Assessing the impact of hurricane frequency and intensity on mortgage default risk

Clifford V. Rossi[1]

Abstract

Considerable meteorological research suggests that the frequency and intensity of North Atlantic hurricanes is rising. This analysis focuses on estimating the impacts of hurricane intensity and frequency on mortgage default. Based upon a large loan level dataset of mortgages purchased by Freddie Mac between 2000-2013, loans where a Category 3, 4 or 5 hurricane occurred during a loan's life were found to be 13-18 percent more likely to become delinquent than other loans in the same locations, controlling for all other risk factors. In addition, loans that experienced more than 12 hurricanes during a loan's life were two times more likely to default than loans experiencing 1 or fewer hurricanes on average over time. These results have major implications for mortgage and insurance markets and homeowners.

First, if long-term hurricane trends bear out, mortgage default risk in areas with a higher incidence of major hurricanes will likely rise significantly over time. Second, investors in mortgage credit risk from these locations will face higher default losses in the future. Third, private investors in mortgage credit-risk transfer (CRT) securities could experience higher credit losses of loans from hurricane-prone areas. Investors in lower-rated tranches would be particularly impacted given the nature of their exposure to losses earlier than more highly-rated tranches. Catastrophe bonds could be used to diversify hurricane risks to investors that may be in a better position to assess and hold this risk.

Keywords Hurricane Risk, Mortgage Default, Risk Management, Reinsurance

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[1] Professor-of-the Practice and Executive-in-Residence, Robert H. Smith School of Business, University of Maryland, College Park, Maryland. The author thanks Michael Fratatoni, Daniel Wu, Russ Wermers, Greg Young, and Joe Mattey for their review of and insightful comments on this paper. Any errors or omissions remaining are those solely of the author. I would also like to acknowledge the excellent technical support by Shivam Choudhary for this work. Comments and perspectives provided in this paper those of the author and do not reflect the views of the University of Maryland or the Robert H. Smith School of Business.

1 Introduction

Considerable meteorological research suggests that the frequency and intensity of North Atlantic hurricanes is on the rise. The destructive power of these storms is well documented, that in addition to deaths and injuries causes significant economic losses, business disruption and life- changing dislocation for individuals and families. The Congressional Budget Office estimates that annual economic losses from hurricanes in the United States are $54 billion, with losses from the residential sector accounting for $34 billion of that amount.[2] Moreover, according to Pielke et al., 85% of damage caused by hurricanes is associated with hurricanes rated 3-5 on the Saffir-Simpson Hurricane Wind Speed Scale.[3]

Extensive modeling of hurricanes suggests that while the overall frequency of hurricanes in the future may actually decline over the next century, the frequency and intensity of the strongest hurricanes i.e., those rated Category 4 and 5 is likely to significantly increase over this period. At the upper end, one study suggests that the aggregate strength of North Atlantic hurricanes could rise 300% above where they have been in the recent past.[4] Other studies suggest a more moderate path for future hurricane intensity and frequency despite the fact that the aggregate power of hurricanes as measured by the Power Dissipation Index (PDI) in 2007 was approximately 6 times the PDI level of the early 1980s, signaling that this recent period was not only marked by more hurricanes, but ones with greater intensity.[5]

The linkages between hurricanes and mortgage default are emerging from a variety of empirical studies on this topic. Fannie Mae, for example found mixed results when reviewing the impacts from two major hurricane events; Hurricanes Katrina (August 2005) and Sandy (October 2012).[6] In the months immediately following Hurricane Katrina for instance, loans delinquent 180 days or more (D180+) peaked at a rate approximately 5 times the D180+ rate in the months leading up to the storm. By contrast, Fannie Mae found that D180+ rates following Hurricane Sandy remained

[2] Congress of the United States, Congressional Budget Office, Expected Costs of Damage From Hurricane Winds and Storm-Related Flooding, April, 2019, pg. 1-2.
[3] R.A. Pielke, Jr. et al., "Normalized Hurricane Damage in the United States: 1900-2005", Natural Hazard Review (2008).
[4] Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration, Global Warming and Hurricanes, An Overview of Current Research Results, June 12, 2020.
[5] Emanuel, K.A. 2016 update to data originally published in: Emanuel, K.A. 2007. Environmental factors affecting tropical cyclone power dissipation. J. Climate 20(22):5497–5509
[6] Fannie Mae, Historical Data Provides Insights Into Past Hurricane Experience, November 6, 2017.

relatively steady. Underscoring the magnitude of potential risk for the mortgage sector, CoreLogic estimates that 7.4 million residential and multifamily properties, accounting for approximately $1.8 trillion in replacement costs would be affected by storm surge from hurricanes in the U.S.[7]

The focus of this analysis is to understand the specific impacts of hurricane intensity and frequency on mortgage default. Using a sample of 100,000 mortgage loans purchased by Freddie Mac that were originated between 2000-2013, models describing a borrower's probability to default as defined by either loans that become delinquent 90 days or more (D90+) or D180+, and augmented with data on hurricanes from the FEMA Disaster Declarations Summaries, were estimated. In addition to standard risk attributes associated with the borrower, loan product, and property, factors describing the frequency and intensity of hurricanes experienced in counties where these properties are located were found to be statistically significant.

Loans where a Category 3, 4 or 5 hurricane was experienced during the loan's life were found to be 13 - 18 percent more likely to become 180 days or 90 days delinquent or more, respectively than other loans in the same locations, controlling for all other risk factors. In addition, loans that experienced more than 12 hurricanes during the loan's life were two times more likely to default than loans experiencing 1 or fewer hurricanes on average over time. These results were comparable for the D180+ model and both models' results have major implications for mortgage and insurance markets and homeowners.

First, if long-term hurricane trends bear out, mortgage default risk in areas with a higher incidence of major hurricanes will likely rise significantly over time. Second, investors in mortgage credit risk from these locations will face higher default losses in the future. At the same time, unless the government sponsored enterprises (GSEs) Fannie Mae, Freddie Mac and the FHA factor such risk into their pricing of credit risk, these agencies would be underpricing hurricane risk effects on default. This could also affect risk-based capital requirements and loan loss reserve estimates for Fannie Mae and Freddie Mac over time. Third, private investors of GSE credit-risk transfer (CRT) securities could experience higher credit losses associated with pools of loans from hurricane-prone areas. Those investors in lower-rated tranches would be particularly impacted given the nature of their exposure to losses earlier than more highly rated tranches. Further use of

[7] CoreLogic, 2020 CoreLogic Storm Surge Report, May 28, 2020.

catastrophe bonds (cat bonds) could be one vehicle to diversify hurricane risks away from specific investors that may be in a better position to assess and hold this risk. A cat bond could be set up as part of a CRT transaction that would transfer hurricane default risk to another investor such as a reinsurer.

2 Theoretical Linkages between Mortgage Default and Hurricane Risk

This study builds upon a large academic literature treating mortgage default in an option-theoretic framework. The contingent-claims literature starting with Black and Scholes (1973) and Merton (1973) serves as the foundation for describing mortgage cash flows.[8] Examples of early work to describe mortgage valuation in an option-theoretic framework included Cunningham and Hendershott (1984) and Epperson, Kau, Keenan, and Muller (1985).[9] Completing the contingent-claim mortgage valuation framework requires consideration of the competing risk nature of the default (put option) and prepayment (call option) options as described in Kau, Keenan and Muller and Epperson (1992).[10] Fundamentally, mortgage value (V_M) can be viewed as comprising three components as described in Equation 1; the value of a risk-free bond (V_{RF}) less the value of two embedded borrower options; the option to default on the mortgage (V_D) and the option to prepay the mortgage (V_{PP}); where ΔH represents changes in home prices which affects property value and hence the borrower's incentive to exercise the default option where unpaid principal balance (UPB) of the loan at time of default represents the default option strike "price", Δr represents changes in mortgage rates which affects the borrower's incentive to exercise their prepayment option and Δt reflects changes in time over which the value of all three components change.

$$(1)\ V_M(\Delta H,\Delta r,\Delta t) = V_{RF}(\Delta H,\Delta r,\Delta t) - V_D(\Delta H,\Delta r,\Delta t) - V_{PP}(\Delta H,\Delta r,\Delta t)$$

The focus of the present analysis is to empirically analyze the effect of hurricane intensity and frequency on the mortgage default component V_D of equation 1. The classic depiction of a mortgage default option is of a borrower ruthlessly exercising that put option whenever the value

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[8] Black, F. and M.S. Scholes (1973), " The pricing of Options and Corporate Liabilities," Journal of Political Economy, 81: 637-654., and Merton, R.C., (1973), "Theory of Rational Option Pricing," Bell Journal of Economics and Management Science, 4, 141-183.

