Assessing the impact of hurricane frequency and intensity on mortgage delinquency

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Abstract Considerable meteorological research suggests that the frequency and intensity of North Atlantic hurricanes are rising. This analysis focuses on estimating the impacts of hurricane intensity and frequency on mortgage delinquency. Based upon a large loan-level dataset of mortgages purchased by Freddie Mac between 1999 and 2015, loans with an average lifetime Saffir–Simpson hurricane rating of 3 or more were found to be 88 per cent more likely to become delinquent than other loans in the same locations, controlling for all other risk factors. This result has important 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. Secondly, investors in mortgage credit risk from these locations will face higher default losses in the future. Thirdly, 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*

INTRODUCTION

Considerable meteorological research suggests that the frequency and intensity of North Atlantic hurricanes are on the rise. The destructive power of these storms is well documented, that in addition to deaths and injuries, major hurricane events cause 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 US$54bn, with losses from the residential sector accounting for US$34bn of that amount.[1] Moreover, according to Pielke et al., 85 per cent of damage caused by hurricanes is associated with hurricanes rated 3–5 on the Saffir–Simpson Hurricane Wind Speed Scale.[2]

Extensive modelling 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, that is, those rated Category 3–5, are 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 per cent above where they have been in the recent past.[3] 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 six times the PDI level of the early 1980s, signalling that this recent period was not only marked by more hurricanes but ones with greater intensity.[4]

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).[5] In the months immediately following Hurricane Katrina for instance, loans delinquent 180 days or more (D180+) peaked at a rate approximately five times the D180+ rate in the months leading up to the storm. By contrast, Fannie Mae found that D180+ rates following Hurricane Sandy remained relatively steady. The impact of hurricanes on mortgage delinquency could be affected by various risk mitigation practices put in place by credit investors. For instance, following hurricanes in 2017, government-sponsored enterprises (GSEs) provided relief to affected borrowers in the form of forbearance and modification plans.[6] Early analysis of borrowers offered modifications following Hurricanes Irma, Harvey and Maria indicated that 97 per cent were current or had prepaid.[7] These policies were not in place at the time of Hurricanes Sandy or Katrina. Underscoring the magnitude of potential risk for the mortgage sector, CoreLogic estimates that 7.4 million residential and multifamily properties, accounting for approximately US$1.8tn in replacement costs would be affected by storm surge from hurricanes in the United States.[8]

The focus of this analysis is to understand the specific impacts of hurricane intensity and frequency on mortgage delinquency. Using a sample of more than 100,000 mortgage loans purchased by Freddie Mac that were originated between 1999 and 2015, a model describing a borrower's probability to default as defined by either a loan that becomes delinquent 90 days or more (D90+) or not, and augmented with data on hurricanes from the Federal Emergency Management Agency (FEMA) Disaster Declarations Summaries was estimated. In addition to standard risk attributes associated with the borrower, loan product and property, a factor describing the intensity of hurricanes experienced in counties where these properties are located was statistically significant.

Loans where a Category 3, 4 or 5 hurricane was experienced during the loan's life were found to be 88 per cent more likely to become 90 days delinquent or more, respectively than other loans in the same locations, controlling for all other risk factors. Moreover, a machine learning analysis of the data revealed that the average hurricane rating and number of hurricanes experienced by borrowers in the sample ranked second and third in feature importance to predicting D90+ rates among all risk attributes. Only current loan to value (LTV) ranked higher in explaining mortgage delinquency. These findings have significant implications for credit investors, whether they are GSEs, portfolio lenders or investors in credit risk transfer securities.

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. Secondly, investors in mortgage credit risk from these locations will face higher default losses in the future. At the same time, unless the GSEs Fannie Mae, Freddie Mac and the Federal Housing Administration (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. Thirdly, 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 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. Alternatively, a residual tranche specifically allocated to hurricane-related defaults could be added to CRT issues in the future.

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.[9,10] 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).[11,12] 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, Muller and Epperson (1992).[13] 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 that affect property value and hence the borrower's incentive to exercise the default option where unpaid principal balance (UPB) of the loan at the 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.

$$\begin{aligned} V_M (\Delta H,\Delta r,\Delta t) = {} & V_{RF} (\Delta H,\Delta r,\Delta t) \\ & - V_D (\Delta H,\Delta r,\Delta t) \\ & - V_{PP} (\Delta H,\Delta r,\Delta t) \end{aligned} \tag{1}$$

The focus of the present analysis is to empirically analyse 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 of the property falls below the UPB at the 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; we can, however, characterise 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 3Cs 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 LTV ratio and with house price volatility, among others. Borrower underwriting takes into account the LTV at origination; as both the loan amount and property value, however, vary over time and especially at the time of default, current LTV (CLTV) 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 CLTVs above 100 per cent, 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; that is, whether the loan is a fixed-rate amortising 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 amortisation 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 amortising 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 remodelling project or nonresidential purpose (eg 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 nonretail 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, second home and investor-owned. The latter typically is a riskier outcome followed by second-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 they are routinely included in loan pricing and loss measurement modelling 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 delinquency is posited to come about in several ways through key economic relationships that affect the borrower's default option. Hurricanes, depending on their severity, can directly and indirectly affect a borrower's propensity to default on their mortgage. Indirect effects include business interruptions with the potential for job loss, infrastructure damage and other negative effects on an impacted area for some time that could lead to borrowers defaulting on their mortgage.

