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A Comparison of Hurricane Loss Models

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A Comparison of Hurricane Loss Models

ABSTRACT

Hurricane models are a significant tool used in estimating loss costs in catastrophe-prone areas. While the major hurricane loss cost models consider a consistent set of factors, there are variations in how the factors are treated in the models. This can lead to considerable variation in the modeled average annual losses (AALs), even at the exposure level, based on the catastrophe model used. As such, the model selected could have a dramatic impact on price. Given that in some states, such as Florida, insurers are only allowed to use a single model in rating, an understanding of what drives the differences in AALs is critical. This paper uses a large dataset of wind-only policies in order to analyze the impact of housing, insurance, and mitigation characteristics on AALs for four hurricane loss models. We find that while there is some correlation among the modeled loss costs, the extent of the correlation does vary overall and with respect to housing, insurance, and mitigation characteristics. In addition, our results indicate that there are significant differences in the direction and magnitude of the relation of AAL and housing, insurance, mitigation characteristics across the models. These results are of interest to insurers, consumers, and regulators as they indicate that the insurer's selection and use of a particular model is likely to impact the cost of coverage.

Key Words: loss modeling, insurance pricing, catastrophes

1. INTRODUCTION

Since 1970, 13 of the most costly insured catastrophes in the world have occurred in the United States. Of those, all but two, the Northridge Earthquake in 1994 and the terrorists attacks on 9/11, were the result of hurricanes or tropical storms (Wharton Risk Management and Decision Processes Center, 2008). Florida is one of the states that has historically been susceptible to hurricane damage.[1] In addition, a report by the U.S. Department of Commerce (2005a) finds that Florida was the leading state in terms of population growth between 1980 and 2003 and Florida was the top state in terms of building permits for both single-family and multi-family units from 1999 to 2003. This growth in both population and building is expected to continue with Florida becoming the third most populous state by 2011 (U.S. Department of Commerce, 2005b). Regardless of whether the growth continues over time, the changes in population and building stock create a challenge for those tasked with modeling future losses as the trended losses from prior catastrophes are likely not reflective of potential future losses given the change in exposures.[2]

Florida has been considered by many to be the epicenter of the public policy debate on catastrophic storm risk management (e.g. Grace and Klein, 2009). Over time, the State has made a variety of changes in an attempt to stabilize the market place.[3] Studies such as Grace

[1] Over time, there has been an increase in the level of losses stemming from hurricanes in Florida. For example, losses from Hurricane Andrew in 1992 were approximately $15 billion while losses from the 2004 and 2005 hurricane seasons totaled $33 billion (My Safe Florida Homes, 2008). This is at least partially attributable to the rapid growth that has occurred in coastal counties.

[2] More specifically, the rapid growth in Florida illustrates the importance of capturing not just loss patterns and building stock within the models, but changes in population as well (Musulin, 1997). It also highlights the increasing interest in using catastrophe models rather than just trended losses over the last decade (e.g. Kozlowsiki and Mathewson, 1997).

[3] After both Hurricane Andrew and the 2004/2005 hurricanes, the Florida legislature made significant changes aimed at stabilizing the homeowners insurance marketplace (My Safe Florida Homes, 2008). This included the creation of the Citizens Property Casualty Insurance Company as well as the Florida Hurricane Catastrophe Fund (FHCF).[3] Though Citizens was originally created to be the insurer of last resort in the state, over time, Citizens' role has been expanded to allow it to be competitive with other homeowners insurers in the state (Ch. 2007-1, Laws of Florida).

and Klein (2009) and Cole, Macpherson, Maroney, McCullough, Newman, and Nyce (2009) provide a discussion of the evolution of the Florida homeowners insurance market and government policies during this period.[4] This has resulted in a variety of changes in the homeowners insurance marketplace, including the rapid growth in Citizens Property Insurance Company (Citizens), the residual market insurer, which is now the largest homeowners insurer in Florida with over one million policyholders (Citizens, 2009).

In addition to the changes outlined above, in 2001, Florida created the Florida Commission on Hurricane Loss Projection Methodology (the Commission).[5] The Commission is charged with providing "the most actuarially sophisticated guidelines and standards for projection of hurricane losses possible" (Florida Statutes, s. 627.0628(c)).[6] The Statute also specifies that the standards and guidelines must be used by the State Board of Administration in developing reimbursement premium rates for the Florida Hurricane Catastrophe Fund, and…..insurers in rate filings" (Florida Statutes, s. 627.0628(c)). As such, the work of the Commission impacts the pricing of both insurance, through the models it approves for use by insurers in projecting hurricane loss costs, as well as reinsurance, through its creation of reimbursement premiums for use by the FHCF.[7]

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[4] The FHCF was created to provide mandatory reinsurance to insurers writing personal and commercial residential coverage in Florida (Chapter 93-409, Laws of Florida). In an effort to control property insurance premiums, the rates charged by the FHCF are, by design, substantially lower than the rates charged in the private market. For more specific information regarding the development of Citizens and the FHCF, see Cole et al (2009).

[5] For a description of the need and purpose of the Commission, see Florida Statute 627.0628. For a description of the evaluation procedures of the Commission, see Dumm, Johnson, and Simons (2009).

