Climate Risk and Commercial Mortgage Delinquency

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Working Paper

March 2022

Abstract

Natural disasters such as hurricanes, floods, heatwaves and wildfires are projected to become more prevalent in the foreseeable future. Climate risk is therefore increasingly recognized as an important factor by policy makers, the investment community, and financial markets. Due to the immobility of assets, the commercial real estate industry is especially vulnerable to climate risk, and there is an increasing interest to understand the impact of climate risk on the value of commercial real estate. For commercial real estate lenders, changes in collateral value are only of partial importance. The ability of borrowers to meet their payment obligations is equally, if not more important. By combining historic data on two major climate-related disasters – Hurricanes Harvey and Sandy – with longitudinal information on commercial mortgage performance, this paper identifies the impact of climate risks on mortgage delinquency rates for commercial real estate mortgages. The results show that both Harvey and Sandy led to elevated levels of commercial mortgage delinquency, with significant heterogeneity based on the extent of damage in the Census block group. Information provided through FEMA 100-year floodplain maps partially mitigates the effects, an indication that lenders incorporate flood risk information in the underwriting process.

JEL Codes: G14, G40, G41, Q54, R33
Keywords: Natural Disasters, Climate Risk, Mortgage Delinquency, Commercial Real Estate

The Real Estate Research Institute and the 21st Century Cities Initiative at Johns Hopkins provided financial support for this research. We are grateful to David Ling and participants at the 2020 Real Estate Research Symposium at the University of North Carolina at Chapel Hill. All errors pertain to the authors.

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I. Introduction

Climate change risk is rapidly emerging as a factor that is relevant not just to forward-looking policymakers, but also to financial markets and, more broadly, the global financial system. Indeed, central banks around the world, including the Bank of England, the European Central Bank, and more recently the Federal Reserve, have started to devote attention to the implications of climate risk on balance sheets of lenders (see, for example, Carney, 2015). The sequence of superstorms that occurred in major U.S. cities and territories such as New York, Houston, and San Juan over the past decade, as well as subsequent flooding, serves as a tangible reminder of the significant impact of weather-related events. Such events are of course not limited to storms and flooding, but also include cold spells, heatwaves, drought, periods of extended precipitation, and tidal flooding. While climate shocks already happen on a frequent basis, there is reason to believe that both their incidence *and* intensity will increase going forward. The New York City Panel on Climate Change, re-convened in the wake of Hurricane Sandy, projects an increase in the most intense hurricanes and increased precipitation from hurricanes.

An industry that is particularly prone to climate risk is real estate. When it comes to natural disasters, buildings, once constructed, are much like sitting ducks. Natural disasters following "climate shocks," including for example storms, heatwaves, and floods, thus pose a significant risk to buildings, whether commercial or residential. For investors in and lenders to real estate, be they shareholders of real estate investment trusts (REITs), investors in residential and commercial mortgage-backed securities, direct investors or lenders to commercial real estate, or investors through private equity firms, assessing the exposure to and impact of climate shocks increasingly becomes a critical task. But firms, as well as their investors and lenders, struggle with understanding the financial implications of climate risk on the value of assets, the future income stream of these buildings, and the impact climate risk may have on the ability of borrowers to make timely payments.

At the macro level, it is both intuitive and evident that climate shocks have a significant impact on the local economy. Boustan et al. (2020) document that, between 1930 and 2010, severe disasters have increased out-migration rates at the county level by 1.5%, as well as affecting household finances, measured by poverty rates. At the micro level, there is some nascent evidence on the impact of climate shocks and future climate risks, but most of the academic and industry research focuses on the implications of flooding events and flood risk on single-family home prices, whereas studies on commercial real estate are few and far between.

Focusing on residential real estate, Boustan et al. (2020) document that over the past 80 years, natural disasters led to decreases in house prices by some 5%. Bernstein et al. (2019) find that homes exposed to sea level rise sell for approximately 7% less than observably equivalent unexposed properties equidistant from the beach, although Baldauf et al. (2020) show that the extent to which prices are affected is influenced by the heterogeneity in beliefs about long-run climate change risks. Outside of the U.S., these results are confirmed by Rajapaksa et al. (2016), who document a 6-7% price drop for homes in a flood zone based on Australian data, and by Belanger and Bourdeau-Brien (2017) in a study based on U.K. data. There is also some emerging evidence on the impact of flood risk on commercial real estate values. Bernstein et al. (2019) report that effects of sea level rise on the housing market are most pronounced for professional market participants (i.e. investors), and that the heterogeneity of capitalization of sea level rise is determined partially by the relative liquidity in local markets – commercial real estate is characterized by low liquidity, suggesting that the impact of climate risk might be more salient in this market. Focusing on commercial real estate, Addoum et al. (2021) show that following Hurricane Sandy, the risk premium (measured through capitalization rates) of waterfront assets in New York increases, although these deviations are merely temporary, reverting back to market means in three years. In the same spirit, Fisher and Rutledge (2021) find significant short-term impacts of large hurricanes on commercial real estate pricing, with price effects fading out in 4-5 years.