A direct effect from a hurricane occurs when damages are sustained on a borrower's property from high winds and/or extensive flooding events. In the specific case of Hurricane Harvey, Kousky, Palim and Pan found a statistically significant relationship between property damage and 90-day delinquency rates.[14] Hurricane damage tends to lower values of affected properties, thus raising the likelihood of default.[15] Notwithstanding the existence of national flood insurance and homeowner hazard insurance policies, high deductibles (eg 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 towards rebuilding. A potential mitigant to hurricane damage-induced default could be strengthening building codes in areas where moderate-to-severe flood and wind events from hurricanes are likely to occur. The combination of above and below-ground improvements such as high wind-rated windows and shutters, sealed roofing structures and sump pumps could reduce damage and thus limit direct factors that could trigger a default.

Research findings on the effect of hurricanes on mortgage default, not surprisingly 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 five times greater than D180+ rates preceding the storm.[5] Fannie Mae reported that weighted average delinquency rates (30 days and greater) were 4.24 per cent in Katrina-affected areas versus 1.99 per cent elsewhere.[5] After Hurricane Sandy, however, Fannie Mae found no such spike in D180+ delinquency rates, although weighted average 30+delinquency rates were higher for affected areas (8.4 per cent) versus those not affected by the hurricane (5.31 per cent). Analysis on Hurricane Florence in 2018 by CoreLogic found mortgage default rates doubled 3 months following the storm.[16]

Hurricane Katrina, the costliest hurricane affecting the United States started 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 US$125bn in damage.[17] Hurricane Sandy was the second costliest hurricane in US history at US$50bn.[18] It started as a Category 3 hurricane before weakening to a Category 1 when it made landfall along the northeast coast of the United States. Looking at hurricane risk at a macro level, Kahn and Ouazad examined the impact of hurricane events over a 180-year period in the United States and found that a natural disaster would increase the probability of foreclosure by 1.6 per cent taking into account a variety of the risk factors described earlier.[19]

This analysis is unique in that it is the first to examine the intensity and frequency of hurricanes on mortgage delinquency. 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 was 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 damages such as surge, rainfall and tornadic events that 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 m.[20] Historical trends of hurricanes along two important dimensions of frequency and intensity provides some insight into

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

hurricane dynamics. Figure 2 summarises the annual frequency of hurricanes in the United States between 1851 and 2006.[3] The number of hurricanes has risen over time overall and for major hurricanes.

Figure 3 plots the PDI and sea surface temperatures (SST) over time.[4] Consistent with Figure 2, between 1980 and the mid-2000s, the PDI

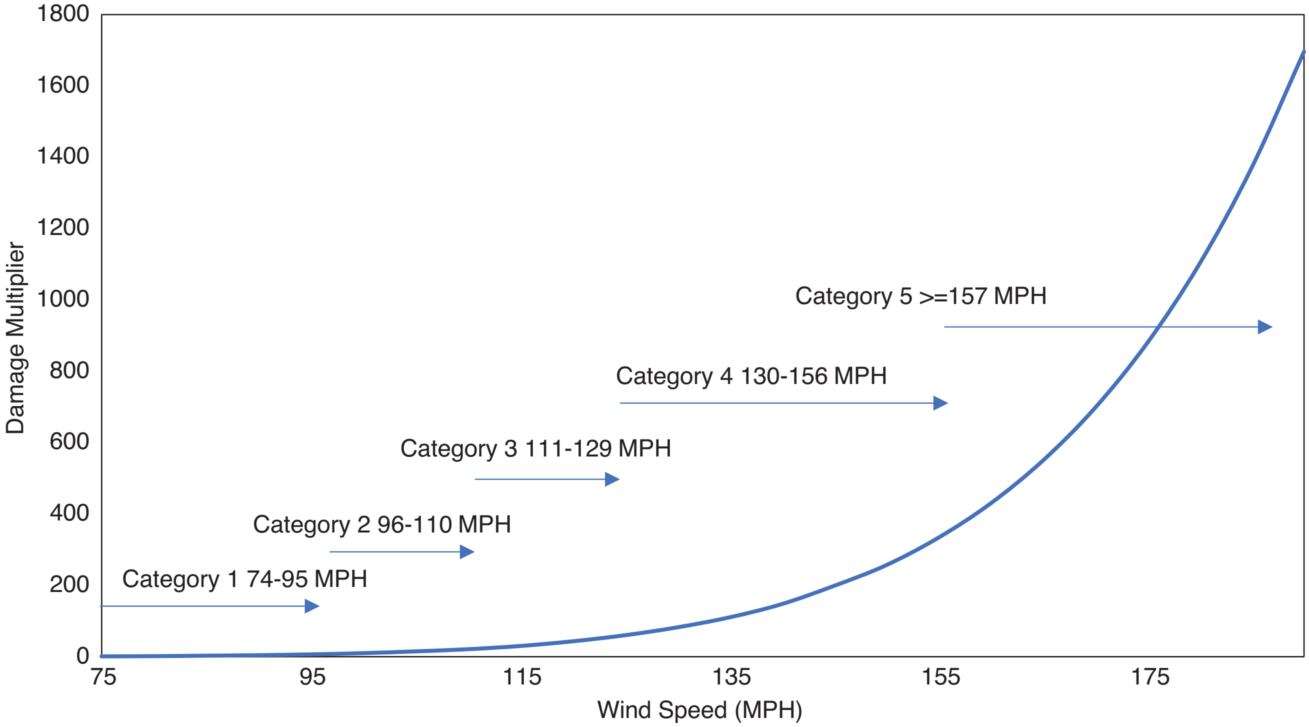

Figure 1: Saffir–Simpson hurricane wind speed and potential damage relationship[21]

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.