[9] Cunningham, D.F., and P.H. Hendershott, (1984), "Pricing of FHA Mortgage Default Insurance," Housing Finance Review, 13, 373-392 and Epperson, J.F., J.B. Kau, D.C. Keenan, and W.J. Muller III (1985), "Pricing Default Risk in Mortgages," Journal of the American Real Estate and Urban Economics Association, 13, 261-272.

[10] Kau, J.B., D.C. Keenan, W.J. Muller, and J.F. Epperson (1992), "A Generalized Valuation Model for Fixed-Rate Residential Mortgages," Journal of Money, Credit and Banking, 24, 279-299.

of the property falls below the UPB at time of default. In reality, borrowers are not perfectly efficient in exercising their default option due to a variety of friction costs and other contributing factors or default triggers that can induce a default event. Friction costs include the impact of default on borrower credit and future foregone access and cost of credit opportunities following default. Default trigger events include job loss, reduction in income, divorce, serious medical or other catastrophic life event. Empirically, we are typically unable to observe the actual trigger event that is the catalyst for mortgage default, however, we can characterize the risk factors into several categories; borrower-specific, product- or loan-specific, property-specific, macroeconomic-specific, and external-specific.

In terms of borrower-specific risk factors, mortgage underwriting has been influenced for decades by the 3C's of underwriting, representing credit, capacity and collateral. The credit factor represents the borrower's willingness-to-repay the mortgage obligation. Typical proxies for borrower creditworthiness include credit score and/or detailed credit attributes from the borrower's credit report. Capacity represents the borrower's ability-to-repay the obligation and typical proxies include borrower income or relative measures such as borrower debt-to-income ratios (DTI). Multiple borrowers on the mortgage note tend to reduce default propensity due to income diversification. Finally, collateral measures the borrower's leverage in the property, or alternatively their equity stake. This factor may be captured in various ways including the loan-to-value (LTV) ratio and with house price volatility, among others. Borrower underwriting takes into account the LTV at origination, however, since both the loan amount and property value vary over time and especially at the time of default, current LTV is more representative of default over time. Collateral risk factors lie at the heart of the borrower's default option decision as the underlying property value changes relative to the borrower's remaining loan balance. A good example of this interaction was during the financial crisis of 2008 when many residential properties declined significantly below the value of the mortgage balance due to plummeting home values during this time. The crash in home prices drove many borrower current LTVs above 100%, leaving them effectively "underwater" on their mortgages and thus incented to default, notwithstanding the friction costs mentioned earlier.

Loan product risk factors may also influence the borrower's incentive to default. Factors such as product type; i.e., whether the loan is a fixed-rate amortizing mortgage (FRM) or adjustable-rate mortgage (ARM), or has a 30-year or 15- or 20-year term, for example can affect mortgage default. The variable nature of the ARM product along with potential borrower selection issues can elevate default risk relative to fixed-rate products. Likewise, loans with shorter amortization periods, despite their higher monthly payments may reflect borrower preferences, financial wherewithal and intentions to pay off the mortgage more quickly. The borrower's note rate, relative to prevailing mortgage rates may provide market signals regarding the borrower's credit risk. For example, if the spread between the prevailing fixed-rate 30-year amortizing mortgage rate at the time of origination and the actual 30-year note rate obtained by the borrower is positive, this could be an indication that the borrower carries incrementally higher credit risk that is priced into the mortgage rate. Subprime borrowing rates are an example of how credit risk can be priced into a mortgage rate. Another important risk factor affecting default is loan purpose. There are several reasons why a mortgage is taken out. One reason is the borrower is purchasing a home, another is they are taking advantage of lower mortgage rates on an existing property (hence exercising their prepayment option to refinance the home), or they could be extracting equity from the property for other uses such as a remodeling project or nonresidential purpose (e.g., taking a vacation). The latter purpose tends to be a riskier proposition than the other two alternatives. Lastly, the channel through which the loan was originated can contribute to credit risk. Loans that are originated through retail branches of the lender tend to have lower default risk than broker- and correspondent loan channels. These non-retail outlets may reflect issues associated with less robust loan manufacturing processes.

Property attributes can also affect mortgage default. Dwellings other than single-family homes such as condominiums, manufactured housing or mobile homes and coop units may influence the default outcome. Likewise, whether the home is a 1- unit or 2-4 unit property can affect default. The occupancy status of the property can affect default. This factor embodies the borrower's psychic attachment to the property as well as an indication of the potential leverage in housing assets a borrower has and the stability of income flows on investment properties. Occupancy status is usually reflected by three categories; primary residence; 2nd home, and investor-owned. The latter typically is a riskier outcome followed by 2nd home properties.

As described earlier several macroeconomic factors can affect default including changes in home prices, unemployment rates and mortgage rates. Underwriting models do not include these factors in arriving at loan decisions, but will be found in loan pricing and loss measurement modeling where intertemporal changes in default and prepayment are captured in computing discounted mortgage payment cash flows, defaults and prepayments over the life of the loan.

External events such as natural disasters form the last category of risk factors in mortgage default analysis. Specifically, for this analysis, the impact of hurricane events is of primary interest. Over the years, a number of studies have examined the impact of floods and hurricane events on mortgage default, but until now, none have directly measured the impact of hurricane intensity and frequency on mortgage default propensity. The linkage between hurricanes and mortgage default is posited to come about in several ways through key economic relationships that affect the borrower’s default option. When a hurricane event occurs, depending on its severity it can have economic impacts on an affected area for some time. A direct effect from a hurricane is damage it inflicts on the borrower’s property from high winds and extensive flooding events. Notwithstanding the existence of national flood insurance and homeowner hazard insurance policies, high deductibles (e.g., hurricane events often require higher deductibles) and in some cases undervalued policies may leave homeowners with few options than to default on their mortgage if the costs to rebuild exceed insurance payouts plus any additional resources the borrower may have to put toward rebuilding. Further, potential job or income loss due to a hurricane can put further pressure on borrowers after the hurricane event.

Research findings on the effect of hurricanes on mortgage default, not surprising vary given the specific focus of hurricane research. At the individual storm level, for instance, Fannie Mae’s assessment of two major hurricane events; Hurricanes Katrina and Sandy show divergent results. Hurricane Katrina exhibited a clear spike in D180+ delinquency rates in the 6 months afterward that were approximately 5 times greater than D180+ rates preceding the storm. Fannie Mae reported that weighted average delinquency rates (30 days and greater) were 4.24% in Katrina-affected areas versus 1.99% elsewhere. However, after Hurricane Sandy, Fannie Mae found no such spike in D180+ delinquency rates, although weighted average 30+delinquency rates were higher for affected areas (8.4%) versus those not affected by the hurricane (5.31%). Analysis on

Hurricane Florence in 2018 by CoreLogic found mortgage default rates doubled 3 months following the storm.[11]

Hurricane Katrina, the costliest hurricane affecting the United States started out as a Category 5 hurricane before weakening to become a Category 3 by the time it made landfall in Louisiana and Mississippi and eventually causing $125 billion in damage.[12] Hurricane Sandy was the second costliest hurricane in U.S. history at $70 billion.[13] It started out as a Category 3 hurricane before weakening to a Category 1 when it made landfall along the northeast coast of the U.S. Looking at hurricane risk at a macro level, Kahn and Ouazad examined the impact of hurricane events over a 180 year period in the U.S and found that a natural disaster would increase the probability of foreclosure by 1.6% taking into account a variety of the risk factors described earlier.[14]