For real estate lenders such as banks and insurance companies, as well as investors in securitized debt (e.g. mortgage-backed securities), changes in the value of the underlying collateral following climate shocks are only of partial importance. The critical question is how concurrent climate shocks and future climate risks affect borrowers' ability to make timely payments of interest and principal. Historically, most studies have focused on bank lending rather than studying actual mortgage delinquency. Garmaise and Moskowitz (2009) show that earthquake risk decreased commercial real estate bank loan provisions by 22% in California properties in the 1990s, hampering neighborhood revitalization in disadvantaged areas. Cortés and Strahan (2015) investigate bank lending following natural disasters, documenting that small banks respond to climate shocks by increasing credit in affected areas and taking credit away from other markets in which they have extended credit. A more recent series of papers investigates the impact of climate risk on residential mortgage delinquency. Issler et al. (2020) study the impact of California wildfires on residential mortgage delinquency, with delinquency rates on residential mortgages increasing by 1% after a wildfire – at the intensive margin, the effects become smaller as the wildfire is larger, suggesting the presence of a coordination mechanism following large fire events. Kousky et al. (2020) document increased delinquency rates following hurricane Harvey, with flood insurance mitigating some of the effects. Importantly, Ouazad and Kahn (2021) show that bank lenders offload some of the credit risk from mortgages in areas that have high climate risk, through securitization by Fannie Mae and Freddie Mac, thus putting the ultimate burden of climate risk exposure onto the shoulder of U.S. taxpayers.

To date, there are no existing papers that focus on the relationship between climate shocks and ex-post mortgage performance in the *commercial* real estate market. By all measures, the commercial real estate market is large, and arguably of systemic important to the U.S. financial market. The total size of the commercial real estate market in the U.S. is estimated to be some $21 trillion, about half of the value of all homes.[1,2] The outstanding commercial mortgage debt is some $4 trillion, of which about 14% has been securitized – the remaining 86% sits on the balance sheets of banks, insurance companies, and alternative lenders (which are often funded by public and private pension plans).[3] Importantly, while climate risk may affect the long-term valuation of commercial real estate assets, for lenders it is important to understand the ability of borrowers to make timely and whole payments of interest and principal, at least in the short run following a large climate shock.

This paper investigates the impact of climate shocks on payment behavior on commercial real estate mortgages. Climate shocks can be defined broadly as historical events that include hurricanes, tornadoes, inland and coastal flooding, wildfires, and earthquakes. In this paper, we take a more narrow definition and focus on two major climate shocks from the recent past – hurricanes Harvey (2017) and Sandy (2012). While hurricanes represent extreme examples of climate shocks, climate models project increasing probabilities of similar rainfall levels as the climate warms (Emanuel, 2017). As such, understanding the economic impacts of these types of storm events is of critical importance. Payment behavior on commercial real estate mortgages is assessed using data on commercial mortgage-backed securities (CMBS), which, at 14%, represent a significant share of the commercial mortgage market.

The results show that both Harvey and Sandy led to significantly higher delinquency rates on commercial mortgages in Houston and New York, respectively. The effects commence one quarter after each storm and last for about four to eight quarters, with the strongest impact

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[1] See https://www.reit.com/news/blog/market-commentary/estimating-size-commercial-real-estate-market.
[2] Zillow estimates the total value of private residential real estate in the U.S. in 2021 at $43.4 trillion, retrieved from https://www.zillow.com/research/us-housing-market-total-value-2021-30615/.
[3] Data retrieved from the Mortgage Bankers Association's report on 2021 Q3 Commercial/Multifamily Mortgage Debt Outstanding. https://www.mba.org/Documents/Research/3Q21MortgageDebtOutstanding.pdf

on office and retail (Houston) and multifamily residential (New York) real estate. At the intensive margin, we find that in those areas with a larger share of damaged homes, delinquency rates are substantially higher. Importantly, if lenders have access to data on flooding risk, for example through the flood maps provided by the Federal Emergency Management Agency (FEMA), we find some evidence of an anticipation effect – delinquency rates are not different in FEMA zones after landfall of a hurricane. This finding suggests that perceived flood risk, in the form of FEMA's 100-year floodplain, is incorporated at the time of underwriting.

This paper has some implications for policymakers and financial market participants. First, understanding the historical impact of climate-related events on local financial markets is important for lenders and investors to accurately price in climate risk, but also for insurance firms (setting rates). Second, for policy makers, understanding the relationship between climate risks and financial markets is relevant in the perspective of the projected increase in climate-related events, and the effect that may have on solvency of local businesses, the health of the local real estate market, and ultimately, the taxable base and its tax revenues for the municipality, county, and state. Third, and quite practically, financial institutions need better, more accurate tools to assess climate risk exposure at the micro level. While the FEMA 100-year floodplain has its uses, the delineation of flood zones is imprecise, and there is a plethora of tools that investors and lenders can now use to better understand their exposure to flood risk and other climate risks, with quite a high level of precision.