[6] As outlined in Florida Statutes, Section 627.0628, the Commission's 11 members include a consumer advocate; employees of the State Board Administration, Citizens, Division of Emergency Management of the Department of Community Affairs, the FHCF, and the office "responsible for property insurance rate filings and who is appointed by the director of the office;" and five members appointed by the Chief Financial Officer of the state. These are to include an actuary of a property/casualty insurer; a faculty member of Florida State University who is an expert in insurance finance; and three other faculty members of the State University System who are experts in statistics, computer system design, and meteorology.

[7] It is important to note that while insurers must use "a model or method found to be acceptable or reliable" (Florida Statutes, s. 627.062(2)(b)(11)) by the Commission in establishing hurricane loss costs, the ultimate responsibility for approval of insurer rates is borne by the Office of Insurance Regulation. For a more detailed review of the process

In general, the hurricane models used in creating average annual losses (AALs) are based on a relatively consistent set of factors. However, as noted by Watson and Johnson (2004), seemingly small differences in design and input can significantly impact modeled losses. Hence, the choice of loss model will impact insurer pricing. As noted in Section 627.0628 (3)(d) of the Florida Statutes, all insurers are required to use a model that has been accepted by the Commission.[8] This is generally interpreted by the Office of Insurance Regulation as meaning that since the Commission has not approved a blended model, only single models can be used by insurers in their rate filings.

The purpose of the study is to identify the factors related to the differences in modeled AALs for individual properties in an effort to better understand the source of the variation in modeled loss costs. As such, we analyze differences in the modeled AALs for a large number of properties using data we obtain from Citizens. In an effort to reduce the potential confounding effects based on multi-peril properties, we focus on the wind-only policies in the high risk account (HRA).[9] As of year-end 2008, this accounts for more than 36 percent of the total Citizens policies in force (Citizens, 2010). We incorporate a variety of insured-specific factors including housing, mitigation, and insurance characteristics for each property in order to better understand differences in modeled AALs. We examine both the factors that impact the magnitude of the variation across models as well as the relation of the housing, mitigation, and insurance characteristics with the AAL for each model.

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used by the Commission see Dumm, Johnson, and Simons (2009). For a review of the decisions made by other states with respect to reviewing and incorporating loss model see Nordman and Piazza (1997).

[8] During 2008, the approved models were generated by AIR Worldwide Corporation (AIR Model); EQECAT, Inc (EQECAT Model); Risk Management Solutions, Inc (RMS Model); Applied Research Associates, Inc (ARA Model); and Florida International University in conjunction with other Florida universities (Public Model).

[9] Results of modeled AALs for single family dwellings insured in the Citizens personal lines account are included for robustness purposes.

The results of this research have implications for a number of stakeholders since accurately predicting hurricane exposure has become increasingly important, not just to insurers, but consumers and regulators as well. For example, due to the fact that loss costs directly relate to premiums, the impact of model selection is of interest to consumers as accurate loss modeling based on characteristics of the individual property should lead to more focused pricing as well as potentially more stable pricing (Musulin, 1997). This also is a benefit to insurers. In addition, these findings have implications for regulators as they work to continue to improve the accuracy of the rates for hurricane-related losses in order to ensure the solvency of insurers operating in their state. Due to the potential impact on national insurers, even those regulators in states without significant catastrophe exposure have an interest in developing modeling processes which create focused and accurate rating structures (Musulin, 1997).

The remainder of the paper is organized as follows. The following section provides a summary of the relevant prior literature as well as a brief description of the loss costs models examined in the study. We also discuss the housing, insurance, and mitigation, characteristics hypothesized to impact the AALs considered in the current study. The data, methodology and results are presented in the next section, followed by the conclusion.

2. BACKGROUND

2.1. Literature Review

Hurricane models have attracted a great deal of attention in academic research as well as among practitioners and regulators. As documented by studies such as Watson, Johnson, and Simons (2004), the hurricane models are different than traditional actuarial methods that determine rates based on prior losses for a given exposure. The authors also note that in modeling low probability high severity events such as windstorm, the actuarial methods may lose credibility. In theory, accurate hurricane loss models based on current exposures should produce more accurate rates. However, these models are often based on proprietary data that is difficult to analyze from both the standpoint of data availability as well as the complexity of the models (e.g., Watson, Johnson, and Simons; 2004). As such, it can be difficult for regulators and others involved in the process to assess the validity of these models. In addition, insurers face challenges in incorporating the models into fair and accurate rates.

A wide variety of meteorological, engineering, and insurance research has focused on the differences in hurricane models. These studies have found differences based on meteorological assumptions including wind fields, topography, landfall frequencies, and decay rates (e.g. Huang, Rosowsky, and Sparks, 2000; Iman, Johnson, and Schroeder, 2002a; Iman, Johnson, and Schroeder, 2002b; Watson and Johnson, 2004; Watson, Johnson, and Simons, 2004). Additional studies have found differences in the way in which the models account for structural characteristics of the buildings (e.g. Canabarro, Finkemeier, Anderson, and Bendimerad, 2000). Factors such as demand surge, loss adjustment expenses, insurance contracts, global climate change, and climate conditions also have been identified as important factors (Canabarro et al, 2000).