This analysis is unique in that it is the first to examine the intensity and frequency of hurricanes on mortgage default. The reason why this aspect of hurricane event dynamics is critical to understand is that a number of meteorological studies are finding that the strength and frequency of these natural disasters could be on the rise over this century. The Saffir-Simpson Hurricane Wind Scale is a familiar metric for relating wind intensity to damage on a logarithmic scale. Figure 1 provides insight into the relationship between wind speed and potential damage. For instance, when Hurricane Katrina first came ashore in Louisiana as a Category 3 hurricane with sustained winds of 125 mph, the potential damage from those winds were 60 times worse than a Category 1 hurricane with 75 mph winds. The Saffir-Simpson scale thus illustrates the wide divergence in potential hurricane impacts. The scale also does not account for other storm damage such as surge,

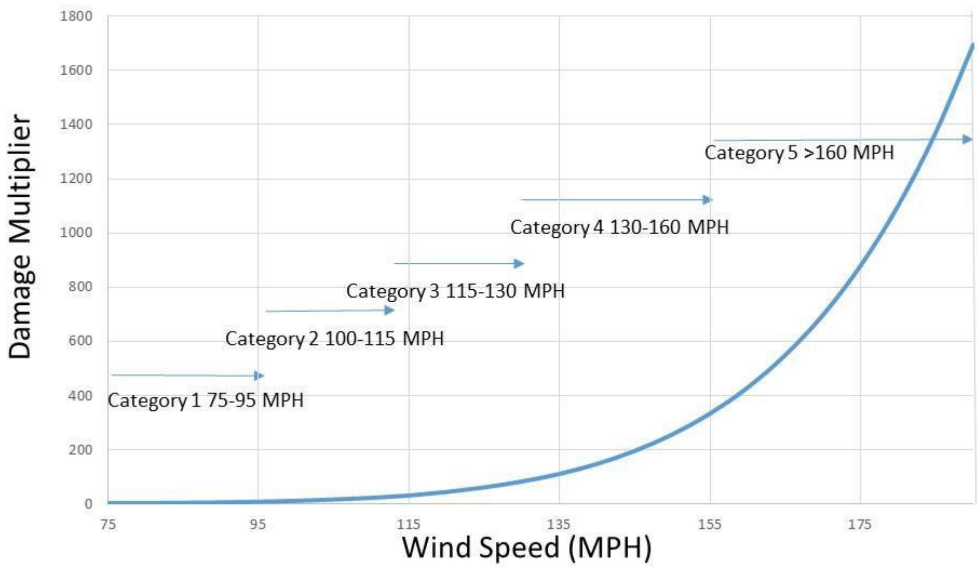
[11] CoreLogic, Press Release, Corelogic Estimates Nearly 7.4 Million Homes are at Risk of Storm Surge Ahead of Hurricane Season and an Uncertain Economy, May 28, 2020.

[12] National Oceanic and Atmospheric Administration. "Costliest U.S. Tropical Cyclones Tables Updated," Page 2. Accessed Jan. 28, 2020.

[13] FEMA Fact Sheet: Mitigation Assessment Team Results – Hurricane Sandy

[14] Ouazad A. and M.E. Kahn, Mortgage Finance in the Face of Rising Climate Risk, NBER Working Paper 26322, September 2019.

Fig. 1: Saffir-Simpson Hurricane Wind Speed and Potential Damage Relationship[15]



rainfall and tornadic events which if accounted for would drive the potential damage multipliers higher.

To measure the combined effects of hurricane frequency, intensity and duration, Emanuel (2005) developed the Power Dissipation Index (PDI). PDI is defined according to equation 2 where V^3 is the cubed maximum sustained wind speed at an altitude of 10 meters.[16] Historical trends of hurricanes along two important dimensions of frequency and intensity provides some insight into

$$(2) \quad PDI = \int_0^{\tau} V_{Max}^3 \, dt$$

hurricane dynamics. Figure 2, summarizes the annual frequency of hurricanes in the U.S. between 1851 and 2006.[17] The number of hurricanes has risen over time overall and for major hurricanes.

[15] Adapted from data provided in National Weather Service, National Oceanic and Atmospheric Administration, Hurricane Damage Potential.
[16] Emanuel K. (2005), Increasing Destructiveness of Tropical Cyclones Over the Past 30 Years, Nature, 436, 686-688.
[17] Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration, Global Warming and Hurricanes, An Overview of Current Research Results, June 12, 2020.

Fig. 2 – Atlantic Basin Hurricane Counts (1851-2013)

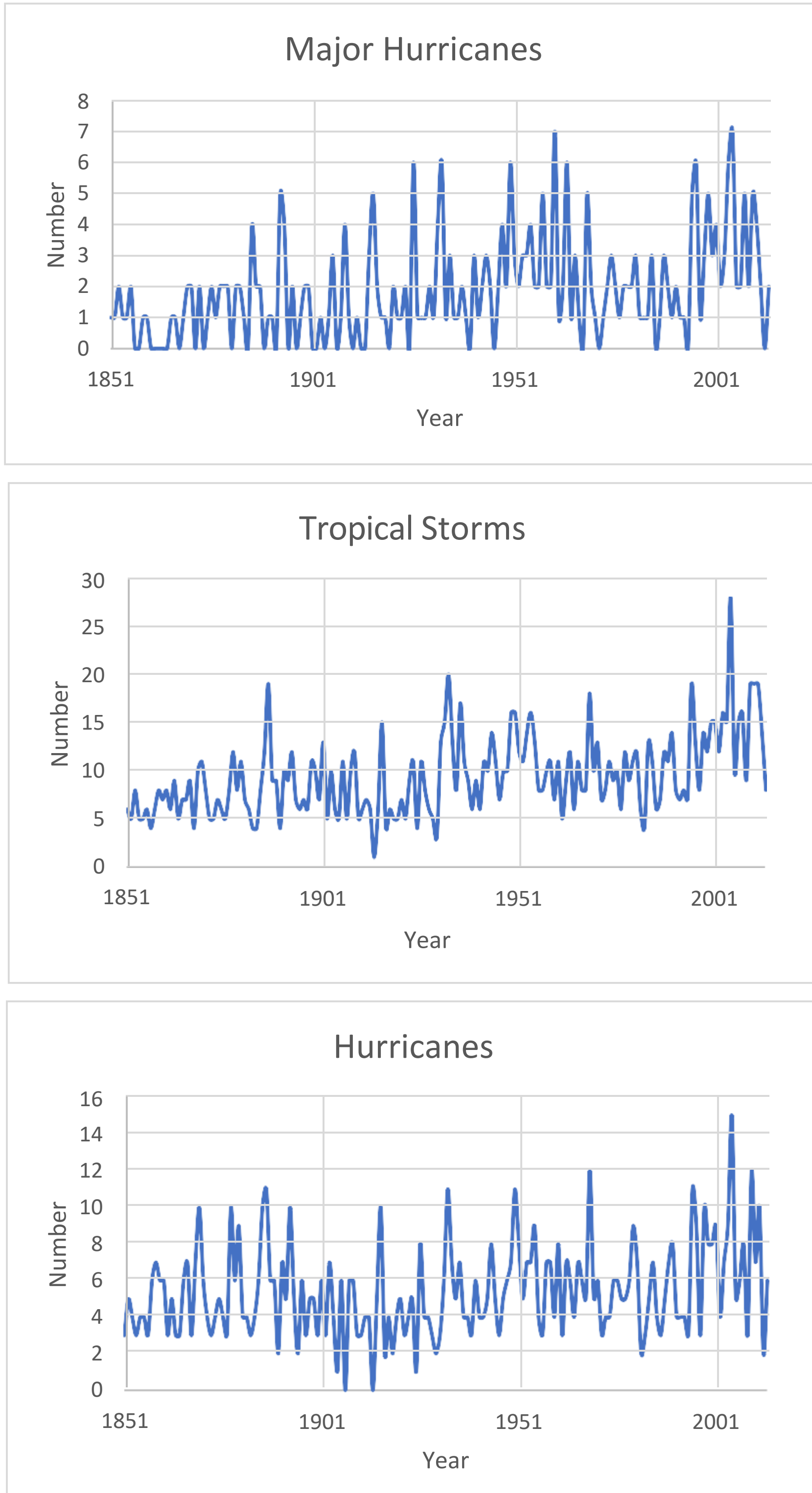
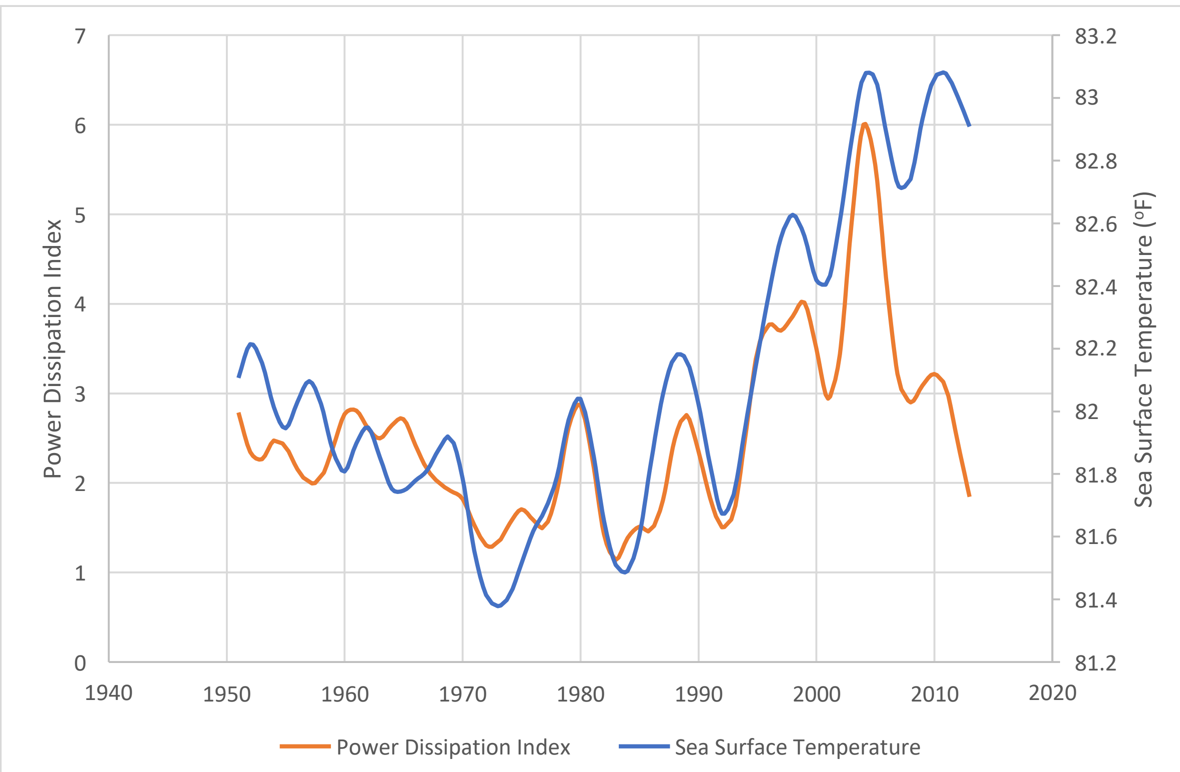