The remainder of this paper is structured as follows: the next section discusses the methodology, followed by a description and non-parametric presentation of the main data sources used in the analysis. Outcomes of the estimations are presented in the results section, followed by a discussion of implications and concluding remarks.

II. Methodology

Our main interest is to relate payment behavior on commercial mortgages to the occurrence of two significant climate shocks – hurricanes Harvey and Sandy. To empirically assess this relationship, we estimate a logit model using a set of panel data. For each loan, we construct monthly event-histories from loan origination to loan termination or the end date of data collection, whichever comes first. In the event-histories, we have the presence of a climate shock, as well as other dynamic and static loan and building characteristics. The climate shock indicator is time-varying, and can be included for one or more months, to reflect the fact that economic effects of a climate shock may be persistent over a longer time period.

We employ a logit model to predict the likelihood of delinquency in commercial mortgages (i.e. payments being 60 days or more past due) as a function of a climate shock (i.e. hurricanes Harvey and Sandy), while controlling for mortgage attributes, property characteristics, and macro-economic indicators. The model follows the form:

$$\Pr(default_{i,j}) = damage_{b,i} * post\ hurricane_i + \ post\ huricane_i + \ damage_{b,i} + X_{i,j} + \ \varepsilon_{b,i,j} \tag{1}$$

where $default_{i,j}$ is the dependent variable and takes the value of one if mortgage i is delinquent in period j and zero otherwise. In addition to our control group, loans on assets located within a 10-mile radius of the impact area, we exploit the variation in the severity of damage by Census block group to assess the impact of hurricanes Harvey and Sandy on the likelihood of delinquency – $damage_{b,i}$ is the share of homes damaged in the respective Census block group b for mortgage i. $post\ hurricane_i$ is an indicator variable taking the value of one for the two-year period after Harvey or Sandy made landfall and zero for the two-year period preceding the event. In subsequent analyses, we include quarterly time dummies to model the temporal effect of the climate shock on delinquency. $X_{i,j}$ is a set of control variables including dynamic and static mortgage attributes, property characteristics, and macro-economic indicators. Control variables include those identified by the existing literature as significant drivers of commercial mortgage default risk or their equivalents. $\varepsilon_{b,i,j}$ is the error term. Robust standard errors for all empirical analyses are clustered at the loan level.

$$\Pr(default_{i,j}) = damage_{b,i} * post\ hurricane_i * FEMA\ zone_i + \ post\ huricane_i + damage_{b,i} + \ FEMA\ zone_i + \ X_{i,j} + \ \varepsilon_{i,h,j} \tag{2}$$

Equation (2) extends our initial model by including an indicator variable that takes the value of one if an asset is in a 100-year floodplain as designated by FEMA or zero otherwise. All other variables are as defined in Equation (1). The inclusion of the FEMA floodplain indicator allows us to assess whether perceived flood risk leads to an anticipation effect, which may result in differing likelihoods of delinquency following the event.

The identifying assumption in our models is that the climate shock is exogenous. While that is a reasonable assumption when it comes to the timing and intensity of the hurricanes, it is no secret that the Southern seaboard is prone to hurricanes. For the Northeastern seaboard, hurricane risk was less obvious, until Sandy. But even in New York, well-informed lenders may be aware of climate risks and incorporate the extent of climate-risk exposure (e.g. flooding risk) into lending decisions, and/or mortgage terms (e.g. loan-to-value ratio, interest rate, etc.). We circumvent some of this issue by focusing the analysis on the effects of climate shocks *within* a 10-mile radius of the affected area, while controlling for observable characteristics like interest rate and loan-to-value ratio. Moreover, to further isolate the impact of a climate shock on commercial mortgage default risk we restrict our analysis to a two-year period pre and post the occurrence of the event. So, conditional upon loan terms that might already reflect heightened climate risk, we identify the effect of climate shocks on ex-post mortgage performance.

III. Data

A. Commercial Mortgage Data

We source data on commercial mortgage performance through an academic engagement with Trepp, Inc. Trepp partners with the Commercial Real Estate Finance Council (CREFC) to gather detailed information from monthly master servicer reports on all loans in the CMBS market.[4] The dataset includes all CMBS deals in the Trepp database, including conduit and single-asset securities. Within those securities, we focus on loans with a single-note capital structure and just one associated building, so they can be tied to a specific location for analytical purposes.[5] Nationally, the loan dataset covers 106,969 loans, pooled into some 1,200 deals, since 1965. Those loans represent about USD 1.14 trillion in commercial mortgages.

