Pricing of Climate Risk in Options Market

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ABSTRACT

Pricing of Climate Risk in Options Market

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I analyze the pricing of climate risk by studying on implied volatility in option markets before Atlantic Hurricane Season peaks. I find that climate risk is priced in the equity option market. Put options whose lives span peak period of hurricane season become more expensive compared to call options in hurricane season. In addition, price differences between OTM put options and ATM call options covering the peak period of hurricane season is higher than price differences of the same type of options in non-hurricane season. The results also suggest that hurricane season forecasts and property information of REITs in affected regions together influence the price of options through implied volatility skew of equity options.

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INTRODUCTION

In today`s world, climate risk has started to be regarded as one of the important risks which may affect sectors, businesses and financial markets significantly. Floods, frost, hurricane are mostly known climate risks that people face every day all around the world. Some of these catastrophic incidents happen in certain seasons and in certain regions of the world. For example, severe floods generally occur in Southeastern Asia in summer whereas hurricanes happen in Atlantic region between June and November.

Among all types of climate risks and events, hurricane is one of the most devastating natural phenomenon. According to the report of National Hurricane Center (2018), there have been 41 major hurricanes occurred between 1965 and 2017 and damage of each is above 1 billion USD. Their total damage is more than 600 billion USD. In the light of this fact, hurricanes can be considered as one of the most significant climate incidents that strikes sectors in the US financially.

When it comes to pricing of climate risks in financial markets, do investors consider forecasts of hurricane season or information regarding risks of firms which they are interested in when they decide to take action in the financial markets? Does the market price climate risk or hurricane risk? In this study, I aim to answer these questions by looking at the price of equity options of REITs covering the peak season of the hurricane season and compare them to price of options with the same maturity and underlying in non-hurricane season. In my study, I take hurricane season as starting from mid-August and ending in October because hurricane risks reach highest probability in this period according to NOAA. I focus on Real Estate Investment Trusts (REITs) because real estate sector is one of the most vulnerable sectors. The reason of vulnerability is the drop in sales and the damage to commercial/residential real estates.

Hurricane hits houses or commercial real estates directly and causes their prices to drop during hurricane season due to huge property damages. In other words, REITs might possibly suffer from damage and revenue drops during hurricane seasons. According to the article of Your Castle Real Estate (2018) which is a real estate company in the US, house sales decreased by 48 percent in Ft. Pierce and Port St. Lucie in September, and dropped again in October by an additional 22 percent because of Hurricanes Frances and Jeanne in 2005. In the same article, it states that house sales in Fort Walton Beach fell by 29 percent at the same month after Hurricane Opal hit the Florida in October of 1995. Panama City, which was also directly hit by Hurricane Opal, saw a sales decline of 31 percent.

It is likely that stock prices of REITs operating in susceptible region by hurricane might fall because of property damage and sales drops of real estate. Despite all these damages and sales drop, there are financial instruments that enable investors to protect or hedge themselves financially against drops in the prices of stocks of REITs due to hurricane risk. One of the effective tools for hedging is the equity option of REIT. Investors can take positions in option markets when they anticipate fall in equity prices of REITs.

I expect that prices of put options become more expensive than call options before hurricane risk becomes severest and strongest. To analyse price change, I look at the implied volatility, which is one of the determinants of options prices according to Black-Scholes model. Implied volatility of the option shows the expected volatility of the option`s underlying asset over the life of the option. Thus, expectations of investors about stock prices are reflected by implied volatility in the option prices.

Implied volatility skew is a measure of options that can be used to observe difference in implied volatilities between put and call options. Implied volatility skew is defined as the difference in implied volatilities between out of money (OTM) put option and at the money (ATM) call option. Because OTM put options are cheap and attractive hedging instruments for investors, OTM put options become more demanding when there is uncertainty in the market. Therefore, in my study, I decide to use an indicator involving implied volatility of OTM put options. Details of the implied volatility skew calculations are explained in the methodology part.

First hypothesis of my study states that IV skew of REITs equity options covering peak period of hurricane season is higher than IV Skew of options covering non-hurricane season because OTM put options become more demanding than ATM call options for hedging purposes in the hurricane season just before it gets peak. In non-hurricane seasons, this kind of difference in implied volatility is not expected because investors do not have hedging concerns at that time.

My second hypothesis states that forecasts of NOAA regarding hurricane seasons and property size information together affects implied volatility skew of REITs equity options positively. In other words, investors consider property and forecast information together and these two factors together affect option prices via implied volatility.