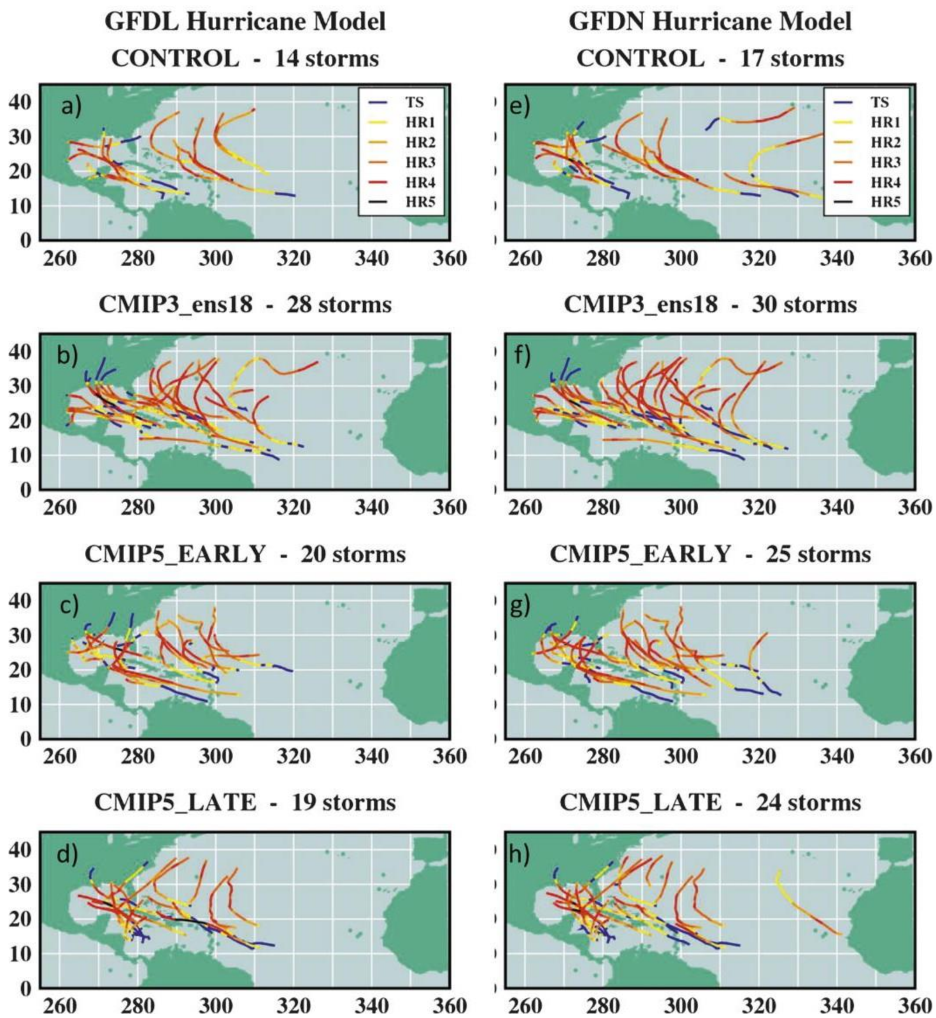
Figure 3 plots the PDI and sea surface temperatures (SST) over time. Consistent with Figure 2, between 1980 and the mid-2000's, the PDI of hurricanes rose sharply. Considerable research has been conducted to understand the degree to which anthropogenic causes such as man-made fossil fuel emissions and other sources have resulted in higher sea surface temperatures and their impact on hurricanes. Debate continues among meteorological researchers as to the extent to which climate change from whatever source poses a long-term increase in the frequency and intensity of North Atlantic hurricanes.

Fig. 3 – North Atlantic Tropical Cyclone Activity According to the Power Dissipation Index 1951-2013



Changes in SST over time as a result of man-made activities have been a central focus of much of the research to understand the trajectory of future hurricane risk. Research examining historical correlations between SST and hurricane PDI results in a wide range of potential outcomes over this century in terms of PDI. On an absolute basis, the relationship between SST and PDI for tropical Atlantic hurricanes applied to 24 different hurricane models suggest a 300% increase in hurricane PDI by the year 2100.[18] Alternatively, if SST is measured relative to mean tropical SST

Fig. 4 Simulated Category 4 and 5 Hurricane Tracks[19]



[18] Vecchi, G.A., K.L. Swanson, B.J. Soden, (October 31, 2008), "Whither Hurricane Activity," Science, 322, 688-689.