We note that commercial real estate mortgages securitized through CMBS represent just one part of total commercial real estate lending activity. In 2021, securitized loans made up some 14% of total commercial real estate debt that was issued. Importantly, securitized loans might be different from non-securitized loans both in terms of observable characteristics, but also as it relates to climate risk exposure (see, for example, Ouazad and Kahn, 2021). Given the private nature of commercial mortgage lending, we cannot compare our sample of securitized mortgages with the characteristics of balance sheet loans, and assuming some degree of moral hazard in the securitization process, our estimates should be interpreted as an upper bound of the effect across the remainder of the commercial mortgage universe.

[4] For more information, please visit https://www.trepp.com/cmbs-solutions.

[5] This restriction reduces the Trepp dataset from 116,969 to 106,969 loans, which also includes address cleaning to facilitate geocoding the location of the assets.

The scope of the data set includes office, retail, and multifamily buildings, with a mortgage originated between 1998 and Q2 2019. We use monthly information on the status of each loan (prepaid, delinquent, foreclosed or current) and the updated loan balance, debt-service-coverage ratio (DSCR), and building occupancy rate. Static information on each loan includes the origination date, original loan balance, actual rate (mortgage note rate adjusted by points), maturity term, amortization period, interest-only (IO) period, prepayment provisions, originator, master and special servicers, securitization date (deal cut-off date), face value, original LTV, net operating income (NOI) and DSCR at securitization. The information on each collateralized asset includes the collateral property type, year built, and location. We only include fixed-rate loans and exclude adjustable-rate mortgages, which comprise about 3% of the original data set. The data set is comparable to the data used by An and Pivo (2018) and An et al. (2013).

Filtering the universe of CMBS loans on our two locations of interest – a 10-mile radius around the areas affected by Hurricanes Harvey and Sandy – the sample of commercial mortgages used in the analysis contains 9,463 loans. This represents about 8.8% of the total CMBS universe by number of loans. For our analysis we include just the two-year event windows around the respective climate shocks. Based on these constraints, the final sample includes 2,644 unique loans and 83,352 loan-month observations.

B. Hurricane Data

Information on hurricanes is collected from the HUD GIS Helpdesk of the U.S. Department of Housing and Urban Development.[6] Hurricane Sandy made landfall on the East Coast of the U.S. in October 2012 and caused severe flooding in the New York Metropolitan Area, with $65 billion in estimated damages. Hurricane Harvey made landfall on Texas in August 2017, causing catastrophic flooding across Houston and surrounding areas, inflicting $125 billion in damages.[7] Data on these two hurricanes, derived from FEMA home inspections, includes the event date, the affected regions, and the extent of damage. Panel A of Figures 1 and 2 show the spatial boundaries of both hurricanes and the local intensity measured by the home damage ratio by Census block group.

[6] The U.S. Department of Housing and Urban Development's Geospatial Data Storefront can be accessed at https://hudgis-hud.opendata.arcgis.com/.
[7] Billion-Dollar Weather and Climate Disasters: Events (Report). National Oceanic and Atmospheric Administration. Retrieved March 2, 2022.

In addition to the disaster information, we use the 100-year floodplain maps developed and administered by FEMA, to measure the ex-ante perceived flood risk of a given area.[8] The FEMA floodplain maps are used to determine whether an asset is within the 100-year floodplain (a 1% chance of flooding per year). Buildings within the FEMA flood zone are potentially more severely affected by future hurricanes and flooding events. Panel B of Figures 1 and 2 display the location of the assets collateralizing the CMBS loans in our sample with respect to the 100-year floodplain maps provided by FEMA.

C. Descriptive Statistics

Table 1 contains descriptive statistics for the main variables in the sample, split between the two hurricanes, Harvey in Panel A (left), Sandy in Panel B (right). As documented in the top rows, the average home damage ratio in each Census block group is about 4.3% for Hurricane Harvey and 1.7% for Hurricane Sandy. In addition, about 8.1% and 5.9% of commercial assets collateralizing a CMBS loan are in a FEMA flood zone for Harvey and Sandy, respectively. Even though this percentage is notably higher for those Census block groups where homes were damaged during the hurricanes, the fraction of damaged homes that is also in a FEMA flood zone remains low – only about 10% of the Census block groups with damaged homes in Houston were designated by FEMA as risky. For New York, only about a quarter of the Census block groups with damaged homes were deemed flood-prone.

The sample covers the main property types in commercial real estate – office, retail, and multifamily. With respect to property attributes, buildings in areas with damage seem to be built more recently, both for Harvey and for Sandy. Clearly, the vintage of buildings in New York is much older than the building stock in rapidly expanding Houston, where a third of the sample was built during the last two decades. Moreover, retail buildings represent a disproportionate share of observations in damaged areas compared to the other two asset types.