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 per cent increase in hurricane PDI by the year 2100.[22] Alternatively, if SST is measured relative to mean tropical SST rather than to tropical Atlantic SST, the impact on PDI is slight. Other studies tend to support the results of Vecchi et al. that a long-term increase in hurricane PDI would be small.[23, 24] Bender et al., however, found that the number of Category 4 and 5 Atlantic hurricanes could increase 90 per cent over time. Corroborating this result, Knutson et al. reported large percentage increases in Category 4 and 5 hurricanes in the early (45 per cent) and late (39 per cent) part of the 21st century.

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 2020. Monthly performance updates on each loan are

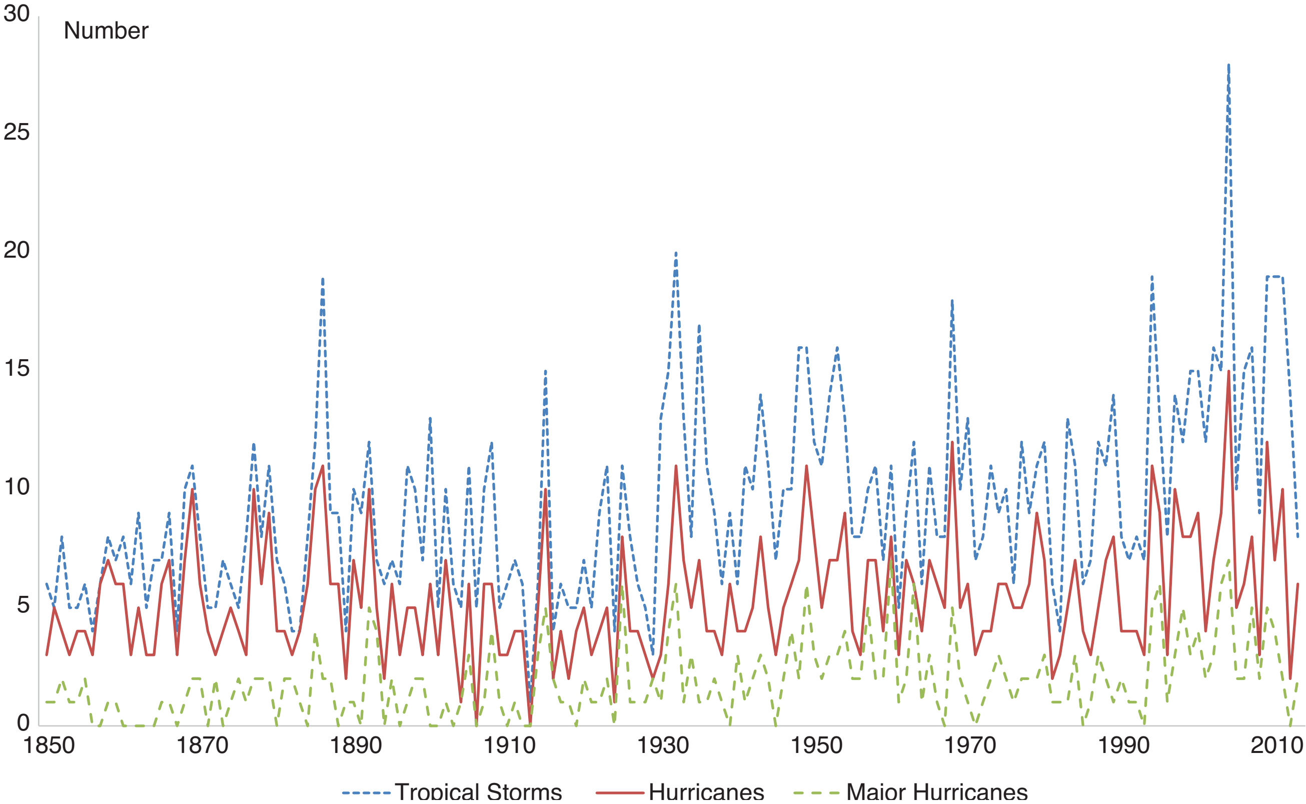

Figure 2: Atlantic basin hurricane counts (1851–2013)

available through December 2020. Key risk factors described earlier are included in the data files such as Fair, Isaac and Company (FICO) score, original and combined LTV, debt-to-income ratio, loan purpose, amortisation, owner-occupancy, first-time homebuyer indicator, number of units, number of borrowers, property type, loan amount (UPB) and origination channel. UPB was transformed into a relative median UPB measure. That is, each loan's UPB was divided by the median UPB of the MSA or state (if identified as a rural property). 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. The 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 and Virginia. A random sample of 102,620 loans originated between 1999 and 2015 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. The definition of delinquency applied in the analysis was any loan that became 90 days past due or more (D90+). For the final sample, the mean D90+ rate was 5.4 per cent. A summary of key attributes of the Freddie Mac data is found in Tables 1–11.