[19] Knutson, T.R., J.J. Sirutis, G.A. Vecchi, S. Garner, M. Zhao, H.S. Kim, M. Bender, R.E. Tuleya, I.M. Held, G. Villarini, (2013), "Dynamical Downscaling Projections of Twenty-First Century Atlantic Hurricane Activity: CMIP3 and CMIP5 Model-Based Scenarios," Journal of Climate, 26(17):6591-6617. The authors compared two different hurricane models (GFDL and GFDN) with two versions of climate change models (CMIP3 and CMIP5) in producing the simulated tracks shown in Figure 4.

rather than to tropical Atlantic SST, the impact on PDI is slight. Other studies tend to support the results on Vecchi et. al in Figure 4b that a long-term increase in hurricane PDI would be small.[20] However, Bender et. al found that the number of Category 4 and 5 Atlantic hurricanes could increase 90% over time. Corroborating this result, Knutson et. al reported large percentage increases in Category 4 and 5 hurricanes in the early (45%) and late (39%) part of the 21st century.

3 Mortgage and Hurricane Data Structure and Summary

The statistical analysis of mortgage default and hurricane intensity and frequency is based on two datasets. Data on individual mortgage performance is sampled from the Freddie Mac Single-Family Loan-Level Dataset. The data includes details on 27.8 million fixed-rate mortgages purchased by Freddie Mac originated between 1999 and 2018. Monthly performance updates on each loan are available through June 2019. Key risk factors described earlier are included in the data files such as FICO score, original and combined LTV, debt-to-income ratio, loan purpose, amortization, owner-occupancy, first-time homebuyer indicator, number of units, number of borrowers, property type, loan amount, and origination channel.[21] A random sample of 100,000 loans originated between 2000 and 2013 was taken from the full dataset for properties in Gulf and east coast states impacted by hurricane events during this period according to FEMA records.[22] Two definitions of default were applied in the analysis, loans that were 90 days past due or more (D90+) and 180 days past due or more (D180+) to gain a sense of the impact on different definitions of late-stage mortgage delinquency. For the final sample, the mean D90+ and D180+ rates were 6.1% and 5.6%, respectively. A summary of key attributes of the Freddie Mac data is found in Tables 1-11.

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[20] Bender, M.A., T.R. Knutson, R.E. Tuleya, J.J. Sirutis, G.A. Vecchi, S.T. Garner, I.M. Held, (January 2010), "Modeled Impact of Anthropogenic Warming on the Frequency of Intense Atlantic Hurricanes," *Science* , 327, Issue 5964, 454-458.

[21] UPB was transformed into a relative median UPB measure. That is, the median UPB of the MSA or state (if identified as a rural property) was used to divide each loan's UPB. Relative median UPB is a more accurate reflection of the relative size of each loan in its MSA or state in terms of its relationship with default.

[22] States included in the analysis were Alabama, Connecticut, Florida, Georgia, Louisiana, Massachusetts, Maryland, Maine, Mississippi, North Carolina, New Hampshire, New Jersey, New York, Rhode Island, South Carolina, Texas, Virginia.

Table 1 – Key Risk Factor Statistics

Attribute	Mean	Standard Deviation	Minimum	Maximum
FICO	730	56.2	356	840
Original LTV	73.4	15.8	6.0	100
DTI	35.2	12.0	1.0	65.0
Relative Median UPB	108.0	49.3	6.8	496.5

Table 2 – Occupancy Status

Attribute	Number	Percent of Total	D90+ Rate (%)	D180+ Rate (%)
Investor-owned	5,136	5.14	8.45	7.36
Primary Residence	89,533	89.53	6.06	5.60
Second Home	5,331	5.33	4.60	4.18

Table 3 – Property Type

Attribute	Number	Percent of Total	D90+ Rate (%)	D180+ Rate (%)
Condominium	8,818	8.82	6.91	6.43
Planned Unit	20,184	20.18	5.08	4.69
Single-Family	70,998	71.00	6.30	5.77

Table 4 – Loan Purpose

Attribute	Number	Percent of Total	D90+ Rate	D180+ Rate
Cash-out Refinance	26,276	26.28	9.51	8.88
Rate & Term Refinance	23,468	23.47	4.84	4.41
Purchase	50,256	50.26	4.92	4.47

Table 5 – First-time Homebuyer

Attribute	Number	Percent of Total	D90+ Rate	D180+ Rate
No	86,557	86.56	6.20	5.70
Yes	13,443	13.44	5.53	5.04

Table 6 – Number of Units

Attribute	Number	Percent of Total	D90+ Rate	D180+ Rate
1	97,217	97.22	6.01	5.52
2	2,200	2.20	9.77	9.00
3	399	.40	10.28	9.27
4	184	.18	7.61	5.98

Table 7 – Origination Channel

Attribute	Number	Percent of Total	D90+ Rate	D180+ Rate
Broker	30,394	30.39	8.24	7.81
Correspondent	26,266	26.27	5.37	4.69
Retail	43,340	43.34	5.06	4.64

Table 8 – Number of Borrowers

Attribute	Number	Percent of Total	D90+ Rate	D180+ Rate
1	45,570	45.57	8.36	7.70
2	54,430	54.43	4.22	3.86

Table 9

Attribute	Number	Percent of Total	D90+ Rate	D180+ Rate
<=620	3,799	3.80	19.03	17.72
620-660	8.996	9.00	16.08	15.03
660-700	15,916	15.92	9.88	9.09
700-750	26,808	26.81	5.57	5.07
>750	44,481	44.48	1.96	1.76

Table 10 = LTV

Attribute (%)	Number	Percent of Total	D90+ Rate	D180+ Rate
<= 50	9,676	9.68	2.19	1.96
50 - 80	62,571	62.57	5.59	5.18
80 - 90	14,035	14.04	8.56	7.78
>90	13,418	13.42	8.71	7.94

Table 11 – DTI

Attribute (%)	Number	Percent of Total	D90+ Rate	D180+ Rate
< 30	33,149	33.15	3.25	2.88
30 - 40	30,038	30.04	5.26	4.81
➢ 40	36,813	36.81	9.37	8.73

The bivariate results of individual risk factors by the two default definitions in Tables 2-11 generally conform to the earlier discussion of how borrower, loan, and property factors relate to mortgage default risk. Noticeably, key variables such as LTV, FICO and DTI exhibit a nonlinear relationship to default. For example, D90+ and D180+ rates for borrowers with FICOs at or below 620 are approximately 10 times greater than those with FICO scores over 750. Likewise, borrowers with LTVs greater than 90% experience D90+ and D180+ rates that are about 4 times higher than borrowers with LTVs less than or equal to 50%. Of course, these summary results are uncontrolled for other factors which will be examined in more detail in the next section.

The other dataset used in the analysis is the FEMA OpenFEMA Dataset: Declarations Summaries. The data consists of information on each federally declared disaster since 1953. The data include information on the type of disaster such as a hurricane, the hurricane name, beginning and end date of the event, state, and county. In order to merge this data with the Freddie Mac loan level data, several additional steps were taken. First, only hurricane and tropical storm events occurring during the loan origination periods of the Freddie Mac data; i.e., 2000-2013 were included. The Saffir-Simpson Hurricane Category for each named hurricane for each storm was obtained from National Hurricane Center Tropical Cyclone Reports and the category at the time of first landfall in the U.S was used to designate the initial hurricane strength in the modeling. It is recognized that strength of each storm could change as it moved inland or over water, however, the initial rating used provides a reasonable benchmark for gauging overall impact relative to other storms and categories during the 2000-2013 period of interest. According to the FEMA data, there were 41 named hurricanes in the Atlantic region that resulted in a disaster declaration. A distribution of storms by category is shown in Table 12. Figures 5 and 6 display the average number of hurricanes experienced for each property by county and the average hurricane rating by property. The D90+ and D180+ rates for each category of hurricane are displayed in Table 13. On an uncontrolled basis there appears to be some association between hurricane rating and default rates, although that relationship is not monotonic for category 4 or 5 storms. Further analysis is required on a multivariate basis to determine the nature of this relationship in a more robust fashion. Table 14