National Oceanic and Atmospheric Administration (NOAA) release its forecasts about upcoming hurricane seasons in May, in the name of Atlantic Hurricane Season Outlook. Since 2002, NOAA provides specific predicted ranges of hurricane activities, which are minimum and maximum number of normal storms, hurricanes, major hurricanes forecasted. It is expected that investors, who hedge themselves against hurricane risk, take into account NOAA forecasts about hurricane seasons. Because forecast information regarding number of hurricanes was started to be released in 2002, my study covers the period from 2002 to 2018. From SNL Financial data, I obtain property information of REITs. In this dataset, there are property size (sq. ft.) information of REITs in the states of U.S. between 2002 and 2018. Investors of REITs consider whether REITs have property in hurricane susceptible regions and the percentage of their portfolios in those regions.

The mean difference test and regression analysis are implemented to test the first and second hypothesis. Placebo analysis is also carried out to observe whether forecasts and property information have any effect on implied volatility skew in non-hurricane season. As a result of mean difference test, I find that implied volatility skew is larger in hurricane season on average than non-hurricane season. The difference in implied volatility skew is statistically significant. Regression analysis gives the result that forecast, and property information together affect implied volatility skew. The article continues with literature review. Data, methodology and results are explained in upcoming parts. In these parts, data collection process, methods adopted, and results of the analysis are explained in detail. In the discussion part, the background of the findings in the financial market is explained. In the conclusion part, methodology and main findings are reviewed.

LITERATURE REVIEW

Unlike other investment instruments, options have unique feature as implied volatility that indicate future perceptions of investors about the underlying. By looking at the implied volatility before major events, market`s expectations about those events can be inferred. In this study, I look at whole hurricane season instead of specific events. To observe the pricing of hurricane risk in financial markets, I use options in my analysis because there are options whose lives span the peak period of hurricane seasons before it happens. There are no studies in the literature that show pricing of climate risk in option markets. In this sense, its contribution to literature makes my study unique. However, researchers have studied on implied volatility regarding other major events. In addition, there are some studies in the literature showing relationship between options and stock returns.

The findings of Emanuel (2005) propose that future warming may bring about an increasing trend in tropical cyclone power and consequently a significant rise in hurricane-related losses in our century. From his findings, it can be inferred that effect of the hurricane on financial market may be stronger in the future than today. This may cause hedging with options to become more essential and common in the future

Kelly, Pastor, Veronesi (2016) analyze the pricing of political uncertainty in the equity option market. They find that options whose lives span political events are more expensive because options spanning political events have higher implied volatilities by 1.43% on average than options not spanning political events. Such options enable investors have valuable protection against the price risks associated with political events, which are elections and summits. Ewing et al (2006) explore how the stock prices of insurance firms respond before, during, and after Hurricane Floyd by taking characteristics of storm into account. Their study shows that changes in climate variables gives rise to changes in the excess return of insurance companies. They find that increases in extreme climate conditions, as measured by the CEI Index, increase earnings rates in the subsequent quarter for all reinsurance and insurance companies except for Swiss Re. They also reach the result that increases in the Atlantic Accumulated Cyclone Index are also related with an increased rate of return to Munich Re, ING, and the NASDAQ insurance index.

Like my study, they use measurements of NOAA in their regression analysis. One of them is the Accumulated Cyclone Energy Index used by the National Oceanic and Atmospheric Administration (NOAA). In the study, I use different estimation of NOAA about number of hurricanes expected during the hurricane season. Moreover, I consider whole hurricane season in the analysis. In that sense, my study draws more general conclusion about the effect of hurricane on financial markets. I do not focus on single hurricane unlike that study. In addition, the sample is composed of REITs and I incorporate property information into the analysis.

Feria-Domínguez et al. (2017) analyze the effect of hurricanes on the P&C Insurance Firms. They study on seven major hurricanes which happened between 2005 and 2012. They conclude that there are noticeable abnormal returns during hurricanes Rita, Felix, Ike, Igor and Ophelia but not during Katrina or Sandy. Blau et al. (2008) find a significant increase in short-selling activity in the trading days prior to the landfall of Rita and relatively less short-selling activity in the trading days after landfall.

In their study, Rehse et al. (2019) compare the market reactions of REITs with and without properties in the evacuation zone of New York City prior to landfall. They use the week prior to Hurricane Sandy's landfall in October 2012. They compare the trading volume and the bid-ask spread of stocks of REITs with and without property in the affected area. They find results of less trading and larger bid-ask spreads in affected REITs.

Chan, Ge and Lin (2015) study on the informational content of option trading in merger and acquisition (M&A) events and they find that implied volatility (IV) spread predicts positively on the announcement return, while implied volatility (IV) skew predicts negatively on the announcement return. They conclude that a larger IV skew is a proxy for a higher buying pressure on OTM put relative to ATM call, showing that investors are anticipating a negative return in future and so IV skew should negatively predict M&A acquirer announcement return. In my study, I use also IV skew variable which formula is very similar to the formula used in that study. In the literature, some research has done studies regarding stock returns and option prices by basing on informative features of options about future stock movements.