The bivariate results of individual risk factors by D90+ delinquency rate in Tables 2–11 generally conform to the earlier discussion of how borrower, loan and property factors relate to mortgage delinquency risk. Noticeably, key variables such as CLTV, FICO and DTI exhibit a nonlinear relationship to default. For example, D90+ rates for borrowers with FICOs at or below 620 are more than 12 times greater than those with FICO scores over 750. Likewise, borrowers with CLTVs greater than 80 per cent experience D90+ rates that are over

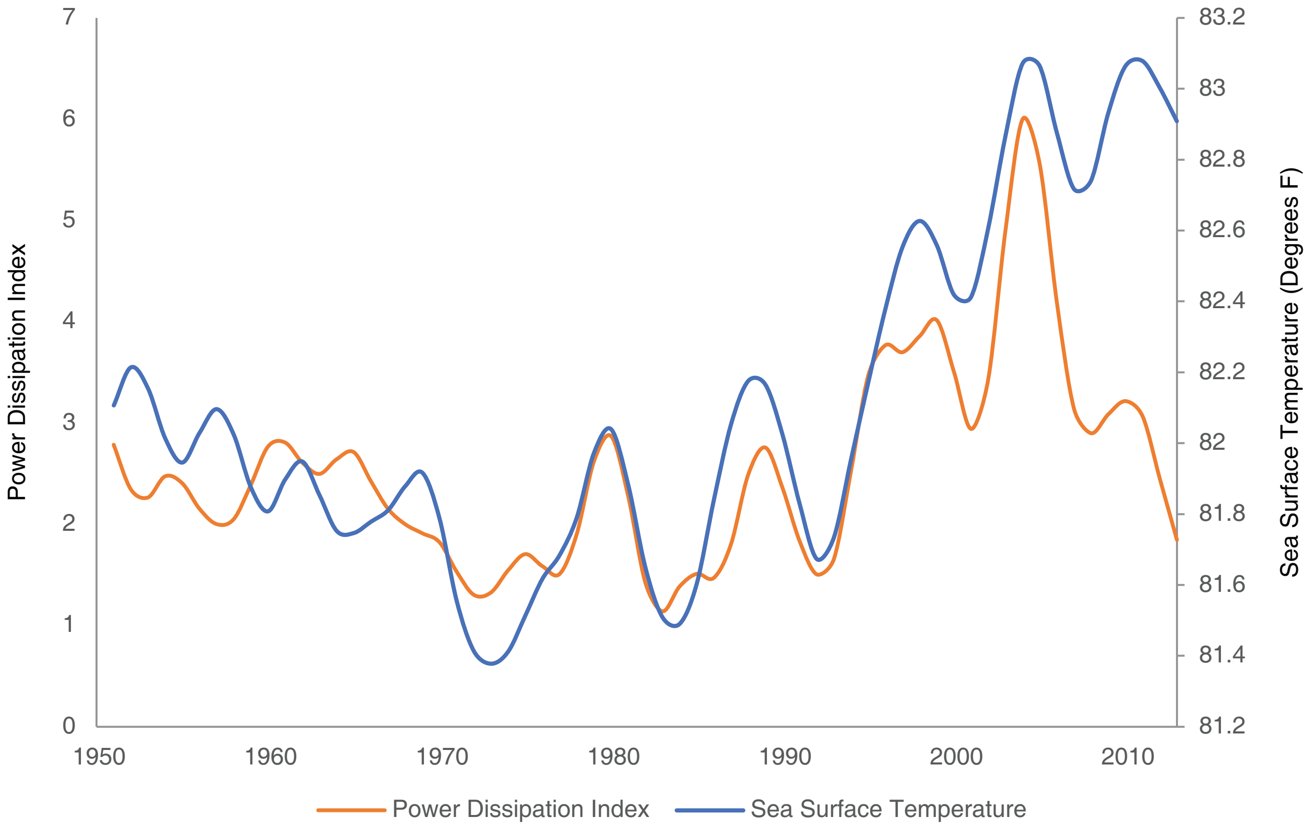

Figure 3: North Atlantic tropical cyclone activity according to the power dissipation index 1951–2013

Table 1: Key risk factor statistics

Attribute	Mean	Standard deviation	Minimum	Maximum
FICO	735	55.0	300	850
Current LTV (%)	14	23.7	0	178.1
DTI (%)	34	11.4	1.0	65.0
Relative median UPB	105.0	51.7	7.4	440.6

DTI, Debt-To-Income ratio; FICO, Fair, Isaac and Company score; LTV, Loan to Value; UPB, Unpaid Principal Balance.

Table 2: Occupancy status

Attribute	Number	Percentage of total	D90+ rate (%)
Investor owned	5,580	5.44	5.41
Primary residence	91,161	88.83	5.48
Second home	5,879	5.37	3.67

Table 3: Property type

Attribute	Number	Percentage of total	D90+ rate (%)
Condominium	7,756	7.56	5.48
Co-op	495	.48	3.43
Planned Unit	24,534	23.91	3.44
Manufactured housing	603	.59	14.10
Single family	69,232	67.46	5.98

Table 4: Loan purpose

Attribute	Number	Percentage of total	D90+ rate
Cash-out refinance	25,648	24.99	6.92
Rate and term refinance	29,290	28.54	4.38
Purchase	47,682	46.46	5.14

Table 5: First-time homebuyer

Attribute	Number	Percentage of total	D90+ rate
No	58,654	30.22	3.07
Yes	12,954	57.16	6.54

Table 6: Number of units

Attribute	Number	Percentage of total	D90+ rate
1	100,554	97.99	5.33
2	1,654	1.61	7.01
3	272	.27	8.46
4	140	.14	5.00