Table 12 – Tropical Storm and Hurricane Summary for Sample

Storm Category	Number in Sample Data
Tropical Storm	9
1	11
2	7
3	9
4	2
5	3

Fig. 5 – Number of Hurricanes of Freddie Mac Sample Loans Originated 2000-2013

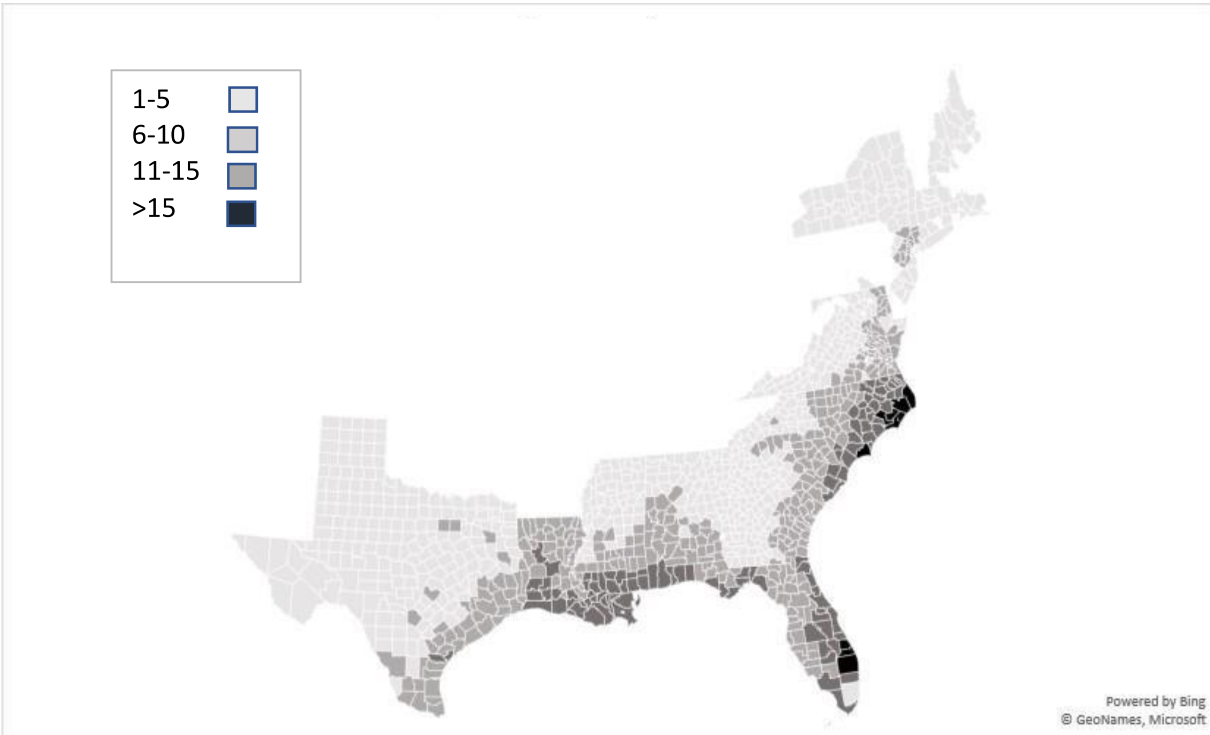
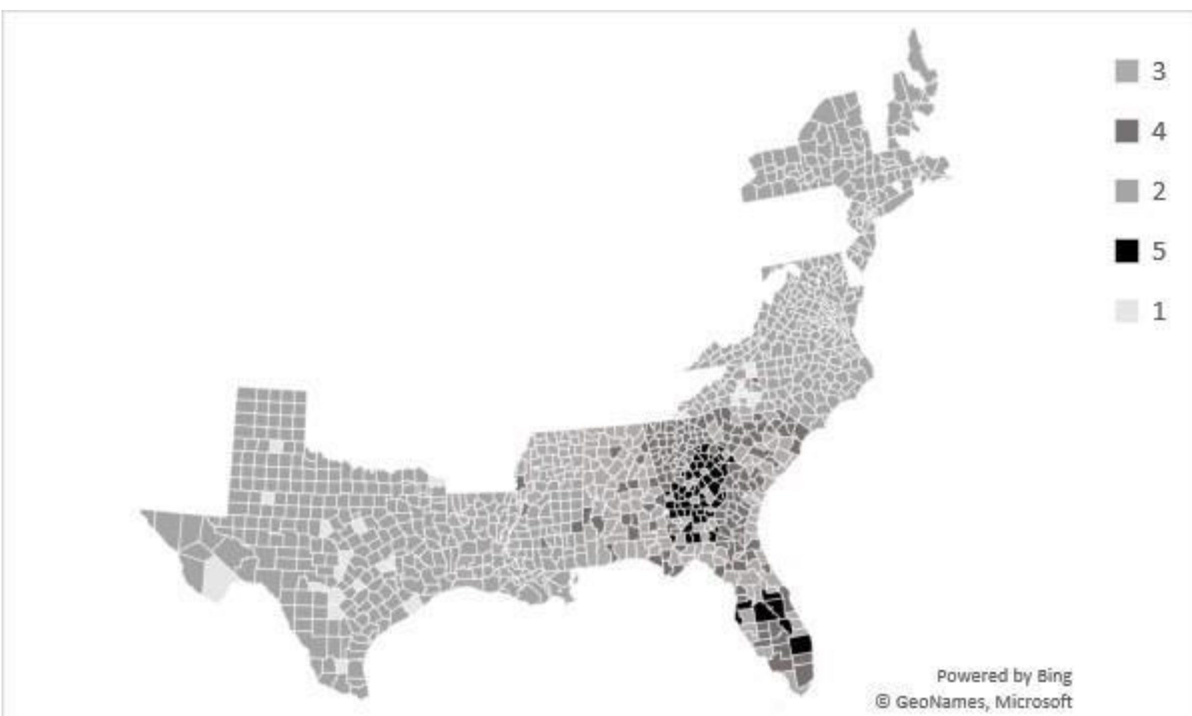


Fig. 6 –Average Hurricane Ratings of Freddie Mac Sample Loans Originated 2000-2012



depicts the relationship between the average number of hurricanes experienced by each property in the sample and D90+ and D180+ rates. The uncontrolled bivariate results show a monotonic increase in both D90+ and D180+ rates.

Table 13 – Hurricane Rating by D90+ and D180+ Rates

Category	D90+	D180+
Tropical Storm or Category 1	5.34	5.02
2	5.30	4.92
3	7.47	6.86
4	6.63	5.71
5	3.45	3.45

Table 14 – Average Number of Hurricanes and Default Rates

Average Number of Hurricanes	Number	D90+ Rate	D180+ Rate
0-1	2,227	4.31	3.95
2-3	7,588	5.40	4.89
>3	90,185	6.21	5.72

4 Methodology and Empirical Approach

To analyze the impact of hurricane intensity and frequency on mortgage default, a standard logistic regression model applied in underwriting borrowers is used. Two logistic regression models are specified reflecting two different definitions of the binary choice dependent variable; D90+ and D180+ with the default event taking on a value of 1 and nondefault events are treated as 0 otherwise. This ensures the estimated probabilities are confined to the 0-1 domain. Following the theoretical model of mortgage default presented earlier, mortgage default in both models is a function of borrower, product, property and hurricane risk factors. The general form of the regression models is presented in equation 3 and 4 below:

(3) $P_{Default} = \frac{1}{1+e^{-Z}}$

(4) Z = f(FICO, CLTV, LTV, DTI, NUMUNIT, OCC, CHANNEL, < PROPTYPE, PURPOSE, NUMBORR, FTHB, HURFREQ, HURINT, AGE)

A description of the candidate variables for analysis are found in Tables 15 and 16. Several transformations of key variables were made prior to modeling. Due to inherent nonlinearities in FICO and credit score, a set of splined variables were created and tested with different knot points. The general form of each spline is shown in equation 5.

$$(5) \quad \beta_i VAR_i + \sum_{m=1}^{M} \beta_m (Max(VAR_i - KP_m, 0))$$

where VAR_i is variable i to be splined, and KP_m is the mth knot point chosen. For FICO, a set of knot points consistent with industry practice were tested at 620, 660, 700, 720 and 750. For CLTV, candidate knot points tested included 50%, 80%, 85%, 90%, and 95%. Final estimates for the number of splines and knot point settings were based on statistical significance of each spline and contribution to model performance. The variable AGE, was included to control for the age of each loan from its origination.