In the study of Easley, Hara and Srinivas (1998), their model states the result that buying a call or selling a put delivers positive information about future stock prices. Similarly, selling a call or buying a put delivers negative information about future stock prices. I can draw a conclusion from findings of this study that equity options have information about future stock price movements. If investors expect that stocks drop in the future, they will buy related put options or sell call options. If they expect other scenario, they will buy related call options or sell put options. In my hypothesis, I state that equity put options become more demanding than equity call options during hurricane season because of hurricane`s financial damages to REITs and possible drop in value of their stocks. Therefore, my hypothesis and their findings are parallel.

Ortega and Taspinar (2016) study on the effects of hurricane Sandy on the New York City housing market. They find that Sandy brought about a significant fall in prices in the affected neighborhoods. Properties that had more damage actually involved larger falls in value. Lamb (1995) find that Hurricane Andrew caused a significant negative property-liability stock price respond on insurers with direct premium volume in Florida or Louisiana. Insurers with no exposure in those states maintained no important stock price reaction. Worthington and Valadkhani (2004) carried a study regarding market returns and natural disasters. They study on natural disasters other than hurricanes. They reach the result that the shocks caused by natural events and disasters have an effect on market returns in Australian equity market. The study of Robinson and Bangwayo (2016) shows that major hurricanes making landfall in Jamaica produce stock markets losses that can be ten times larger than losses from damage to property and infrastructure. Lanfear et al. (2017) examine gold-related stocks when there is uncertainty generated by hurricanes. They find that gold-related stocks experienced appreciation during these times unlike many industries. Hiranto (2019) find that the stock market fell when the hurricane occurred in US. Results of the study of Vlady (2015) indicate that climate change does not significantly affect big Australian companies or all the Australian market. He also concludes that investors are rational, and the climate change information is value relevant for the refining company which suffer from Australian climate conditions. Chen et al. (2012) examine whether climate risk is priced by the capital market. They find that the cost of equity and debt financing rise with the level of exposure to climate risk. Atreya and Ferreira (2015) study on flood risk and they find that the price discount for properties in the inundated area is significantly bigger than in comparable properties in the floodplain that was not inundated.

DATA

National Oceanic and Atmospheric Administration (NOAA) was established in 1970 as an agency within the Department of Commerce. Its mission is to understand and predict changes in climate, weather, oceans and coasts, to share that knowledge and information with others and to conserve and manage coastal and marine ecosystems and resources. Starting from 1999, NOAA has been realising its forecasts about hurricane season in the reports called as Atlantic Hurricane Outlook. Since 2002, NOAA has shared minimum and maximum numbers of hurricane/major hurricanes in each year that it expected. I take that information from these reports and numbers about forecasts are confirmed. Forecasts are seen in **Table 1** in Appendix.

[Table 1 about here]

Averages of minimum and maximum hurricane/major hurricane numbers are taken to use them in the regression analysis and additional columns are added in Table 1. Before retrieving property data of each REITs, I determine which states in U.S are more affected by hurricane in the past. By detecting most affected states, I only takes SNL data of properties regarding these states so that I can only focus on properties of REITs, which are in mostly affected regions by hurricane. Data regarding affected regions by hurricane is retrieved from NOAA website. **Table 2** shows that 66% percent of all major hurricanes have occurred in **Florida, Texas and Louisiana** between 1851 and 2018.

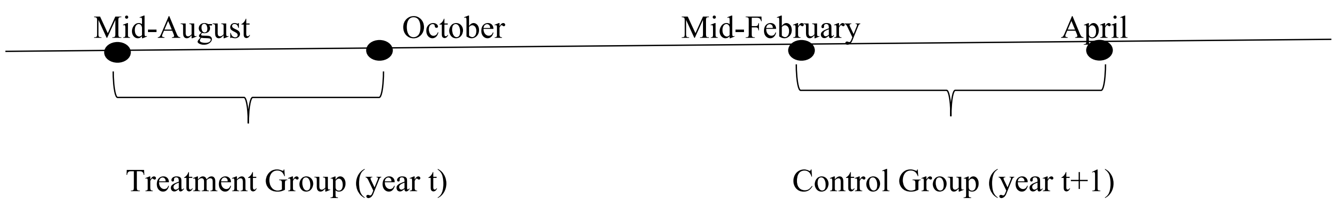
[Table 2 about here]

Property data of REITs is obtained from SNL Financials. SNL Financial LC provides business intelligence services. The Company supplies the collection and standardization of corporate, financial, and mergers and acquisitions (M&A) data. SNL Financial serves the banking, insurance, real estate, energy, media, and communications industries worldwide. I take property data of US REITs in these three cities from SNL Financial for the period of 2002 and 2018. This dataset includes institution name, property name, address, SNL institution key, city of the property, state of the property, property size (sq. ft.). CUSIP number of each firm is added to the dataset by retrieving them from Compustat. Also, I calculate how many percentages of their portfolios are located totally in these three cities for each year between 2002 and 2018. The reason of the calculation is that I create interaction variable in the regression analysis according to these percentages of REIT`s portfolios in these three states. In this way, effect of having properties in affected regions and effect of hurricane forecasts together on pricing of equity options of REITs can be observed.