Nordman and Piazza (1997) note that the variation in model output has caused concern for some in the regulatory community. Additionally, in a report to the Florida House of Representatives, the Commission examined the variation across all models using county-level benchmarks and found that the Public Model and the ARA Model had the greatest number of observations outside of the benchmarks (Florida Commission on Hurricane Loss

Projection Methodology, 2007). Other researchers have found differences in the ultimate modeled loss costs based on the assumption in the models. Specifically, in a study of loss models in North Carolina, Watson and Johnson (2004) found that the range of loss costs can be quite large (a 3-to-1 ratio or greater in some cases). Further, they found that divergence of the loss models was considerably higher in inland areas. As explained in, Watson, Johnson, and Simons (2004) the potentially wide variation in loss costs in some locations may lead to a potential disparity in pricing.

Variations exist in the way in which mitigation measures and housing characteristics are included in the hurricane loss models, which also can affect the modeled AALs for a given property, and ultimately the price of insurance coverage. For this reason, understanding the impact of and motives for mitigation is important. There are several studies that focus specifically on the impacts of mitigation. Some of these studies, provide a theoretical examination of mitigation, disaster assistance, and demand for insurance (i.e. Kelly and Kleffner; 2003). Other studies, such as that of the Institute for Business & Home Safety (2007), provide evidence to support some of the theories in prior literature. Specifically the study examines a sample of Florida homeowners after Hurricane Charley and finds there were nearly 60 percent fewer claims reported for homes built under new wind-resistant standards instituted after Hurricane Andrew than for homes built before these standards were in place. It also finds that the average damage from Hurricane Charley was more than 40 percent less for these homes.[10] Related to mitigation, a study by Wharton Risk Management and Decision Processes Center (2008) discusses the potential impact of techniques to strengthen and/or protect roofs and windows as well as changes to building codes. This also

[10] In a more detailed analysis, the study finds that the building components that resulted in a reduction in frequency were those related to roof, windows, and garage doors. The two areas that did not impact claims frequency were pool cages or screened porches and soffits.

is discussed by Sutter (2008), with a greater focus on the role of government in the mitigation process.[11] Our study draws upon the findings of these studies in identifying home characteristics to include in the empirical analysis.

The large weather-related losses experienced since the 1990s lead to a growth in financial products linked to catastrophes. This resulted in research on the potential uses of these products (e.g. Cummins, Lalonde, and Phillips, 2004; Changnon, 2007; Muermann, 2008). However, as noted above, variations in modeling can impact loss costs and premiums, which could ultimately impact these insurance-linked securities. For example, Canabarro et al (2000) note that while average estimates are important, models that underestimate the variance can significantly underestimate the expect losses for Catastrophe bonds. Because of the wide-scale implications of loss costs model decisions, a need exists for additional research in this area that can provide evidence of the source of the variation across the loss costs models as this can be used to determine the potential impact on both insurance and insurance-linked financial products.

2.2. Review of Model Components

As noted earlier, the Office of Insurance Regulation and the Financial Services Commission bear the ultimate responsibility for approving rates. However, in making the decision regarding whether a rate is not "excessive, inadequate, or unfairly discriminatory," insurers

[11] Specifically, the author examines the Building Code Effectiveness Grading Schedule (BCEGS) and the Community Rating System (CRS) of Atlantic and Gulf coastal counties and finds that "no communities or counties exemplify best practices for flood, and only 0.02 percent of communities in all Atlantic and Gulf coast states represent the best practices for building codes." The BCEGS was developed in the 1990s by the Insurance Services Office and is a measure of the enforcement level of building codes within the community based on 21 factors. It operates on a 10-point scale with 1 being the greatest enforcement. Insurers commonly provide discounts based on this rating. The CRS also operates on a 10-point scale but is a measure based on 18 activities related to susceptibility to hurricane damage. As with the BCEGS, insurers commonly offer discounts based on a community's rating. See Sutter (2008) for details on the factors and activities considered in each rating system.

are required to estimate hurricane losses "using a model or method found to be acceptable or reliable by the Florida Commission on Hurricane Loss Projection Methodology" (Florida Statutes, s. 627.062). Three of the five models approved by the Commission as of the time the sample of properties was created are included in this analysis: the AIR Model, the EQECAT Model, and the RMS v6.0 Model.[12] In addition, the new model developed by RMS (RMS v7.0) that has yet to be approved is included. This section provides a brief description of each of the model components utilized in the current study that are expected to impact loss costs.[13]

As discussed in Dumm, Johnson, and Simons (2009), there are four major model components areas: frequency model; wind, friction, and topography; exposure data, and damage function; and the actuarial module. Some factors considered in our analysis are drawn from each of these component areas. The housing characteristics, including age, number of stories, square footage, and roof shape, are part of the frequency model as well as the wind, friction, and topography component. The mitigation measures, including shutters and roof covering, are part of the exposure data and damage function. Finally, insurance policy characteristics, such as the total insured value, are components of the actuarial module.[14]

As indicated in the prior studies, housing characteristics can impact loss costs (i.e. Institutes for Business and Home Safety, 2004; Pinelli, Zhang, Subramanian, Cope, Gurley, Gulati, and Hamid, 2003; Khanduri and Marrow, 2003; and Wyndham Partners, 2004). The housing characteristics considered in the current study are age, number of stories, square

[12] The study includes these three models due to data availability. This is discussed in detail in the following section.
[13] The discussions related to the specific models are obtained from February 2008 reports submitted to the commission and available on the Commission's website.
[14] See Table 1for a list of variables, definitions, and expected signs.

footage, construction type, and roof shape. Age is measured as year built. Given that changes designed to strengthen building codes have been implemented over time, it is likely that there will be a negative relation between year built and the modeled loss costs.[15]

The number of stories represents the number of floors in the home. Since multiple story homes have a higher probability of increased losses we expect a positive relation between the number of stories and modeled loss costs.[16] The number of total square footage in the residence also is included. This controls for differences in the loss costs based on increasing home values related to the size of the homes.