Table 7: Origination channel

Attribute	Number	Percentage of total	D90+ Rate
Broker	5,460	5.32	2.73
Correspondent	18,549	18.08	1.76
Retail	46,681	45.49	4.36
Third party originated	31,930	31.11	9.40

Table 8: Number of borrowers

Attribute	Number	Percentage of total	D90+ rate
1	47,246	46.04	7.11
2	55,374	53.96	3.89

Table 9: Credit score

Attribute	Number	Percentage of total	D90+ rate
≤620	3,082	3.00	21.12
620–660	8.403	8.19	15.53
660–700	15,920	15.51	9.17
700–750	27,607	26.90	4.63
>750	47,608	46.39	1.72

Table 10: Current loan to value

Attribute (%)	Number	Percentage of total	D90+ rate
<=50	91,356	89.02	1.18
50–80	9,500	9.26	27.87
80–90	796	.78	91.58
>90	968	.94	94.94

Table 11: Debt to income

Attribute (%)	Number	Percentage of total	D90+ rate
<30	40,941	39.90	3.41
30–40	31,946	31.13	5.48
>40	29,733	28.97	7.94

90 per cent. Of course, these summary results are uncontrolled for other factors that 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 includes information on the type of disasters 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, that is, 1999–2015 were included. The Saffir–Simpson Hurricane Category for each named hurricane was obtained from National Hurricane Center Tropical Cyclone Reports and the category at the time of the first landfall in the United States was used to designate the initial hurricane strength in the modelling. It is recognised that the 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 1999–2015 period of interest. According to the FEMA data, there were 122 named hurricanes in the Atlantic region that resulted in a disaster declaration. A distribution of storms by category is shown in Table 12. Figures 4 and 5 display the average number of hurricanes and the average hurricane rating experienced for each property by county. The D90+ rates by average hurricane rating 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 depicts the relationship between the average number of hurricanes experienced by

Table 13: Sample average hurricane rating by D90+ rate (%)

Category	D90+
0–1	4.24
>1–2	6.92
>2–3	5.43
>3–4	5.30
>4–5	11.10

Table 12: Tropical storm and hurricane sample counts

Storm category	Number in sample data
Tropical storm	54
1	61
2	19
3	25
4	8
5	9

Table 14: Sample average number of hurricanes and D90+ rate (%)

Average number of hurricanes	Number	D90+ rate
0–1	87,091	5.42
>1–2	14,006	4.69
>2–3	1,059	8.12
>3	464	9.27

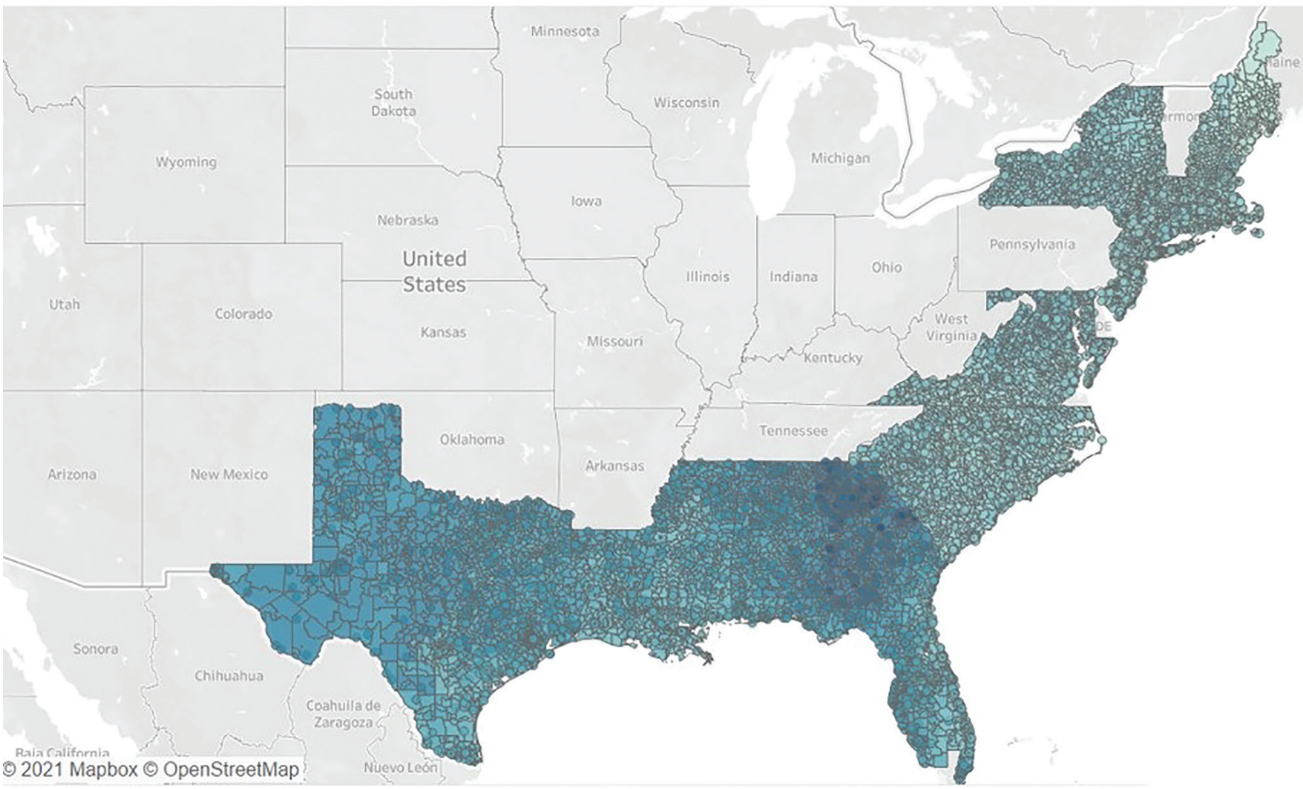

Figure 4: Number of hurricanes of Freddie Mac sample loans originated 1999–2015 by county