The final version of property includes 182 firms. One firm may have property in these three states in one year whereas the same firm may not have property in these states in another year. In other words, firms may have sold its property in these states in any year within the study period. Property data regarding 2008 and 2009 are excluded because of the same reason explained below in the data process of options.

I explain hurricane season, its features and the control/treatment groups before getting into details of options data. According to NOAA, the official hurricane season for the Atlantic Basin (the Atlantic Ocean, the Caribbean Sea, and the Gulf of Mexico) is from 1 June to 30 November. The peak of the season and significant hurricanes are expected to happen from mid-August to late October. Therefore, the treatment group of options cover period between mid-August and late October. Options in the control group covers between mid-February and April because I aim to study on options, which are not in the hurricane season for a reasonable comparison. The periods spanned by options in the treatment and control groups is illustrated in **Figure 1** below.

Figure 1 Illustration of Treatment and Control Group



Equity option data is retrieved from Optionmetrics. In the analysis, end-of-month and American equity options of REITs are used. End-of-month options expire on the Saturday immediately following the third Friday of the expiration month until February 15, 2015. After this date, End-of-month options expire on third Friday of the month. Because it is not possible to download only End-of-month options from Optionmetrics (weekly options also in the dataset), I filter the data according to expiry date of the options and keep only End-of-month options with the help of the software called as Stata.

Two-month maturity options are studied because I want options to cover the period from mid-August to end of October and want all options to have the same characteristics so that I can compare implied volatility skew of equity options in treatment and control group on the same basis. In this way, the problem of different maturities is eliminated, which may affect implied volatility. In addition, two-month maturity options are more liquid compared to longer maturity options. Data regarding assets of REITs is obtained from Compustat to be used in the regression analysis. For treatment group, I form samples of two-month maturity options, which were traded after third Friday of August and until the end of August. I choose this trading period because it is the just before the peak period of the hurricane season and two-month maturity options traded after third Friday of August cover only hurricane season. Likewise, for control group, I create samples of two months maturity options, which were traded after third Friday of February and until the end of February. Options, which have non-zero open interest/volume and have standard settlement, are kept in the samples.

Stock data of REITs from CRSP is retrieved to eliminate options in the sample, which do not meet stock criteria of IV skew. Those criteria are explained in the part of Implied Volatility Skew. As seen in **Figure 1**, options in the treatment groups are two-month maturity option in the same year as the year of relevant hurricane season. Options in the control group are two-month maturity option one year after the year of relevant hurricane season. Thus, type of the option is the same for all firms in the sample of treatment group and control group, which is two-month maturity option. This enables us to compare IV skews of treatment and control groups on the same basis.

In other words, by keeping everything the same in both groups, we can observe the effect of hurricane seasons on implied volatility skews of two-month maturity options. Maturity of options in treatment group is October whereas maturity of options in control group is April. As last selection criteria, I exclude options traded in 2008 and 2009 when mortgage crisis happened because prices of options were far from their fundamental prices. In addition, effect of hurricane season cannot be observed solely due to significant plummet of the asset prices and direct effect of the crisis on REITs.

For the mean difference test, dataset from Optionmetrics and CRSP are merged. After implementing all criteria and requirements, sample size for treatment group is 279 and sample size for control group is 286. In the parts of **Methodology and Main Results**, the mean difference test and selection process for the sample are explained more in detail. For merging process, SAS is used as the software.

METHODOLOGY

In mean difference test/regression analysis, the measurement/dependent variable is implied volatility skew. Formula of IV Skew and selection criteria of options for its calculation are explained in the part below. After IV Skew part, methodology adopted is explained. For analysis, STATA is used as the software.