The construction types of the homes in the sample include wood, steel, and masonry. Since different external construction materials vary in their ability to sustain damage, it is expected that the type of exterior walls will impact loss costs. As evidenced by studies following Hurricane Andrew, wood homes are much more likely to sustain damage than homes made of steel or masonry (Federal Emergency Management Agency, 1992). We include indicator variables for steel and masonry with wood being the omitted category. As such, we expect both variables to be negatively related to AALs. Lastly, we include the roof shape also measured as a series of variables for hip, gable, flat, and unknown roof shapes with the omitted category being hip.[17] The performance of roof types varies in the presence of wind. Hip roofs are generally considered the most storm resistant of the types as evidenced by the highest credits from the models. For example, AIR and EQECAT estimate

[15] Specifically, the Florida Building Code, which was adopted in 2002 and tested by the 2004/2005 hurricane seasons. In response to the information gathered regarding homes damaged, the Code was modified in 2006. One of the changes was related to soffits in an effort to reduce the number of soffit failures. For additional information on the impact of building code changes on storm severity, see Institute for Business and Home Safety (2004).

[16] Given that the study focuses only on residential homes, observations with floors numbering greater than four were removed to prevent the accidental inclusion of other types of structures.

[17] The models acknowledge that there are missing or unknowns in the data used to created the AALs. Depending on the model and the type of information unknown, these are handled differently. For example, the RMS 6.0 model defines the unknowns for home characteristics as zero for the appropriate category. Therefore, no adjustment to the base vulnerability curve is made (RMS, 2008)

that a home with a hip roof is expected to sustain approximately four percent less damage than a home with a roof with gable ends (AIR, 2008; and EQECAT, 2008)[18]. As such, it is expected that since hip roofs are the omitted category in our models, the coefficients on the gable and flat roof type variables will be positively related to AALs.

Mitigation measures are designed to reduce loss costs by reducing the severity of the loss. We include an indicator variable to control for the presence of shutters. The variable is equal to one for homes with shutters and zero otherwise.[19] Given that studies found a significant reduction in losses from mitigation efforts such as the installation of shutters, we expect that the relation of shutters and model AALs will be negative and significant (i.e. Federal Emergency Management Agency, 1992).

The modeling firms vary in their treatment of shutters in modeled loss costs. For example, the RMS Model expects the greatest reduction in damage due to the presence of shutters, with estimates ranging between seven percent and 52 percent depending on the type of shutters, the construction type of the home, and wind speeds (RMS, 2008).[20] Alternatively, the largest estimate of damage reduction for the other two models examined is approximately 17 percent (AIR, 2008; and EQECAT, 2008).

Roof covering is measured as a series of indicator variables identifying whether the roof is concrete, shingle, wind-rated shingle, or unknown. The omitted category in our analysis is concrete. We would expect the wind-rated shingle roof covering to result in the greatest reduction in loss costs as indicated by the models but only for low level winds (AIR, 2008; EQECAT, 2008; and RMS, 2008). In addition, shingled roofs have been found to sustain

[18] Estimates are from Form V-2 Mitigation measures in the firm's 2008 filings with the Commission.
[19] There are three different classes of shutters. However, due to the number of missing observations, we only consider the presence of shutters in our analysis.
[20] Estimates are from Form V-2 Mitigation measures in the firm's 2008 filings with the Commission.

great damage during hurricanes as they are ripped off by the winds. However, concrete roof coverings also can sustain damage in this way if the binding of the tiles is not strong. In addition, these roof coverings can be more susceptible to damage by flying debris (Federal Management Emergency Agency, 1992). As such, we do not have specific predictions for these variables.

The total insured value variable represents the maximum loss that will be paid on a particular home. It is expected that the greater the exposure, the larger the loss costs. Finally, distance to the coast is measured as miles from the coast as defined by Citizens. As mentioned earlier, Watson and Johnson (2004) provides evidence in their study of North Carolina, that loss models were considerable more divergent for inland areas. Further, due to storm decay, overall loss costs are likely to be lower as the distance to the coast increases. Consistent with prior literature, it is expected that the closer the home is to the coast, the greater the exposure. Therefore, this variable is expected to be negatively related to loss costs.

INSERT TABLE 1 ABOUT HERE

3. COMPARISON OF MODELS

3.1. Data

The data used in this study are obtained from Citizens for properties insured as of 2008. In addition to data on the type of property, loss costs for the AIR Model, the EQECAT Model, and the RMS 6.0 and 7.0 Models are included. In 2008, the AIR Model, the EQECAT Model, and the RMS 6.0 Model were approved for use by the Commission, while the RMS 7.0 Model was not.[21] With this data, we are able to: (1) determine whether the AALs are

[21] As indicated earlier, there currently are five models that have been approved for use by the Commission. However, the Public Model and the ARA Model are not included in this analysis because this data is not available in

statistically different across the hurricane loss models, and (2) to better understand the differing magnitude of the relation between the AALs and insurance, housing, and mitigation characteristics across the models.