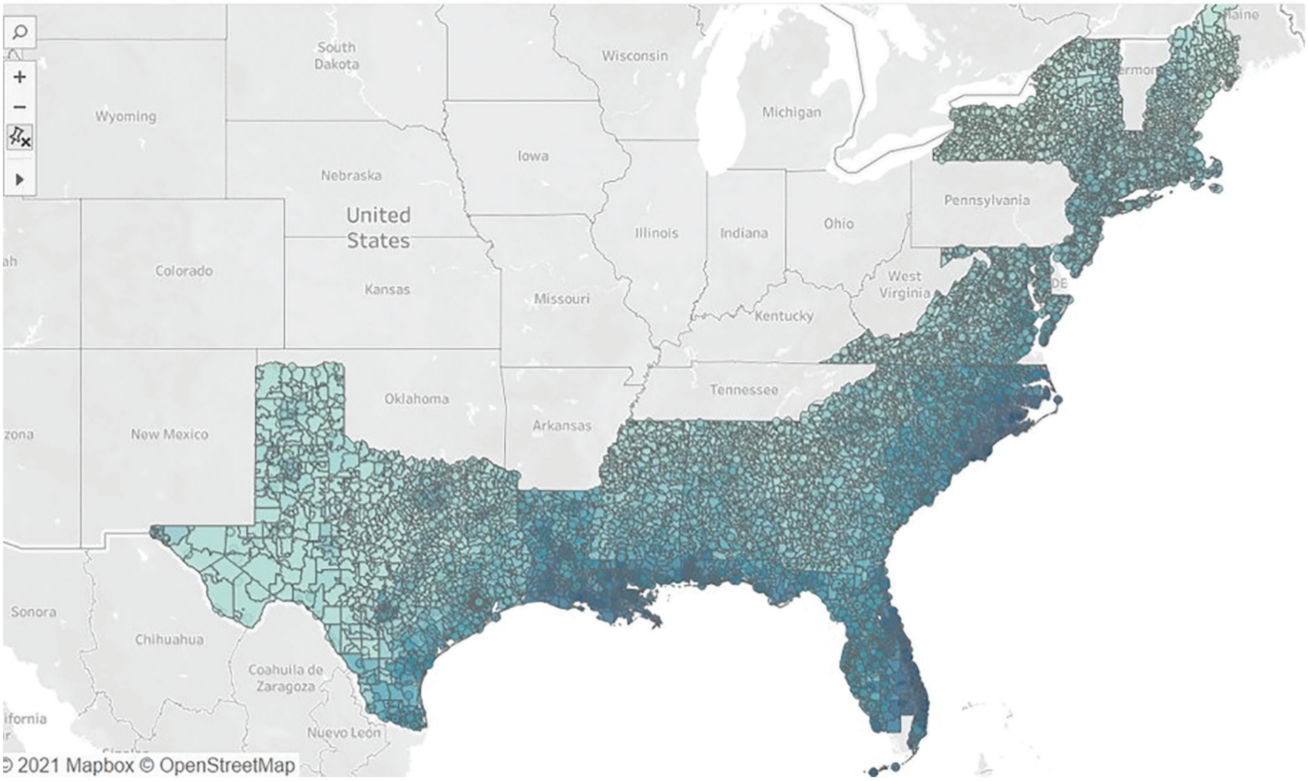

Figure 5: Average hurricane ratings of Freddie Mac sample loans originated 1999–2015 by county

each property in the sample and D90+ rate. The uncontrolled bivariate results show a monotonic increase in both D90+ rates.

METHODOLOGY AND EMPIRICAL APPROACH

To analyse the impact of hurricane intensity and frequency on mortgage delinquency, a standard logistic regression model applied in underwriting borrowers was estimated with the binary choice dependent variable defined as whether a D90+ delinquency event occurred (=1) or not (=0). 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 Equations 3 and 4:

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

$$\begin{aligned} Z = f(&\text{FICO, CLTV, LTV, DTI, NUMUNIT,} \\ &\text{OCC, CHANNEL, PROPTYPE,} \\ &\text{PURPOSE, NUMBORR, FTHB,} \\ &\text{HURNUM, HURINT, AGE}) \end{aligned} \tag{4}$$

To gain a sense of the relative importance of these candidate variables, a machine learning analysis was performed. Specifically, a form of gradient boosted decision trees (XGBoost) was applied to predict a D90+ event. In that analysis, candidate variables were tested in terms of their importance score which reflects a variable's decision tree split contribution to a metric of performance such as a Gini coefficient. The top ten candidate variables by their feature importance are shown in Table 15. Note that among the top three variables in feature importance are the average number and ratings of hurricanes.