Implied Volatility Skew

The option measure adopted in this study is implied volatility (IV) skew. IV skew is used as a proxy for negative price pressure in the options market. In other words, when there is a hedging demand because of the expectation of drop in stock prices in the future, OTM put options are more demanding than ATM call options. In this scenario, IV Skews of options are expected to be positive. I use almost the same calculation as Chan, Ge and Lin (2015) did in their studies except that I multiply implied volatility with weight. They look at the M&A events for the firms and calculate IV skew for firm i on day t. On the other hand, I calculate average of IV skew of two-month maturity option for firm i and for each year`s hurricane and non-hurricane seasons because investors take position with equity options not for a single/major event but for whole season.

$$\text{IV Skew}_{i,j} = \sum_t \text{weight}_{i,j,t} * (\text{IV}_{i,j,t}^{\text{OTMput}} - \text{IV}_{i,j,t}^{\text{ATMcall}})$$

$\text{Weight}_{i,j,t}$= average (open interests of OTM $\text{put}_{i,j,t}$ and ATM $\text{call}_{i,j,t}$) / [$\sum_t$ average (open interests of OTM $\text{put}_{i,j,t}$ and ATM $\text{call}_{i,j,t}$)]

t is number of trading days after third Friday of August and until the end of August for the treatment group while it is number of trading days after third Friday of February and until the end of February for the control group.

Calculation of IV Skew for the control group is the same as for the treatment group except that year is j+1.

The same requirements are set as in the study of Chan, Ge and Lin (2015). Stock volume and option volume are required to positive to eliminate those non-trading cases. In addition, I require stock prices to be bigger than $5, option open interest to be positive, implied volatility of options to be between 3% and 200%, and option's average bid and ask price to be bigger than $0.125.

For the moneyness requirements, I follow the same procedure as Chan, Ge and Lin (2015). Moneyness is as the ratio of strike price to stock price. OTM puts are put options with moneyness between 0.80 and 0.95 whereas ATM calls are call options with moneyness between 0.95 and 1.05. If there are multiple OTM puts and ATM calls, I choose one OTM put with moneyness closest to 0.95 and one ATM call with moneyness closest to 1. During dealing with the data, I come across call options with the same moneyness which is closest to 1. The one with the highest open interest is kept. The same selection criteria are followed for OTM put options. In this approach, I come up with one skew measure for each firm i in August/February in each year j.

Mean Difference Test

To check whether the first hypothesis holds, I compare the mean of the treatment group to the mean of the control group. For this purpose, mean difference test with different sample sizes is carried out because sample sizes of treatment and control groups are different. More details about samples are explained in the part of **Main Results**.

Regression Analysis

To test whether the second hypothesis holds, I carry out regression with time variable for year fixed effect. First, I define interaction variable in order to observe effect of hurricane forecast and property of REITs in most affected regions on IV Skew:

$Interaction_{ij} = forecast_j * property_{ij}$ for every firm i and year j

In the regression analysis, property variable is taken as decimals, not percentages. I implement two regressions to observe the effect of interaction variable on IV Skew distinctly.

The regression equations are:

(1) $IVSkew_{i,j} = \beta_0 + \beta_1 * forecast_j + \beta_{2*}\ property_{i,j} + \beta_{3*}\ \log(asset)_{i,j} + \beta_j * year$

(2) $IVSkew_{i,j} = \beta_0 + \beta_1 * forecast_j + \beta_{2*}\ property_{i,j} + \beta_{3*}\ \log(asset)_{i,j} + \beta_{4*}\ interaction_{i,j} + \beta_j * year$

Forecast is the variable for forecasts of NOAA on hurricane season. There are two kind of forecasts which are number of hurricanes and number of major hurricanes. I run totally four regressions by considering these two different forecast values separately and changing interaction variable accordingly. Because NOAA releases its forecasts as minimum/maximum number of hurricanes/major hurricanes, I take the average of min and max numbers of hurricanes/major hurricanes for each year and use these average values in the regression for the forecast variable. Property variable shows percentage of portfolio of the firm in most affected three states by hurricane. Logarithm of asset variable is asset value of the firm in previous year. Average of forecast values are seen in **Table 1**.

I use robust standard errors which are heteroscedasticity and autocorrelation free for hypothesis test. The sample used in regression is composed of options traded after third Friday of August and until the end of August just before hurricane gets peak and extreme. Regression results are analyzed in **Main Results**. I also implement the same regression analysis on the sample of the options traded after third Friday of February and until the end of February in the part of **Placebo Analysis**.

MAIN RESULTS

The Results of Descriptive Statistics and Mean Difference Test

Results of descriptive statistics regarding the treatment and control group are in **Table 3**.

[Table 3 about here]

The mean value for Treatment Group is 0.055 and for Control Group is 0.050. The difference is 0.005 (10%) on average, which means that difference between implied volatility of OTM options and ATM call options spanning the peak period of hurricane season is higher by 10% than the difference of the same type of options covering non-hurricane season on average. This indicates that investors demand more OTM put options and less ATM call options in the hurricane season than in non-hurricane season. In other words, OTM put options becomes more expensive relative to ATM Call options in hurricane season than non-hurricane season. I run the mean difference test to find out whether the difference is significant. The result of mean difference test is in **Table 4**.