Several screens were applied to the data. First, only single family dwellings are used. This resulted in the elimination of mobile homes and condominiums. Next, observations with non-logical values or missing data are dropped. Specifically, structures with more than four stories, and observations with missing values for items such as total insured value, deductibles, square footage, loss costs, distance to the coast are excluded.

The final screen relates to the types of policies. Citizens is divided into three accounts, two of which contain single family dwellings: the High Risk Account (HRA) and the Personal Lines Account (PLA). While the PLA writes in all 67 Florida counties, the HRA policies, which are wind-only policies and are only available in eligible areas in 29 counties.[22] To avoid potential differences driven by the characteristics of insureds in each account, the HRA account properties are the focus of this study. However, for comparison purposes, the PLA account properties also are included in a robustness test.

3.2. Methodology

the Citizens dataset. Since evidence indicates that the loss costs produced by these two models more greatly deviate from those produced by the other models, this biases against us finding results. For research related to the Public Model, see Powell, Soukup, Cocke, Gulati, Morisseau-Leroy, Hamid, Dorst, and Axe (2005) and Chen, Chen, Zhao, Hamid, Chatterjee, and Armella (2009). For a discussion of potential differences among all of the approved models, see the Report to the Florida House of Representatives (2007).

[22] The 29 counties containing eligible areas are: Bay, Brevard, Broward, Charlotte, Collier, Dade, Duval, Escambia, Flagler, Franklin, Gulf, Hernando, Indian River, Lee, Levy, Manatee, Monroe, Nassau, Okaloosa, Palm Beach, Pasco, Pinellas, Santa Rosa, Sarasota, St. Johns, St. Lucie, Volusia, Wakulla, and Walton. The specific portions of these counties containing the eligible areas can be found on the Citizens website at http://jaxblue.citizensfla.com/windmap.pdf (Citizens Property Insurance Corporation, 2009).

As an initial test, we estimate a regression model of the coefficient of variation (standard deviation/mean) for the four modeled AALs for a given property. This allows us to determine what factors are significantly contributing to the variation amongst the models. The estimated model is shown below:

$$(1)\ CV_i = \beta X_i + \gamma TERR_i + \varepsilon_{i,}$$

where CV is the coefficient of variation for property i, X_i is a vector of housing, insurance, and mitigation characteristics for property i, $TERR_i$ is an array of dummy variables indicating territory for property i, and ε_i is a random error term.

We next turn to an analysis of the impact of various characteristics on AALs. Since the purpose of the analysis is to compare the impact of the housing, mitigation, and insurance variables across the different hurricane models, we first construct a regression framework in which modeled AALs are a function of a variety of factors and include an indicator variable to identify whether the loss costs are from the AIR Model, EQECAT Model, or RMS 7.0 Model (with the RMS 6.0 Model being the base comparison model) as well as housing, mitigation, and insurance characteristics. Specifically, the estimated model is shown below:

$$(2)\ AAL_i = \alpha MTYPE_i + \beta X_i + \gamma TERR_i + \varepsilon_{i,}$$

where AAL is the average annual loss for property i, $MTYPE_i$ is a vector indicating the model type for property i (MTYPE is either AIR Model, EQECAT Model, or RMS 7.0 Model), X_i is a vector of housing, insurance, and mitigation characteristics for property i,

$TERR_i$ is an array of dummy variables indicating territory for property i, and ε_i is a random error term.

In order to provide a more direct comparison of the varying impact on loss costs of the factors examined in this study, a model is constructed in which each loss indicator variable is interacted with each of the housing, mitigation, and insurance characteristic variables, creating four complete sets of these variables. This complete interaction model creates the following interpretation: the interacted housing, mitigation, and insurance variables reflect the relation of the given variable and AAL for each of the loss cost models. The estimated model is shown below:

$$(3)\ AAL_i = \beta X_i * MTYPE_i + \gamma TERR_i + \varepsilon_{i,}$$

where $MTYPE_i$ is a vector indicating the model type for property i, X_i is a vector of housing, insurance, and mitigation characteristics for property i, $TERR_i$ is an array of dummy variables indicating territory for property i, and ε_i is a random error term.

3.3. Summary Information

Table 2 provides a summary of loss costs for each of the models included in the study. As seen in Panel A of the table, the mean, minimum, maximum, and standard deviations vary across the four AAL models. Panel B of this table provides a correlation matrix of the models that shows variation in the different loss costs across the observations in our sample. While the correlation between the two RMS models is in excess of 99 percent, the correlation among all of the other models varies between approximately 51 and 79 percent. This highlights the need to examine not just the impact of various factors on loss costs, but the issue of whether this impact varies across the models with respect to the housing, insurance, and mitigation characteristics. Finally, the summary statistics for the variables included in the analysis are presented in Table 3. The statistics provide information on the housing, mitigation, and insurance characteristics included in the models.

INSERT TABLES 2 AND 3 ABOUT HERE

3.4. Regression Analysis[23]

Table 4 shows the results for the coefficient of variation model. We find that the variation among the models increases as the total insured value increases. In addition, there is more variation among the models for newer homes as well as larger homes; however, the models have less variation with respect to number of stories in the homes.