The loan characteristics of commercial mortgages securitized through CMBS are, economically, very similar between the buildings in damaged areas versus the buildings in unaffected areas, especially in Houston. Interest rates hover around 5%, with loan-to-value ratios of about 69% for buildings in both undamaged and damaged areas. Mortgages on buildings in damaged areas are less likely to be interest-only (or: bullet) loans, which makes those loans less risky. Perhaps the only noteworthy difference is the somewhat lower loan

[8] The Federal Emergency Management Agency's 100-year floodplain maps by state are retrieved from https://msc.fema.gov/portal/advanceSearch.

balance for mortgages on buildings in damaged areas, at \$11.2 million, compared to \$13.1 million in undamaged areas. In New York, there are some more differences between the two samples, with commercial buildings in damaged areas having a higher loan balance, higher loan-to-value ratio, and lower debt-service-coverage ratio (DSCR). However, those buildings are also less likely to be bullet loans.

Figure 2 displays the average delinquency rate 24 months pre and post Hurricanes Harvey and Sandy made landfall, consistent with the event window we apply in our empirical analysis. Panel A documents that the average delinquency rate increases during the first four months following the landfall of Hurricane Harvey. However, in the subsequent months the average delinquency rate decreases sharply to stabilize somewhat towards the end of our event window. Moreover, the average delinquency rate in our sample was already steadily increasing before Harvey. The impact of Hurricane Sandy on the average delinquency rate as documented in Panel B of Figure 2 is even less clear. The average delinquency rate was relatively stable in the 24 months leading up to Hurricane Sandy, to steadily decrease in the 24 months after the event. Taken together, it is not evident from these initial non-parametric inspections that either hurricane had an immediate impact on the average delinquency rate in our sample of CMBS loans.

IV. Results

A. Baseline Effects

To investigate the potential impact of climate shocks on commercial mortgage payment behavior, the baseline analysis relates the severity of the two hurricanes, measured as the share of homes damaged by Census block group, to the likelihood of delinquency, defined as payments being 60-days past due (or more). Importantly, the event window for all specifications is restricted to a two-year period pre and post landfall of Hurricanes Harvey and Sandy.

Table 2 summarizes the results of the analysis using Equation (1). Control variables in the specification behave mostly as expected. Loans with a higher debt service coverage ratio, higher occupancy rate, and shorter term experience a lower likelihood of delinquency. Similarly, newer assets are less likely to become delinquent in the full sample, the reverse holds for office buildings. Interest rate, loan-to-value ratio, original loan balance, and amortization term have a limited impact on the likelihood of delinquency.

Importantly, Column (1) of Table 2 documents that overall, the likelihood of delinquency is 3.3 times higher in the 24-month period after Harvey made landfall, compared to 24 months prior to the event. As indicated by the coefficient on the home damage ratio variable, Census block groups that experienced damage from the hurricane do not exhibit a higher likelihood of default during the entire sample period. However, interacting the Harvey indicator with the damage ratio shows that in the two-year period after Harvey made landfall, the likelihood of default increased significantly with the share of homes damaged in a Census block group. For example, moving from a Census block group with a damage ratio of 10% (i.e., 10% of homes in that particular Census block suffered from damage following Harvey) to a block group with a damage ratio of 20% increases the probability of delinquency by 28%, relative to the two-year period pre–Harvey.

When stratifying the sample by property type, in Columns (2) to (4), it becomes clear that the impact of Hurricane Harvey is heterogenous based on the type of asset. Whereas the baseline likelihood of default in CMBS loans collateralized by office buildings was higher in the 24-month period following the hurricane event, we do not observe heterogeneity in the effect based on the severity of the impact. So, at the extensive margin, the office market in Houston was hit by the impact of Harvey, likely due to employers stopping rent payments on their leases, leading to landlords becoming delinquent on their mortgage loans. Multifamily buildings seem to be least affected by Harvey as the likelihood of delinquency did not significantly change post the event or as a function of the share of homes damaged by Census block group. For retail, the baseline effect is negative (i.e., delinquency rates went down post-Harvey), but for those assets in hard-hit areas, landlords of retail assets stopped mortgage payments right after the hurricane.

To further illustrate the effect of damage on mortgage delinquency at the intensive margin, Figure 4 shows the probability of delinquency relative to the share of affected homes by Census block group in the two-year period post the event for retail assets. The probability of delinquency for retail assets is about double in an area where 40% of the homes are affected as compared to an area where 30% of the homes are affected, compared to 24-months before Hurricane Harvey.

The results of the baseline estimates of the impact of Hurricane Sandy on the likelihood of delinquency in CMBS loans show some interesting differences compared to the analysis for Hurricane Harvey. Table 3 summarizes the results for Hurricane Sandy, the model specification and control variables are identical to the analysis presented in Table 2. For Hurricane Sandy, we do not document an effect of the hurricane on commercial mortgage delinquency at the extensive margin – Sandy does not increase the overall likelihood of delinquency. However, at the intensive margin, taking into consideration the share of a Census block group that was damaged, the likelihood of delinquency increases in CMBS loans on multifamily buildings in the two years following the event.