[Table 4 about here]

The difference is statistically significant at the level of 0.10. Thus, I reach the result that OTM put options becomes more expensive relative to ATM Call options in hurricane season than non-hurricane season. The difference is also economically significant. 10% of change in implied volatility difference means that price of OTM put options relative to ATM call options is economically larger in hurricane season than in non-hurricane season.

The Results of Regression Analysis

Regression analysis is implemented according to variables in Equation (1) and (2). The sample consists of options traded after third Friday of August and until the end of August in each year. The result is in **Table 5.**

[Table 5 about here]

The first column of the table gives the result of regression with hurricane forecast variable regarding Eq(1). Only log(asset) variable is significant and negative. Negative sign for this variable is logical because firm value and stock price are expected to increase when value of firm assets increases. Investors anticipate stocks to increase in the future so they demand ATM call options more and OTM put options less which makes IV skew smaller.

The third column of the table gives the result of regression with hurricane forecast variable regarding Eq(2). Log(asset) and property are significant and negative. Hurricane forecast variable is not significant. Interaction variable is significant at 0.01 level and positive as parallel with the second hypothesis. One percentage increase in interaction variable increases IV skew by 0.019 percentage on average.

The second column of the table gives the result of regression with major hurricane forecast variable regarding Eq(1). Log(asset) variable again is significant and negative. Major hurricane forecast is significant and negative whereas property variable is not significant.

The fourth column of the table gives the result of regression with major hurricane forecast variable regarding Eq(2). Log(asset), property and major hurricane forecast variables are negative and significant while interaction variable is significant at 0.01 level and positive. One percentage increase in interaction variable increases IV skew by 0.025 percentage on average. Interaction of major hurricane forecast, and property information has positive effect on IV Skew. This result also supports the second hypothesis. The results of these two regressions indicate that investors take major hurricane forecasts and property information together into account when they take position in hurricane season.

PLACEBO ANALYSIS

In the Main Results, the sample is composed of options traded in August just before hurricane season gets peak. I find positive and significant interaction term. In this part, I run regressions with sample of options in the control group (traded in February) and I mainly aim to observe whether coefficients of interaction variables change or not. I expect the coefficient of interaction variable to be insignificant because options in the sample are outside the hurricane season. The result of the regression is Table 6.

[Table 6 about here]

The first and second column of the table gives the result of regression with hurricane forecast and major hurricane forecast variable regarding Eq(1). Forecast variable is insignificant for both type of the forecasts. Property variable and log (asset) are significant and negative for both type of the forecasts.

The third and fourth column of the table gives the result of regression with hurricane forecast and major hurricane forecast variable regarding Eq(2). Significant variable is log(asset) and other variables including interaction are insignificant. In other words, interaction variable does not have any significant effect on IV Skew. The results indicate that investors do not take property and forecast information into account when they take position in option market in non-hurricane season. The result in placebo analysis support the second hypothesis.

DISCUSSION

I find that interaction variable has a positive and significant effect on IV Skew. In other words, investors look at forecast and property information together when they take position in option market in hurricane season. According to regression results, when interaction variable increases, IV skew also increases or implied volatility of OTM put options get bigger than implied volatility of ATM call options. How does this statistical result show itself in the financial markets in terms of market forces?

Increase in interaction indicates the condition of worsening NOAA`s forecast about hurricane season and increasing number of properties of REITs in most affected regions. When investors observe these circumstances, they buy more put options and less call options for hedging purpose because they think that stocks of REITs operating in affected areas drop during the peak period of Atlantic Hurricane Season. Chan, Ge and Lin (2015) states in their study that a higher IV skew indicates that investors demand more OTM puts, expecting a drop in the future stock price. Demanding more OTM puts causes of prices of these puts to increase. In other words, significant change in IV Skew implies significant price change in OTM put options compared to call options. Therefore, I can draw a conclusion that investors price hurricane risk/ climate risk by considering NOAA forecasts and property information of REITs in hurricane-affected regions together.

CONCLUSION

Most of the climate incidences like hurricane and flood occur in a certain pattern and in certain months. Because these incidences have certain seasons, financial markets can price climate risk caused by those catastrophes. One of them is hurricane. In this study, I try to find out whether financial markets price hurricane risk by considering Atlantic Hurricane Season. I study on US option markets because one of the determinants of option price reflects investors` future perception about stock movements. This determinant is called as implied volatility. By studying on implied volatility, I delve into pricing of climate risk in option markets. For this aim, I use IV Skew as a measurement for change in implied volatility. IV Skew is defined as difference in implied volatilities of OTM put options and ATM call options.