Table 15: Top ten candidate variables feature importance

Candidate variable	F score
Current LTV	6,176
Average number of hurricanes	6,079
Average hurricane rating	5,980
FICO	5,078
Relative median UPB	4,136
DTI	3,972
Number of borrowers	512
Purchase-only mortgage	481
Broker channel originated	454
Correspondent channel originated	390

DTI, Debt-To-Income ratio; FICO, Fair, Isaac and Company score; LTV, Loan to Value; UPB, Unpaid Principal Balance.
Note: The F score reflects the number of times the variable (feature) is split on the analysis.

A description of the candidate variables for analysis is found in Tables 16 and 17. Several transformations of key variables were made prior to modelling. 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.

$$\beta_i VAR_i + \sum_{m=1} \beta\left(Max\left(VAR_i - KP_m, 0\right)\right) \tag{5}$$

where VARi is variable i to be splined, and KPm 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 per cent, 80 per cent, 85 per cent, 90 per cent and 95 per cent. Final estimates for the number of splines and knot point settings were based on the statistical significance of each spline and contribution to model performance.

Table 16: Candidate variable description

Risk Factor	Variable Name	Definition	Type
Borrower	FICO	Credit score	Continuous
	CLTV	Current 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			
	HURNUM	Average number of hurricanes	Categorical
	HURINT	Average hurricane rating	Categorical

LTV, Loan To Value; UPB, Unpaid Principal Balance.

Table 17: Categorical variable description

Variable name	Category name	Description
OCC	Primary	Primary residence
	Investor	Investor owned
	Second home	Second 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 and term refinance
CHANNEL	R	Retail originated
	B	Broker originated
	C	Correspondent originated
	TPO	Third party originated
HURINT	1	Loan's average hurricane rating <3
	0	Loan's average hurricane rating ≥3–5

A variable, AGE, was included to control for the number of months after origination for each loan. AGE, along with the intercept term, is not reported among the estimated coefficients in Table 18 for ease of exposition but is available from the author upon request.

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 delinquency.

Table 18: D90+ logistic regression results

	Coefficient	Standard error
FICO*	–.0087	.000018
FICO660*	–.0068	.000583
CLTV*	.0873	.00103
CLTV80*	.0515	.0132
CLTV95**	2.7719	1.1933
DTI**	.0064	.00269
DTI43*	.0312	.00722
NUMUNIT2+**	.4159	.1289
PUD*	–.6584	.0564
Cash-out*	.5172	.0468
Channel B or C*	.9307	.0610
Channel TPO*	.9923	.0482
NUMBORR2*	–.4633	.0425
HURINT*	.6335	.0436
KS	.52	
AUC	.83	

Note: Parameters designated * or ** are statistically significant at the 1 per cent and >1 to 10 per cent levels, respectively.

RESULTS

The results from the final set of estimations for the D90+ model are presented in Table 18. To compare alternative specifications when determining the 'best' D90+ model, the Kolmogorov–Smirnov (KS) test and the area under the curve (AOC) were used as model performance criteria. A separate holdout sample of 100,000 Freddie Mac loans not used in estimating the model over the same origination period was used to generate the KS and AUC statistics. Specific attention is paid to these measures used to assess the model's discriminatory power between default and nondefault loans. On this basis, the splined effects for FICO and CLTV resulted in a single knot point for FICO at 660 along with two knot points; 80 per cent and 95 per cent for CLTV and a single knot point at 43 per cent for DTI. 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 significant at the 10 per cent level or lower. The majority of parameters were significant at the 1 per cent level. The model performance statistics are robust as shown in Table 18.

To understand the relative impact of the categorical variables, most notably the hurricane intensity effect, odds ratios were computed and shown in Table 19 along with the reference category for each variable. For example, holding all else constant, the odds ratio for cash-out refinance loans indicates that the incidence of default is 1.68 times that of a purchase-only loan. The other categorical variables have comparable interpretations relative to the reference category indicated in Table 19. Of interest, among these effects is the hurricane intensity variable. The results indicate that controlling for all other factors, delinquency risk is 1.88 times higher for loans experiencing an average hurricane rating 3 and greater than loans experiencing an average rating lower than 3. This result is consistent with the historical meteorological data showing that hurricanes rated 3–5 are associated with greater wind and flooding damage.

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 better understand the sensitivity of mortgage delinquency rates under various assumptions on hurricane frequency and intensity, the estimated model was run to generate predicted delinquency rates for each loan in the sample. The loans were reweighted in the sample reflecting different proportions of borrowers with average hurricane ratings of 3 or greater to reflect the range of potential changes in frequency of major hurricanes from long-range hurricane projections described earlier. The results from this sensitivity analysis are presented in Table 20. In one test, the proportion of borrowers in the sample experiencing an average hurricane rating of 3 and greater was raised 10–100 per cent in the increments shown in Table 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.[23,24]

The results suggest that increasing the proportion of borrowers experiencing major hurricanes and more hurricanes overall has a moderate effect on raising delinquency rates. For example, if the proportion of borrowers experiencing major hurricanes and more hurricanes in general doubled, that would raise the D90+ rate more than 17 per cent above baseline rates (ie sample D90+ rates). These results reflect the fact that the size of the borrower cohorts with average ratings at or above 3 are relatively small (6.8 per cent of the sample). In other words, the incremental effects of more severe hurricanes may

Table 19: Categorical variable odds ratios

Variable	Odds ratio	Reference group
NUMUNIT	1.52	1 unit
PUD	.52	Single family
Cash-out	1.68	Purchase only
Channel B or C	2.54	Retail
Channel TPO	2.70	Retail
NUMBORR2	.63	1 borrower
HURINT	1.88	Average hurricane rating <3

Note: *Odds Ratio* = e^{β}

Table 20: Sensitivity of D90+ rates to increased hurricane intensity and frequency

Percentage increase in intensity	Average D90+ rate (%)	Percentage change from baseline	Basis points change from baseline
Baseline	5.14		
10	5.23	1.75	9
25	5.37	4.36	23
50	5.59	8.72	45
75	5.81	13.08	67
100	6.04	17.44	90

be substantial as shown in Table 20 but are muted to some degree by the larger proportion of borrowers experiencing less severe hurricanes.