Measurement of hurricane frequency and intensity for the models were based on the FEMA hurricane data merged with the Freddie Mac loan level data. The average of the Saffir-Simpson hurricane category of all hurricanes generating a FEMA disaster declaration experienced during the life of each loan in the county where a loan’s property was located was used to measure the impact of hurricane intensity on default. Hurricane frequency was defined as the number of hurricanes or tropical storms generating a FEMA disaster declaration experienced in the county where the property is located over the loan’s life. The default models with the best model performance as discussed below were when the hurricane frequency variable was set delineated by 12 or more hurricanes or tropical storms in a loan’s life. With a weighted average life in the sample of about 4.5 years, that roughly translates into an average of 2.7 storms per year for the highest frequency HURFREQ category.

Table 15 – Candidate Variable Description

Risk Factor Category	Variable Name	Definition	Variable Type
Borrower	FICO	Credit score	Continuous
	CLTV	Original combined LTV	Continuous
	DTI	Debt-to-income ratio	Continuous
	OCC	Occupancy type	Categorical
	NUMBORR	Number of borrowers	Categorical
	FTHB	First-time homebuyer	Categorical
Property			
	NUMUNIT	Number of property units	Categorical
	PROPTYPE	Property type	Categorical
Product/Channel			
	PURPOSE	Loan purpose	Categorical
	RUPB	Relative median UPB	Continuous
	CHANNEL	Origination channel	Categorical
Hurricane			
	HURFREQ	Average number of hurricanes experienced	Categorical
	HURINT	Average hurricane rating	Categorical

5 Results

The results from the final set of estimations for both the D90+ and D180+ models are presented in Table 17.[23] To compare alternative specifications when determining the "best" models for D90+ and D180+, the Kolmogorov-Smirnov (KS) test and the area under the curve (AOC) were used as model performance criteria. Specific attention is paid to these measures used to assess the model's discriminatory power between default and non-default loans. On this basis, the splined effects for

[23] The control variate, AGE is not reported for ease of exposition but are available from the author upon request.

FICO and CLTV resulted in a single knot point for FICO at 660 and two knot points; 80% and 95% for CLTV. Some candidate variables such as relative median UPB and first-time homebuyer were not statistically significant and thus were removed from the models. In the final specifications, all estimated coefficients carry the expected signs and are all are statistically

Table 16- Categorical Variable Description

Variable Name	Category Name	Description
OCC	Primary	Primary residence
	Investor	Investor-owned
	2^{nd} Home	2^{nd} or vacation home
NUMBORR	1	1 borrower
	2+	2 or more borrowers
FTHB	1	First-time homebuyer
	0	Non-FTHB
NUMUNIT	1	1 unit property
	2-4	2-4 unit property
PROPTYPE	SF	Single-family
	PUD	Planned Unit Development
	Condo/Coop	Condominium or Coop
PURPOSE	Purchase	Purchase-only mortgage
	Cash-out	Cash-out refinance mortgage
	R&T	Rate & Term refinance
CHANNEL	R	Retail originated
	B	Broker originated
	C or TPO	Correspondent or third-party originated
HURFREQ	1	12 or more hurricanes over the life of the loan
	0	Less than 12 hurricanes over the loan's life
HURINT	1	Loan's average hurricane rating <=2
	0	Loan's average hurricane rating >2 - 5

significant at the 10% level or lower. The majority of parameters were significant at the 1% level. The model performance statistics are robust as shown in Table 17.

Table 17 – Logistic Regression Results

Parameter	Estimates		Standard Errors	
	D90+	D180+	D90+	D180+
Intercept**	-1.1335	-1.4160	.4716	.4858
FICO*	-.0078	-.0077	.0007	.0007
FICO660*	-.0065	-.0068	.0009	.0010
CLTV*	.0291	.0298	.0016	.0017
CLTV80**	.0099	.0066	.0037	.0038
CLTV95*	.0594	.0654	.0189	.0195
DTI*	.0293	.0304	.0012	.0013
NUMUNIT*	.5183	.5146	.0720	.0749
Investor*	.5034	.4301	.0570	.0603
B*	.2657	.3040	.0318	.0329
C*	.1090	-	.0367	-
Condo	.3000	.3191	.0483	.0499
Cash-out*	.5990	.6147	.0398	.0413
Purchase*	-.4045	-.4029	.0406	.0423
NUMBORR*	.5965	.5972	.0286	.0297
HURINT*	.1627	.1238	.0297	.0309
HURFREQ1*	.7733	.7970	.1129	.1173
HURFREQ2**	.2071`	.2127	.1101	.1145
KS	46.4		47.0	
AUC	80.1		80.4	

Note: Parameters designated * or ** are statistically significant at the 1% and >1% - 10% levels, respectively

To understand the relative impact of the categorical variables, most notably the hurricane frequency and intensity effects, odds ratios were computed and shown in Table 18 along with the reference category for each variable. The odds ratios are consistently stable across default definitions. Holding all else constant, the odds ratio for 2-4 unit properties indicates that the incidence of default is 1.67 times that of a 1-unit property. The other categorical variables have comparable interpretations relative to the reference category indicated in Table 18. Of interest among these effects are the hurricane frequency and intensity variables. The results indicate that controlling for all other factors, default risk is 1.13 to 1.18 times higher for loans experiencing an average hurricane rating over 2. This result is consistent with the historical meteorological data showing that hurricanes rated 3-5 are associated with greater wind and flooding damage. In addition to this incremental hurricane risk, the results indicate that borrowers that have

Table 18 – Categorical Variable Odds Ratios

Variable	Odds Ratio	
	D90+ Model	D180+ Model
2-4 Units (relative to 1 unit)	1.67	1.67
Investor (relative to owner-occupied)	1.65	1.54
Broker (relative to retail_	1.30	1.35
Correspondent (relative to retail)	1.12	1.06
Condo (relative to single-family)	1.35	1.38
Cash-out refinance (relative to R&T refinance)	1.82	1.85
Purchase (relative to R&T refinance)	.67	.67
1 Borrower (relative to 2 or more)	1.82	1.82
Average hurricane rating >2 - 5	1.18	1.13
>1 – 12 hurricanes (relative to 1 or less)	1.23	1.24
12 or more hurricanes (relative to 1 or less)	2.17	2.22

Note: $Odds\ Ratio = e^{\beta}$

experienced 1-12 storms over the loan's life are 1.23 times more likely to default than a borrower that has experienced an average of 1 or fewer such storms. For borrowers experiencing 12 or more storms over the loan's life, default incidence more than doubles. These findings have important implications for mortgage investors now and in the future. If the meteorological research cited earlier bears out that the frequency of major storms rated 3-5 would increase over the next century, the analysis just presented suggests that mortgage delinquency rates in hurricane affected areas of the country would rise considerably from where they are today. To gain a sense of the sensitivity of mortgage default rates under various assumptions on hurricane and intensity, the estimated models were run to generate predicted default rates for each loan in the sample. The loans were reweighted in the sample reflecting different proportions of borrowers with average hurricane ratings above 2 and an increase in the proportion of borrowers experiencing more than 12 hurricanes over the life of the loan. This analysis was conducted for both default definitions and the results are presented in Tables 19 and 20. In one test, the proportion of borrowers in the sample experiencing an average hurricane rating greater than 2 were raised 10-100% in the increments shown in Tables 19 and 20 while reducing the proportion of other borrowers accordingly. The increments provide a reasonable range of long-term hurricane intensity outcomes that are consistent with those reported by Bender et. al and Knutson et.al.[24] In addition to this set of scenarios, a set of tests were included that raised the proportion of borrowers experiencing more than 12 hurricanes in the same percentages (i.e., 10-100%) as before.

The results suggest that increasing the proportion of borrowers experiencing major hurricanes and more hurricanes overall has a moderate effect on raising default rates. For example, if the proportion of borrowers experiencing major hurricanes and more hurricanes in general doubled, that would raise D90+ and D180+ rates 14-15% above baseline rates. These results reflect the fact that the size of the borrower cohorts experiencing major hurricanes and more storms generally is itself relatively small (5.12% of the sample). In other words, the incremental effects of more hurricanes as well as those rated 3-5 may be substantial as shown in Table 18, but are muted by the proportion of borrowers affected by these hurricane attributes.