Figure 5 documents the average marginal effects of Hurricane Sandy on the probability of delinquency for multifamily buildings. The predicted probability of delinquency in multifamily loans increases in the two-year period *post* Sandy as a function of the share of homes damaged in a Census block group. However, we should note the wide confidence bounds in Figure 5, which imply that only the hardest hit block groups experience a significant increase in the likelihood of delinquency following Hurricane Sandy. Compared to the two-year period prior to Sandy making landfall, the likelihood of delinquency in a Census block group where 70% of homes were damaged is 44% higher.

The differences in impact of Hurricanes Harvey and Sandy on the likelihood of delinquency in CMBS loans may partially be explained by the substantial heterogeneity in the severity of the impact across the two locations. On average, 4.25% of homes in a Census block group in our Houston sample were affected by the hurricane whereas this measure of impact is "just" 1.66% for Sandy. In addition, for Harvey the sample of CMBS loans collateralizing commercial buildings is more evenly distributed across areas that incurred damage and areas that were not severely affected by the climate shock. In contrast, the geographic distribution of loans for Sandy is more uneven, relatively fewer loans were in areas impacted by the hurricane. As documented in Figure 3, the average delinquency rate over the period surrounding the two events also follow slightly different patterns, which may indicate that macro-economic conditions differed for both events.

Summarizing, the baseline results for Hurricanes Harvey and Sandy indicate that both events had a significant impact on the probability of delinquency in CMBS loans for the two-year period following the climate shock. For Harvey, these effects are especially salient for office and retail buildings, for Hurricane Sandy the effect is most pronounced in multifamily assets.

B. Duration of the Effect

To better understand the temporal dynamics of the documented impact of Harvey and Sandy on the likelihood of delinquency in commercial real estate loans, we estimate the initial specification of Equation (1) including quarterly time dummies to measure the impact of the climate shock over time. Panel A of Figure 6 summarizes the main findings of modelling the effect over time for Hurricane Harvey.[9] Compared to the two-year period prior to Hurricane Harvey making landfall, the predicted probability of delinquency in eight quarters after the event increases substantially. Similar to findings in the baseline model, the likelihood of delinquency increases as a function of the home damage ratio. Overall, the impact of the climate shock on the probability of delinquency is relatively instantaneous but seems to dissipate over time.

Given that the findings indicate that the effect of Harvey was especially salient for retail assets, Panel B of Figure 6 displays the predicted probabilities of delinquency over time for retail buildings by the share of homes damaged for each Census block group. In line with the findings for the sample including office, multifamily, and retail assets, the predicted probability of delinquency increases sharply in the first couple of quarters following the climate shock (especially so for those Census block groups that experienced more severe damage). Based on the model predictions, the likelihood of delinquency in CMBS loans on retail assets also dissipates quickly and reverts to pre-event levels within a year after Hurricane Harvey.

Figure 7 replicates the same analysis for Hurricane Sandy, with a focus on the full sample in Panel A and on multifamily buildings in Panel B (since this asset type has proven to be most sensitive to the impact of Sandy in the initial analysis). In contrast to the findings for Hurricane Harvey, the effect of Sandy on the likelihood of delinquency lingers on much longer. Admittedly, the average share of homes damaged by Census block group is smaller for Hurricane Sandy as compared to Hurricane Harvey, but especially the predicted probability of delinquency of CMBS loans on multifamily assets shows a clear trend, up to two years after the initial climate shock.

C. FEMA Flood Zones

We have documented that Hurricanes Harvey and Sandy had a significant impact on the probability of delinquency for CMBS loans, and that there is heterogeneity in the impact depending on the severity of damage in the Census block group. However, one could argue that lenders in areas that are prone to climate risk are privy to such information already, through a variety of public sources. In this case, underwriting conditions and criteria might differ based on flood risk data available to lenders. To incorporate a measure of perceived flood risk in our analysis, we rely on public information that has been widely available for many years: FEMA's 100-year floodplain maps.

[9] Appendix Tables B1 and B2 include the complete results of this model specification for Hurricanes Harvey and Sandy, respectively.

Panel B in Figures 1 and 2 provide a visualization of FEMA floodplains in Houston and New York, with an overlay of the buildings in CMBS loans. Clearly, a substantial part of the sample is in designated flood zones. Comparing the FEMA floodplains with our "damage" measure, there is overlap, but a large fraction of Census block groups with damage was located outside of FEMA-designated floodplains. Further analysis shows that 89% (74%) of assets that were in damaged areas were outside a FEMA floodplain for Hurricane Harvey (Sandy).

To control for the fact that loan underwriting may have incorporated flood risk, we include the FEMA measure into the analysis. Presumably, delinquency rates should be lower in FEMA-designated floodplains, given that lenders had the ability to set stricter lending criteria. Table 4 reports the results of Equation (2). Overall, as documented in Column (1), areas that are in a 100-year floodplain as designated by FEMA exhibit a higher likelihood of delinquency before Hurricane Harvey made landfall compared to areas that were not in the floodplain during the same period. After the hurricane makes landfall, areas outside of a FEMA floodplain experience a higher probability of delinquency, whereas the delinquency rate of loans in areas inside of FEMA boundaries remains stable, on average. We do not observe a similar tendency for Hurricane Sandy in Column (3), as the variables differentiating between the pre and post period, and FEMA designation are not statistically significant.