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 rise over the next decades as some meteorological research suggests, more borrowers will be affected, and the resulting wind and flood damage on communities, businesses and residential properties appears likely to lead to much higher delinquency rates in the future. This potential increase in delinquency 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 CRT transactions.

More intense and frequent hurricanes could likewise 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 temporarily roiled starting after Hurricane Harvey in August 2017 and Hurricane Irma in September 2017 as yields on subordinate (B1) CRT tranches widened by 125 bps over a 5-week period.[25] Consistent with this result, Gete, Tsouderou and Wachter found significant increases in spreads on junior CRT tranches associated with loans affected by Hurricanes Irma and Harvey.[26] By contrast, spreads on mezzanine tranches appeared unaffected by these events as indicated in Figure 6 and was also confirmed in the Gete et al. analysis. Nonetheless, the apparent transitory effect on subordinate tranche spreads could become more pronounced if long-term hurricane forecasts prove out over time.

These back-to-back major hurricanes nevertheless caught investors off-guard and eventually led the Association of Mortgage Investors (AMI) to request

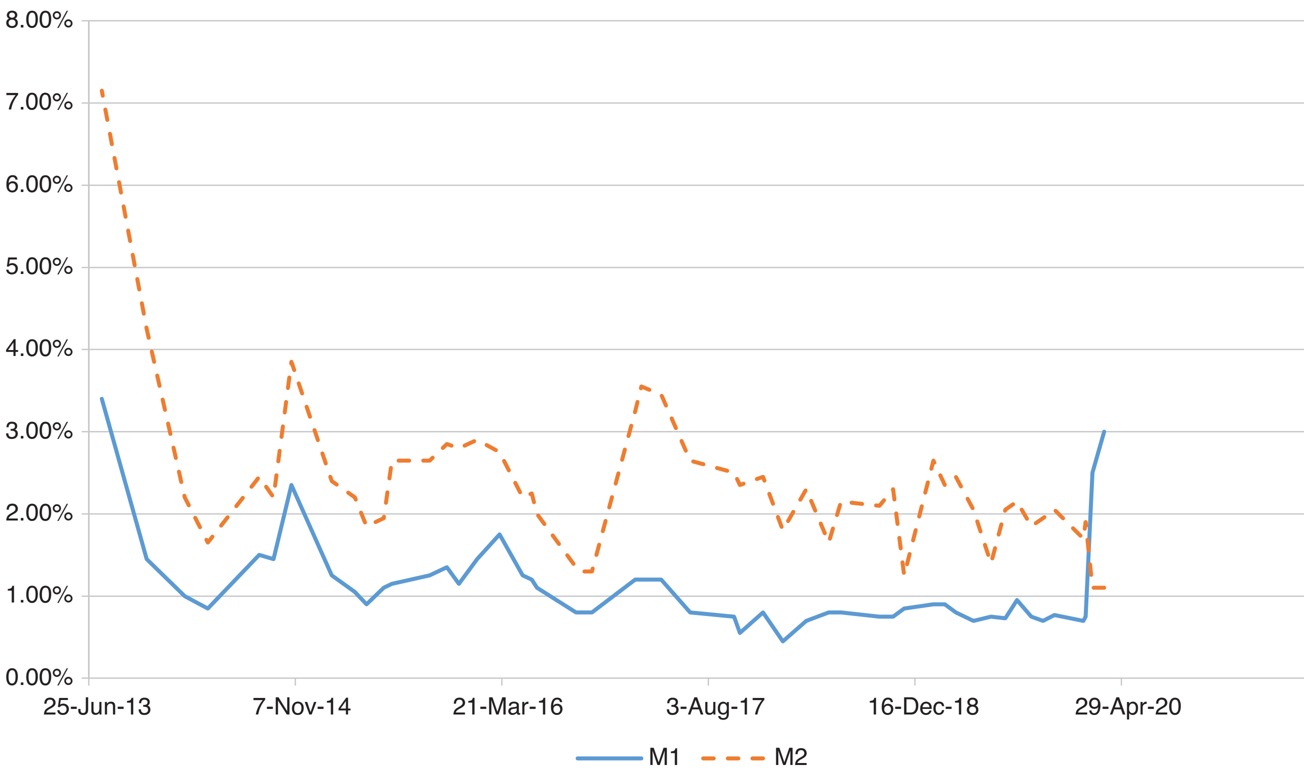

Figure 6: Spreads for M1 and M2 Freddie Mac STACR CRT transactions[27]

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 analyse or price. The GSEs have taken steps since then to moderate the effect of hurricanes in CRT transactions by such actions as no longer counting loans in forbearance as a credit event; an alternative strategy in the future, however, might be to create a separate 'clean-up' or residual 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 obtain 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. As CRT transactions have attracted reinsurance companies as investors over the years, 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.

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