NEISO region impact congestion in energy markets differently.

Looking to the future, we are still unsure about the effect of weather predictions on expected load, and generation by fuel type. However, this paper provides evidence suggesting that the New England Independent System Operator market is, on average, under-preparing power generation and/or transmission for sleet days, tornado days, and days directly following freezing rain and tornadoes. Additionally, this paper provides evidence suggesting that the New England Independent System Operator market is, on average, over-preparing power generation and/or transmission for hail days and days directly following thunderstorms. Traders should continue to adjust for weather events when making decisions. Additional research modelling the day-ahead supply decision would be fruitful.

Appendix.
Table 1 - Regression Results

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<td>(0.00774)</td>
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<td>(0.0115)</td>
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<tr>
<td>tornado</td>
<td>0.0372**</td>
<td>0.0438**</td>
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<td>(0.0122)</td>
<td>(0.0131)</td>
<td>(0.0143)</td>
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<td>0.0356**</td>
<td>0.0347**</td>
<td><strong>0.0293</strong></td>
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<tr>
<td>avgload</td>
<td>0.199***</td>
<td></td>
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<td>(0.110)</td>
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<td>tmaxk</td>
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<td>(337.5)</td>
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<td></td>
<td>(0.551)</td>
<td></td>
<td>(0.593)</td>
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<td>Constant</td>
<td>1,022*</td>
<td>-42,539</td>
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<tr>
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<td>(463.2)</td>
<td>(45,348)</td>
<td>(48,253)</td>
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Observations 20,384 20,358 20,358
R-squared 0.001 0.009 0.024
SE Clustered by Zone YES YES YES
Season*Year FE YES
Day of Week FE YES
Zone FE YES

Robust standard errors clustered by zone in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 2 - Congestion Prices by Zone in dollars per Gigawatt hour ($/GWh)

<table>
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<th>zone</th>
<th>N</th>
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<th>max</th>
<th>min</th>
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<td>53706.25</td>
<td>-20324.58</td>
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<td>100.0294</td>
<td>32870</td>
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<td><strong>Total</strong></td>
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<td>53706.25</td>
<td>-91820.41</td>
<td>2164.232</td>
</tr>
</tbody>
</table>
Figure 1 - Congestion

A
Load = 500 MW

C
Offer = 300 MW
Price = $50

D
Offer = 300 MW
Price = $30

B
Offer = 200 MW
Price = $20

Capacity limit = 800 MW
Capacity limit = 200 MW
Capacity limit = 800 MW
Figure 2 - Outage Map on 3/11/2013
Figure 3 - Map of NEISO Zones
Bibliography.