Due to property damage of hurricane, I compose the sample with REITs so that the effect of hurricane on financial markets can be observed apparently. Stocks of REITs are expected to drop in hurricane season on average compared to non-hurricane season due to drop in sales and damage on residential/commercial real estates. I form two samples of options. One sample belongs to treatment group that is related to hurricane season whereas the other one belongs to control group that is related to non-hurricane season. I take hurricane season as starting from mid-August and ending in October because hurricane risks reach highest probability in this period. The period for control group is from mid-February to April. I use two-month maturity, monthly, standard options in my analysis.

The first hypothesis is that implied volatility skew of REITs options are higher in hurricane season than non-hurricane season because put options are more demanding than call options in hurricane seasons compared to non-hurricane seasons. To check validity of the hypothesis, I carry out the mean difference tests between two samples. The mean of the treatment group is larger than mean of the control group. As a result of mean difference test, I find that the difference between two means is significant. The result supports the first hypothesis.

The second hypothesis is that forecasts of NOAA regarding hurricane seasons and property size information of REITs in most affected states together affect the implied volatility skew of REITs equity options positively. To test the hypothesis, I create interaction variable with forecast and property variables. I run regression and find that interaction variable is significant and positive. Therefore, the second hypothesis is supported with that result.

The study shows that hurricane risk is priced in option markets before the season gets peak and extreme. It is inferred from increase in IV Skew that OTM put options becomes more expensive compared to ATM call options covering hurricane season if other determinants of prices stay constant or do not change significantly. Investors take into account property information of REITs regarding affected regions by hurricane and NOAA`s forecasts about hurricane season. If these two factors both get more negative for investors, they prefer to invest in OTM put options more than in ATM call options. It can be stated that NOAA`s forecasts and property information of REITs affect pricing of hurricane risks in the financial markets.

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Table 1

NOAA Forecasts for Atlantic Hurricane Season

This table shows the minimum/maximum numbers of hurricanes/major hurricanes by NOAA regarding each year`s Atlantic Hurricane Season. To use in the regression analysis, average numbers of forecasted hurricane/major hurricane in each year are calculated and two additional columns are added to show them in the table. The columns are as followed: Minimum number of hurricane **(H Min),** Maximum number of hurricane **(H Max),** Minimum number of major hurricane **(MH Min),** Maximum number of major hurricane **(MH Max)**, Average number of hurricane **(H Avg),** Average number of major hurricane (**MH Avg)**

Year	H Min	H Max	MH Min	MH Max	H Avg	MH Avg
2002	6	8	2	3	7	2.5
2003	6	9	2	4	7.5	3
2004	6	8	2	4	7	3
2005	7	9	3	5	8	4
2006	8	10	4	6	9	5
2007	7	10	3	5	8.5	4
2008	6	9	2	5	7.5	3.5
2009	4	7	1	3	5.5	2
2010	8	14	3	7	11	5
2011	6	10	3	6	8	4.5
2012	4	8	1	3	6	2
2013	7	11	3	6	9	4.5
2014	3	6	1	2	4.5	1.5
2015	3	6	0	2	4.5	1
2016	4	8	1	4	6	2.5
2017	5	9	2	4	7	3
2018	5	9	1	4	7	2.5

Table 2

Hurricane Affected Region 1851-2018

This table shows numbers of hurricanes, major hurricanes, their categories and percentages between 1851 and 2018. Numbers in percentage column calculated by number of major hurricanes/total number of major hurricanes. States are sorted in descending order according to percentages. 66 percentage of all major hurricanes have occurred in top three states between 1851 and 2018.

AREA	CATEGORY						Number of Major Hurricanes	Percentage
	1	2	3	4	5	Number of hurricanes		
Florida	47	36	24	11	2	120	37	34%
Texas	29	16	12	7	0	64	19	17%
Louisiana	23	14	14	2	1	54	17	15%
Mississippi	5	6	7	0	1	19	8	7%
North Carolina	31	12	6	1	0	56	7	6%
Alabama	14	5	5	0	0	24	5	5%
South Carolina	17	8	2	3	0	30	5	5%
Georgia	16	3	2	1	0	22	3	3%
New York	9	3	3	0	0	15	3	3%
Rhode Island	5	2	3	0	0	10	3	3%
Connecticut	7	2	2	0	0	11	2	2%
Massachusetts	7	4	1	0	0	12	1	1%
Virginia	10	2	0	0	0	12	0	0%
Maryland	2	0	0	0	0	2	0	0%
Delaware	2	0	0	0	0	2	0	0%
New Jersey	4	0	0	0	0	4	0	0%
Pennsylvania	1	0	0	0	0	1	0	0%
New Hampshire	0	1	0	0	0	1	0	0%
Maine	2	1	0	0	0	3	0	0%

Table 3

Descriptive Statistics for Treatment and Control Groups

This table reports descriptive statistics on the implied volatility skew used in the main analysis. The implied volatility is difference between OTM put options and ATM call options for a firm in a specific year. First row shows the descriptive statistics for treatment group. The second row shows descriptive statistics for control group. The full sample period for both groups is between 2002 to 2018 (excluding 2008 and 2009).