[24] Bender et. al (2010) and Knutson et. al (2013).

Table 19 - Sensitivity of D90+ Rates to Increased Hurricane Intensity and Frequency

% Increase in Intensity and Frequency	D90+ (%) Rates 3-5 Rated Hurricanes	% Change from Baseline D90+ Rates	Change in D90+ Rates (bps)	D90+ (%) Rates 3-5 Rated **and** 12+ Hurricanes	% Change from Baseline D90+ Rates	Change in D90+ Rates (bps)
Baseline	6.11			6.11		
10	6.14	.57	3.49	6.20	1.55	9.49
25	6.20	1.55	9.49	6.35	4.01	24.49
50	6.30	3.19	19.49	6.56	7.45	45.49
75	6.40	4.83	29.49	6.79	11.22	68.49
100	6.50	6.47	39.49	7.02	14.99	91.49

Table 20 - Sensitivity of D180+ Rates to Increased Hurricane Intensity and Frequency

% Increase in Intensity and Frequency	D180+ (%) Rates 3-5 Rated Hurricanes	% Change from Baseline D180+ Rates	Change in D180+ Rates (bps)	D180+ (%) Rates 3-5 Rated and 12+ Hurricanes	% Change from Baseline D180+ Rates	Change in D180+ Rates (bps)
Baseline	5.61			5.61		
10	5.64	.52	2.93	5.69	1.41	7.93
25	5.68	1.23	6.93	5.81	3.55	19.93
50	5.76	2.66	14.93	6.01	7.12	39.93
75	5.83	3.91	21.93	6.21	10.68	59.93
100	5.90	5.16	28.93	6.41	14.25	79.93

6 Conclusions and Implications

The results from this analysis have several implications for borrowers and investors in mortgage credit risk. First, if hurricane frequency and intensity for major Atlantic hurricanes rises over the next decades as some meteorological research suggests, more borrowers will be affected and the resulting wind and flood damage on businesses and residential properties appears likely to lead to much higher default rates in the future. This potential increase in default rates from hurricane events could leave investors in mortgage credit risk exposed unless that risk is appropriately priced into guarantee fees in the case of the GSEs or tranche pricing of credit risk transfer (CRT) transactions.

More intense and frequent hurricanes could reduce market liquidity in CRT transactions if private investors are not able to assess the impact of hurricane risk in these transactions. There is some evidence that hurricane events in recent years have exposed the CRT market to some volatility. The CRT market was temporary roiled starting after Hurricane Harvey in August 2017 and Hurricane Irma in September 2017 as yields on subordinate (B1) CRT tranches widened by 125bps over a 5-week period. These back-to-back major hurricanes caught investors off-guard and eventually led the Association of Mortgage Investors (AMI) to request that Fannie Mae and Fannie Mae exclude such loans from CRT pools as they contended that catastrophic risk from natural disasters is a risk that investors do not know how to effectively analyze or price.[25] Freddie Mac has taken steps since then to remove loans in CRT transactions that are located in FEMA-designated disaster areas, however, an alternative strategy might be to create a separate "clean-up" tranche in individual or multiple CRT transactions that provides cat risk protection to CRT tranche investors for hurricane risk. While removing loans from CRT deals by the GSEs is a viable alternative to addressing investors' concerns about absorbing cat risk in CRT transactions, it may not be a satisfactory outcome unless the GSEs are obtaining some form of reinsurance of the cat risk they hold. The GSEs are not a natural entity to price or take on natural disaster risk and so should hurricane risk rise in the future, finding alternatives to transfer cat risk from the GSEs to other investors could remedy this exposure the GSEs have retained. Since CRT transactions have

[25] Yoon, A., "DoubleLine, Like-minded Investors, Want Cat Risk Out of CRT," Debtwire, October 2017.

attracted reinsurance companies as investors over the years, it is possible that a cat risk carve-out structure in CRT deals involving reinsurers could be possible.

The future risk to the mortgage market from hurricane risk appears to be on the upswing according to the consensus of scientific research on hurricane intensity and frequency. Prospective homeowners when shopping for a new home should become more informed on where their property is located in terms of flood and hurricane risk before deciding where to buy. Traditional investors in mortgage credit such as the GSEs and private mortgage insurance companies are not well-equipped to assess and price for cat risk, particularly if that risk is rising over time. Instead, alternative financial structures such as cat risk tranches of CRT deals may be a more appropriate way of distributing this risk in the future.

References

Bender, M.A., T.R. Knutson, R.E. Tuleya, J.J. Sirutis, G.A. Vecchi, S.T. Garner, I.M. Held, (January 2010), "Modeled Impact of Anthropogenic Warming on the Frequency of Intense Atlantic Hurricanes," *Science* , 327, Issue 5964, 454-458.

Black, F. and M.S. Scholes (1973), " The pricing of Options and Corporate Liabilities," Journal of Political Economy, 81: 637-654.

Congress of the United States, Congressional Budget Office, Expected Costs of Damage From Hurricane Winds and Storm-Related Flooding, April, 2019, pg. 1-2.

CoreLogic, Press Release, Corelogic Estimates Nearly 7.4 Million Homes are at Risk of Storm Surge Ahead of Hurricane Season and an Uncertain Economy, May 28, 2020.

CoreLogic, 2020 CoreLogic Storm Surge Report, May 28, 2020.

Cunningham, D.F., and P.H. Hendershott, (1984), "Pricing of FHA Mortgage Default Insurance," Housing Finance Review, 13, 373-392.

Emanuel K. (2005), Increasing Destructiveness of Tropical Cyclones Over the Past 30 Years, Nature, 436, 686-688.

Emanuel, K.A. 2016 update to data originally published in: Emanuel, K.A. 2007. Environmental factors affecting tropical cyclone power dissipation. J. Climate 20(22):5497–5509.

Fannie Mae, Historical Data Provides Insights Into Past Hurricane Experience, November 6, 2017.

FEMA Fact Sheet: Mitigation Assessment Team Results – Hurricane Sandy.

Geophysical Fluid Dynamics Laboratory, National Oceanic and Atmospheric Administration, Global Warming and Hurricanes, An Overview of Current Research Results, June 12, 2020.

Kau, J.B., D.C. Keenan, and W.J. Muller III (1985), "Pricing Default Risk in Mortgages," Journal of the American Real Estate and Urban Economics Association, 13, 261-272.

Kau, J.B., D.C. Keenan, W.J. Muller, and J.F. Epperson (1992), "A Generalized Valuation Model for Fixed-Rate Residential Mortgages," Journal of Money, Credit and Banking, 24, 279-299.

Knutson, T.R., J.J. Sirutis, G.A. Vecchi, S. Garner, M. Zhao, H.S. Kim, M. Bender, R.E. Tuleya, I.M. Held, G. Villarini, (2013), "Dynamical Downscaling Projections of Twenty-First-Century Atlantic Hurricane Activity: CMIP3 and CMIP5 Model-Based Scenarios," *Journal of Climate*, 26 (17): 6591–6617.

Merton, R.C., (1973), "Theory of Rational Option Pricing," Bell Journal of Economics and Management Science, 4, 141-183.

National Oceanic and Atmospheric Administration. "Costliest U.S. Tropical Cyclones Tables Updated," Page 2. Accessed Jan. 28, 2020.

Ouazad A. and M.E. Kahn, Mortgage Finance in the Face of Rising Climate Risk, NBER Working Paper 26322, September 2019.

Pielke, R.A. Jr. et al., "Normalized Hurricane Damage in the United States: 1900-2005", Natural Hazard Review (2008).

Vecchi, G.A., K.L. Swanson, B.J. Soden, (October 31, 2008), "Whither Hurricane Activity," Science, 322, 688-689.

Yoon, A., "DoubleLine, Like-minded Investors, Want Cat Risk Out of CRT," Debtwire, October 2017.