INSERT TABLE 4 ABOUT HERE

There also is more variation across the models when shutters are present. This result is not surprising given the variation in the adjustment to the damage estimated by the models as discussed earlier.[24] Further, steel and masonry structures have relatively less variation across models when compared to wood structures (the omitted category). Similarly, gable and flat roofs have less variation in the models when compared to the variation of hip shaped roofs, while there is less variation for shingles and wind-rated shingles across the models when compared to concrete roofs. Similar to prior research, there is significantly more variation across the models as distance to the coast increases. Overall, the results highlight the fact that a portion of the variation in the modeling process is related to the insurance, housing,

[23] The results related to the Citizens PLA account are provided in Appendix A. While there are some variations in the results, there still is significant variation in the housing, insurance, and mitigation characteristics across the models remains.

[24] Note that some of the variation may be due to the fact that there are differences based on the types of shutters used that are not captured in our modeling (the use of a single indicator variable identifying whether or not shutters are present).

and mitigation characteristics. More specifically, the adjusted r-squared of .6047 indicates that slightly more than 60 percent of the variation across the AALs is attributable to these variables.

The results for the base AAL regression model specified in equation (2) are presented in Table 5. All of the loss model indicator variables are significant and positive. These results suggest that all models produce higher loss costs than the RMS 6.0 Model for our sample. We conduct an F-test to determine if the indicator variables are significantly different from one another. The test is significant at the 1 percent level.

INSERT TABLE 5 ABOUT HERE

Also, as expected, the results indicate that homes with higher insured values, more stories, and more square footage are associated with higher AALs. In addition, we find that newer homes are associated with lower AALs. Consistent with studies conducted following hurricanes, this is likely the result of improvements in building materials and changes to building codes that occur over time (i.e. Institute for Business and Home Safety, 2004).

With respect to construction type, we find that, as expected, steel structures are associated with lower AALs compared to wood structures. However, contrary to expectations, we find masonry structures are associated with higher loss costs compared to wood structures. Also, as expected, we find that homes with gable and flat roofs are associated with higher AALs in comparison to homes with hip roofs. Finally, we find that homes with shutters as well as homes further from the coast are associated with lower AALs.

The results for the complete interaction model are shown in Table 6. The results indicate that there are statistically significant differences in the impact of almost all of the variables on AAL. For example, we find that the impact of the age of the home on AALs ranges from \$0.39 per year for the RMS 6.0 Model to -\$16.01 per year for the AIR Model. In addition, while the impact of the number of stories on AALs is positive for the RMS 6.0 and RMS 7.0 Models, it is negative for the AIR and EQECAT Models. Though all models have a lower AAL for properties that are the farther from the coast, the reduction is greatest for the RMS 7.0 Model and least for the EQECAT Model.

INSERT TABLE 6 ABOUT HERE

When examining mitigation efforts, we find that the presence of shutter reduces AALs by by \$910 in the RMS 6.0 Model and \$1,040 for the RMS 7.0 model. However, the presence of shutters reduces AALs by only \$303 and \$78 for the AIR and EQECAT Models, respectively. As noted earlier, this result is not surprising given the numbers cited earlier on the percentage change in damage indicated by each of these models in relation to the presence of shutters.

Additionally, wind-rated roof shingles impacts the AALs for all models, though the magnitude of the impact varies. Finally, there is variation in the impact on loss costs for the other housing characteristics such as building construction type and roof type as well as the insurance policy characteristics such as total insured value.

To verify that these results are statistically significantly different, we conduct F-tests for each of the characteristics examined in the study. The results do indicate that in almost every case, the differences across the models discussed in this section are statistically significant.

4. CONCLUSION

The purpose of this study is to identify the factors driving the differences in modeled loss costs in an effort to better understand the variation in loss costs produced by various models.

The results of our analysis indicate that for given properties, there are significant differences in the AALs produced by all four of the hurricane loss models examined. For example, based on the wind-only properties in the Citizens high-risk account, average AALs range from a low a $1,724 (with RMS 6.0) to a high of over $3,000 (with EQECAT 3.1). In addition, we find that a number of insurance, housing, and mitigation characteristics are significantly related to both the amount of variation in the models as well as the impact on the AAL produced by the loss models. These results indicate that while the models are correlated, they do vary in terms of their treatment of various rating factors.

These results are of interest to insurers, consumers, and regulators since the loss cost model selected by an insurer results in statistically significant AALs which will likely lead to differences in premiums. These findings underscore the important role of those tasked with approving hurricane loss models, like the Commission in Florida, as the insurer's selection and use of the model is likely to impact both insurers and consumers. Further, understanding the sources of variation will help to select the model or models most likely to generate accurate pricing.