Columns (2) and (4) of Table 4 tell a similar story. The main variable of interest in these two specifications is the interaction between our measure of damage severity and the FEMA indicator. Importantly, the results show that the probability of delinquency in CMBS loans increases most significantly for those areas that were affected by Hurricanes Harvey and Sandy but were *not* designated as part of a 100-year floodplain. This might suggest that perceived flood risk, in the form of FEMA's 100-year floodplain, is incorporated at the time of underwriting, explaining the insignificant difference in the probability of delinquency for those areas that were damaged but part of a floodplain.[10]

[10] Of course, a formal analysis of underwriting levels (including DSCR, LTV, etc.) could further support this argument. However, the sample for loans originated "pre" and "post" the hurricanes is quite small, rendering an empirical analysis useless. Non-parametric comparisons provide some support for the thesis that underwriting standards were stricter in FEMA-designated areas.

Conclusion

Climate risk is rapidly emerging not just as a risk to the ecosystem and its population, but also as a systemic risk factor that may have a severe impact on the global economy and the capital market. Indeed, policy makers and a plethora of central banks are now demanding that lenders and equity investors incorporate climate risk assessments into asset pricing, both in liquid assets, such as stocks and bonds, as well as in illiquid assets, such as real estate and infrastructure. There is a rapidly growing body of literature that provides support to the argument of policy makers and central banks, showing that climate risk affects capital allocation (Kreuger, et al., 2020), bank lending (Cortés and Strahan, 2015; Garmaise and Moskowitz, 2009), and home prices (Bernstein et al., 2019; Baldauf et al. 2020; Keys and Mulders, 2020)

The real estate sector stands out in the climate risk debate, due to the immovable nature of such assets, and the cost of protecting structures from rising sea levels, increasingly frequent hurricanes and wildfires, and other forms of climate-related risks. The single-family housing market will feel much of the brunt, but not much attention is given to the commercial real estate market, including multifamily housing, offices, industrial warehouses, and grocery-anchored retail facilities. The "commercial" part of the real estate markets represents $21 trillion in value and forms an important element of the urban fabric, providing essential services to the U.S. economy. There is emerging evidence that climate risk also affects commercial real estate prices (Fisher and Rutledge, 2021; Addoum et al., 2021), but given that real estate is typically financed using mortgages or other form of debt financing for at least 50% of a building's value, implications of climate risk on the performance of real estate debt is of particular relevance to the financial system.

This paper investigates the impact of climate shocks, proxied by two large hurricanes, on the commercial mortgage market. Using the universe of loans securitized by commercial mortgage-backed securities (CMBS), we analyze the impact of Hurricanes Harvey and Sandy on the payment behavior of borrowers following these large climate shocks. We find convincing evidence that the two hurricanes had a significant impact on commercial mortgage delinquency rates, following landfall, while controlling for property and mortgage characteristics. For Harvey, the effects are strongest for office and retail buildings, while for Sandy, payment behavior on multifamily loans suffered most. Importantly, there is heterogeneity in the estimated effect based on the severity of damage – using a measure of damage per Census block group, we find that a 10% increase in damage leads to a 28% increase in mortgage delinquency, for Hurricane Harvey. Furthermore, for those buildings located in

FEMA-designated floodplains, effects are subdued, providing some indication that provision of information on climate risk can (at least partially) mitigate the effects of climate shocks on the lending market.

The results in this paper complement recent findings on the impact of climate risk on the residential mortgage market. Kousky et al. (2020) document increased delinquency rates on residential mortgages following Harvey, Issler et al. (2020) find similar results following wildfire events in California, while Garmaise and Moskowitz (2009) find that lenders restrict credit supply to buildings *post* catastrophic events. Our paper provides the first evidence on the impact of climate shocks on the performance of mortgages on commercial buildings, an important cornerstone of both the U.S. economy and the banking system.

Importantly, our results show that the provision of climate-related information through the FEMA system seems to be quite effective in providing lenders with relevant data during underwriting – mortgages in FEMA-designated flood zones do not show elevated levels of delinquency. However, the precision of FEMA flood maps leaves something to be desired – 89% (74%) of assets that were in areas affected by Hurricane Harvey (Sandy) are not designated as located in flood zones according to FEMA. Over recent years, various stakeholders in the financial sector have started to recognize the importance of appropriately assessing climate risk. A growing number of service providers have identified the need for more sophisticated models and are supplying different industries with so-called "climate analytics." These considerations and more widespread access to frequently updated and improved climate risk assessment models are both relatively nascent, but may have the ability to reduce the impact of climate shocks on the financial system, through more effective (or: prudent) underwriting.