Variable	Obs	Mean	Std. Dev.	Min	Max
IV Skew (Treatment Group)	279	0.0546698	0.035803	-0.070275	0.270707
IV Skew (Control Group)	286	0.0500633	0.0434574	-0.3031368	0.337897

Table 4

Result of Mean Difference Test

The table shows the result of mean difference test where the tested variable IV skew. The difference (0.005) is significant at 10% level. This means that the IV Skew is larger in hurricane season than non-hurricane season statistically at 10% significance level.

Two-sample t test with unequal variances						
Variable	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf. Interval]	
IV Skew of Treatment Group	279	0.05467	0.002144	0.035803	.0504503	.0588893
IV Skew of Control Group	286	0.050063	0.00257	0.043457	.0450054	.0551213
combined	565	0.052338	0.001678	0.039893	.0490415	.0556346
diff		0.004607	0.003346		-.0019666	.0111796

diff = mean(IV Skew of Treatment Group) - mean(IV Skew of Control Group) t = 1.3766

Ho: diff = 0 Welch's degrees of freedom = 549.604

Ha: diff < 0	Ha: diff != 0	Ha: diff > 0
Pr(T < t) = 0.9154	**Pr(|T| > |t|) = 0.1692**	**Pr(T > t) = 0.0846**

Table 5

Main Regression Results

The table shows the regression results by basing on Equation (1) and (2). Options in the sample are traded after third Friday of August and until the end of August in each year of study period. Dependent variable is IV Skew for each firm and each year. Independent variables are forecasts, property, logasset, interaction and time variables. There are two types of forecast variables which are hurricaneforecast and majorhurricaneforecast. Regression is run separately for these two variables. Property variable shows the percentage of REIT`s portfolio in three states. Logasset variable indicates logarithm of each firm`s asset in previous year. Interaction variable is interaction of forecast and property variable. Last variable is year as time variable for fixed year effect.

	(1)	(2)	(3)	(4)
VARIABLES	IV Skew	IV Skew	IV Skew	IV Skew
hurricaneforecast	0.038		0.037	
	(0.029)		(0.028)	
majorhurricaneforecast		-0.123**		-0.123**
		(0.056)		(0.055)
property	-0.038	-0.038	-0.168***	-0.109**
	(0.025)	(0.025)	(0.056)	(0.043)
logasset	-0.007**	-0.007**	-0.008***	-0.008**
	(0.003)	(0.003)	(0.003)	(0.003)
interaction			**0.019*** **	**0.025** **
			(0.006)	**(0.01)**
Constant	-0.096	0.481***	-0.076	0.488***
	(0.18)	(0.17)	(0.179)	(0.169)
Year Type FE	YES	YES	YES	YES
Observations	275	275	275	275
R-squared	0.117	0.117	0.136	0.129

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

Table 6

Result of Regression in Placebo Analysis

The table shows the regression results by basing on Equation (1) and (2). Options in the sample are traded after third Friday of February and until the end of February in each year of study period. Dependent variable is IV Skew for each firm and each year. Independent variables are forecast, property, logasset, interaction and time variables. There are two types of forecast variables which are hurricaneforecast and majorhurricaneforecast. Regression is run separately for these two variables. Property variable shows the percentage of REIT`s portfolio in three states. Logasset variable indicates logarithm of each firm`s asset in previous year. Interaction variable is interaction of forecast and property variable. Last variable is year as time variable for fixed year effect.

VARIABLES	(1) implied volatility skew	(2) implied volatility skew	(3) implied volatility skew	(4) implied volatility skew
hurricaneforecast	0.025		0.025	
	(0.018)		(0.018)	
majorhurricaneforecast		-0.022		-0.022
		(0.022)		(0.022)
property	0.037*	0.037*	0.039	0.024
	(0.02)	(0.02)	(0.069)	(0.047)
logasset	-0.015***	-0.015***	-0.015***	-0.015***
	(0.004)	(0.004)	(0.004)	(0.004)
interaction			0	0.004
			(0.009)	(0.014)
Constant	0.018	0.249***	0.018	0.248***
	(0.118)	(0.068)	(0.119)	(0.068)
Year Type FE	YES	YES	YES	YES
Observations	286	286	286	286
R-squared	0.155	0.155	0.155	0.155

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