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Table 1: Variable List, Definitions, and Expected Signs

Variable	Definition	Expected Sign
Total Insured Value	Total insured value in dollars	+
Year Built	Year in which home was built	-
Number of Stories	Number of stories in the home	+
Square Footage	Total square footage of home	+
Building Structure (Wood reference group):		
Steel Structure	Indicator variable equal to one for steel structures and zero otherwise	-
Masonry Structure	Indicator variable equal to one for masonry structures and zero otherwise	-
Shutters	Indicator variable equal to one if home has storm shutters and zero otherwise	+
Ln Distance to the Coast	Natural logarithm of distance to the coast in miles	-
Roof Shape Type (Hip Roof reference group):		
Gable Roof	Indicator variable equal to one for gable roof and zero otherwise	+
Flat Roof	Indicator variable equal to one for flat roof and zero otherwise	+
Roof Unknown	Indicator variable equal to one if roof type unknown and zero otherwise	+/-
Roof Covering Type (Metal Roof reference group):		
Concrete	Indicator variable equal to one for concrete roof covering and zero otherwise	+/-
Roof Shingle	Indicator variable equal to one for shingles and zero otherwise	+/-
Wind Rated Single	Indicator variable equal to one for wind-rated shingles and zero otherwise	+/-
Roof Covering Unknown	Indicator variable equal to one if roof covering unknown and zero otherwise	+/-

Table 2: Loss Costs Summary Statistics

Panel A: Loss Costs

	Mean	Std. Dev.	Min	Max
RMS 7.0	$ 2,609.28	$ 2,483.91	$ 24.96	$ 140,716.00
RMS 6.0	$ 1,724.09	$ 1,637.53	$ 18.04	$ 85,798.63
AIR 9.5	$ 2,510.34	$ 2,785.39	$ 32.30	$ 134,544.30
EQECAT 3.1	$ 3,030.98	$ 3,888.69	$ 2.65	$ 176,318.60

Panel B: Correlation Matrix

	RMS 7.0	RMS 6.0	AIR 9.5	EQECAT 3.1
RMS 7.0	1			
RMS 6.0	0.9948	1		
AIR 9.5	0.7861	0.7552	1	
EQECAT 3.1	0.5547	0.514	0.7618	1

Table 3: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Total Insured Value	$ 442,994.50	$ 437,548.50	$ 12,000.00	$ 14,300,000.00
Year Build	1972	19	1800	2008
Number of Stories	1.2692	0.5169	1	5
Square Footage	1978	1085	1	15000
Wood Structure	0.1943	0.3956	0	1
Masonry Structure	0.7226	0.4477	0	1
Steel Structure	0.0831	0.2761	0	1
Concrete	0.0058	0.0758	0	1
Roof Shingle	0.7716	0.4198	0	1
Wind Rated Single	0.1327	0.3393	0	1
Roof Covering Unknown	0.0899	0.2860	0	1
Shutters	0.2290	0.4202	0	1
Roof Unknown	0.0000	0.0063	0	1
Hip Roof	0.3020	0.4591	0	1
Gable Roof	0.6218	0.4849	0	1
Flat Roof	0.0761	0.2652	0	1
Distance to the Coast	-1.4158	2.4171	-11.9894	3.2763

Table 4: Regression Results – Coefficient of Variation

	Coefficient (SE)	
Constant	-2123	***
	(-9.01)	
Total Insured Value	0.00197	***
	(328)	
Year Built	1.374	***
	(12.3)	
Number of Stories	-87.49	***
	(-21.8)	
Square Footage	0.0160	***
	(6.42)	
Steel Structure	-959.4	***
	(-127)	
Masonry Structure	-408.7	***
	(-81.8)	
Shutters	209.1	***
	(46.0)	
Distance to the Coast	4.303	***
	(5.03)	
Gable Roof	-36.75	***
	(-9.94)	
Flat Roof	-22.13	***
	(-3.36)	
Roof Unknown	836.9	***
	(3.39)	
Roof Shingle	-42.86	**
	(-2.03)	
Wind Rated Single	-210.4	***
	(-9.84)	
Roof Covering Unknown	621.2	***
	(28.4)	
Territories Included	Yes	
Observations	251654	
Adjusted R-squared	0.6047	

Table 5: Regression Results – High Risk Account Base Model

	Coefficient (SE)	
Constant	13933	***
	(50.9)	
RMS 7.0 Indicator	885.2	***
	(174)	
AIR 9.5.0 Indicator	786.2	***
	(155)	
EQECAT 3.1 Indicator	1307	***
	(257)	
Total Insured Value	0.00415	***
	(596)	
Year Built	-7.345	***
	(-56.7)	
Number of Stories	102.2	***
	(21.9)	
Square Footage	0.0617	***
	(21.4)	
Steel Structure	-94.95	***
	(-10.8)	
Masonry Structure	349.7	***
	(60.3)	
Shutters	-583.2	***
	(-110)	
Distance to the Coast	-65.91	***
	(-66.4)	
Gable Roof	529.1	***
	(123)	
Flat Roof	544.2	***
	(71.3)	
Roof Unknown	-873.6	***
	(-3.05)	
Roof Shingle	1075	***
	(43.8)	
Wind Rated Single	1055	***
	(42.5)	
Roof Covering Unknown	-171.8	***
	(-6.77)	
Territories Included	Yes	
Observations	1006616	
Adjusted R-squared	0.6008	

Table 6: Regression Results – High Risk Account Individual Models

	RMS 6.0		RMS 7.0		AIR 9.5		EQECAT 3.1	
Model Indicator	1307	***	16045	***	32745	***	8611	***
	(3.38)		(41.4)		(84.6)		(22.2)	
Total Insured Value	0.00242	***	0.00374	***	0.00389	***	0.00656	***
	(219)		(340)		(353)		(595)	
Year Built	0.390	**	-7.139	***	-16.01	***	-6.620	***
	(2.03)		(-37.2)		(-83.4)		(-34.5)	
Number of Stories	333.6	***	495.4	***	-47.81	***	-372.4	***
	(46.3)		(68.8)		(-6.64)		(-51.7)	
Square Footage	-0.175	***	-0.196	***	0.370	***	0.248	***
	(-39.2)		(-43.9)		(82.9)		(55.6)	
Steel Structure	-1057	***	-982.8	***	206.9	***	1453	***
	(-79.3)		(-73.7)		(15.5)		(109)	
Masonry Structure	-598.6	***	-584.5	***	-219.1	***	2801	***
	(-70.5)		(-68.9)		(-25.8)		(330)	
Shutters	-910.9	***	-1040	***	-303.4	***	-78.83	***
	(-112)		(-128)		(-37.4)		(-9.72)	
Ln Distance to the Coast	-90.30	***	-144.7	***	-19.45	***	-9.224	***
	(-66.9)		(-107)		(-14.4)		(-6.83)	
Gable Roof	603.6	***	900.0	***	327.3	***	285.5	***
	(88.7)		(132)		(48.1)		(42.0)	
Flat Roof	555.5	***	915.8	***	306.6	***	399.1	***
	(45.7)		(75.4)		(25.2)		(32.8)	
Roof Unknown	-1808	***	-2638	***	6.364	***	945.3	***
	(-3.95)		(-5.76)		(0.014)		(2.06)	
Roof Shingle	151.7	***	149.1	***	395.6	***	3605	***
	(3.89)		(3.83)		(10.2)		(92.5)	
Wind Rated Single	63.80	***	199.9	***	530.0	***	3428	***
	(1.61)		(5.06)		(13.4)		(86.7)	
Roof Covering Unknown	-1061	***	-1617	***	-1490	***	3481	***
	(-26.4)		(-40.2)		(-37.0)		(86.5)	

Territories Included	Yes
Observations	1006616
Adjusted R-squared	0.8536

Appendix

A1: Regression Results – Personal Lines Account Base Model

	Coefficient (SE)	
Constant	7146	***
	(122)	
RMS 7.0 Indicator	375.1	***
	(342)	
AIR 9.5.0 Indicator	98.50	***
	(89.9)	
EQECAT 3.1 Indicator	580.7	***
	(530)	
Total Insured Value	0.00311	***
	(585)	
Year Built	-4.312	***
	(-148)	
Number of Stories	-12.12	***
	(-10.3)	
Square Footage	-0.0354	***
	(-28.9)	
Masonry Structure	131.8	***
	(97.5)	
Shutters	-367.6	***
	(-256)	
Distance to the Coast	-77.89	***
	(-251)	
Gable Roof	295.1	***
	(267)	
Flat Roof	329.1	***
	(126)	
Roof Unknown	455.8	***
	(199)	
Roof Shingle	582.8	***
	(46.4)	
Wind Rated Single	528.5	***
	(42.0)	
Roof Covering Unknown	335.5	***
	(26.5)	
Territories Included	Yes	
Observations	1765888	
Adjusted R-squared	0.6378	

Note: The dependent variable is the average annual loss for the property.

A2: Regression Results – Personal Lines Account Individual Models

	RMS 6.0		RMS 7.0		AIR 9.5		EQECAT 3.1	
Model Indicator	-1117	***	2269	***	20465	***	8021	***
	(-12.5)		(25.3)		(228)		(89.5)	
Total Insured Value	0.00242	***	0.00336	***	0.00206	***	0.00461	***
	(278)		(386)		(237)		(530)	
Year Built	0.404	***	-1.386	***	-10.60	***	-5.666	***
	(9.06)		(-31.1)		(-238)		(-127)	
Number of Stories	10.63	***	67.14	***	-93.86	***	-32.41	***
	(5.47)		(34.6)		(-48.3)		(-16.7)	
Square Footage	-0.199	***	-0.196	***	0.209	***	0.0443	***
	(-99.6)		(-97.7)		(105)		(22.1)	
Masonry Structure	-215.5	***	-125.1	***	-84.62	***	952.4	***
	(-102)		(-59.3)		(-40.1)		(451)	
Shutters	-524.9	***	-626.7	***	-277.0	***	-41.71	***
	(-225)		(-268)		(-119)		(-17.8)	
Distance to the Coast	-93.44	***	-111.0	***	-73.95	***	-33.15	***
	(-213)		(-252)		(-168)		(-75.4)	
Gable Roof	372.4	***	566.4	***	114.6	***	127.2	***
	(204)		(311)		(62.9)		(69.8)	
Flat Roof	335.1	***	562.0	***	176.3	***	242.8	***
	(77.2)		(129)		(40.6)		(55.9)	
Roof Unknown	471.6	***	871.9	***	273.3	***	206.1	***
	(126)		(233)		(73.1)		(55.1)	
Roof Shingle	273.7	***	251.1	***	86.52	***	1720	***
	(13.1)		(12.0)		(4.14)		(82.3)	
Wind Rated Single	119.3	***	210.0	***	20.22	***	1765	***
	(5.70)		(10.0)		(0.97)		(84.3)	
Roof Covering Unknown	22.08		-229.5	***	-77.19	***	1636	***
	(1.05)		(-10.9)		(-3.66)		(77.2)	
Territories Included	Yes							
Observations	1765888							
R-squared	0.8995							

Note: The dependent variable is the average annual loss for the property.