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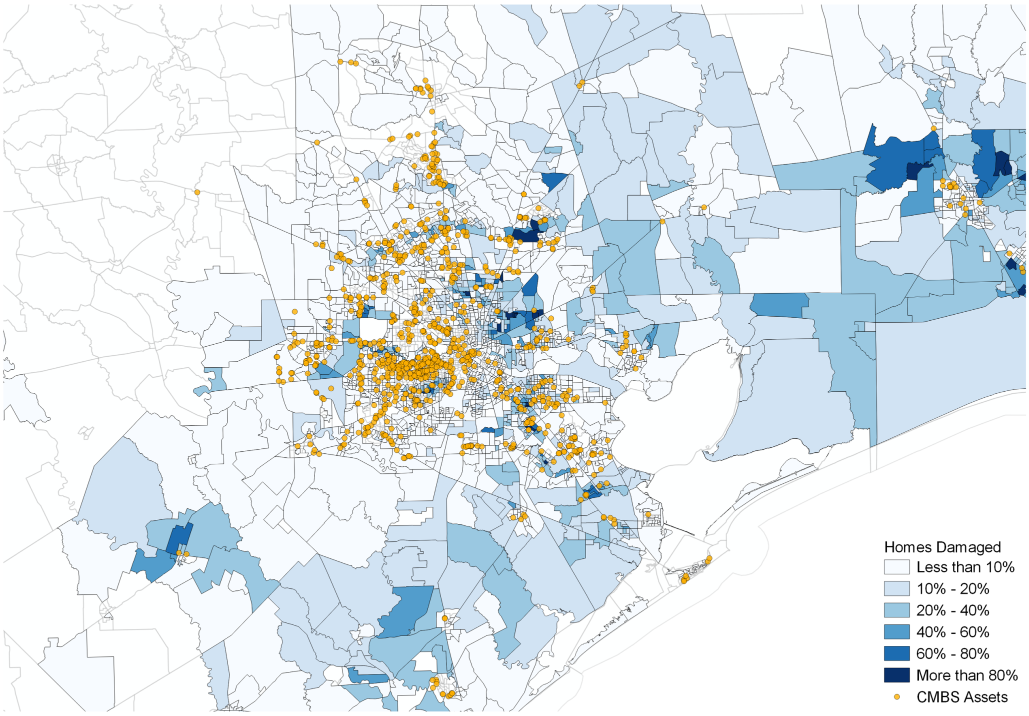
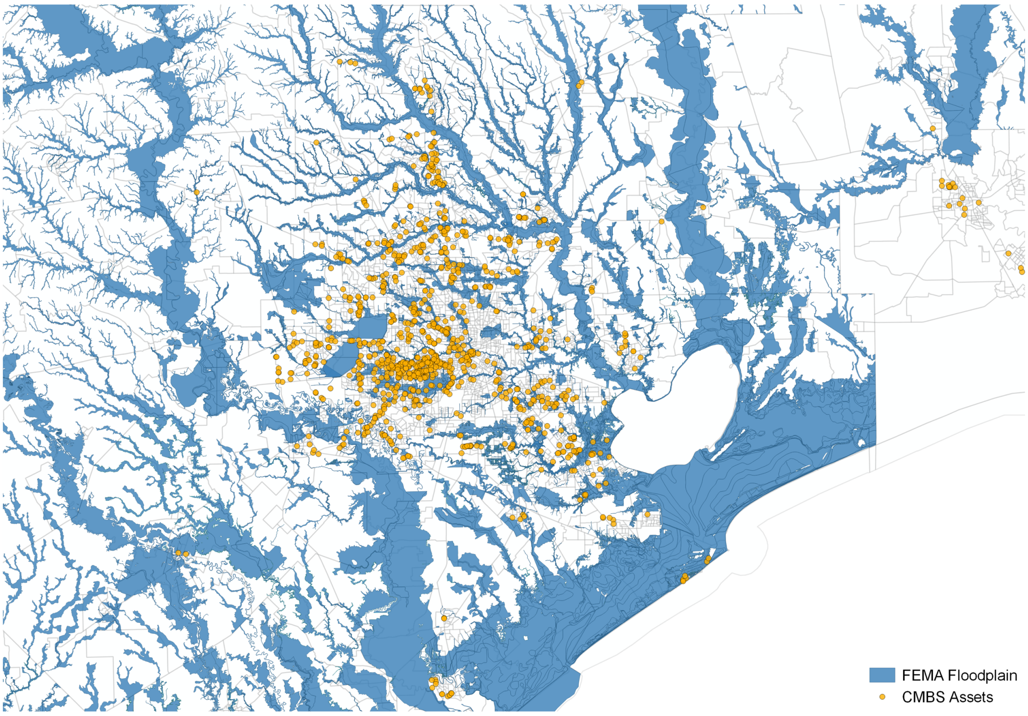
Figure 1
Hurricane Harvey

Panel A: Spatial Distribution of Damaged Homes by Census Block Group



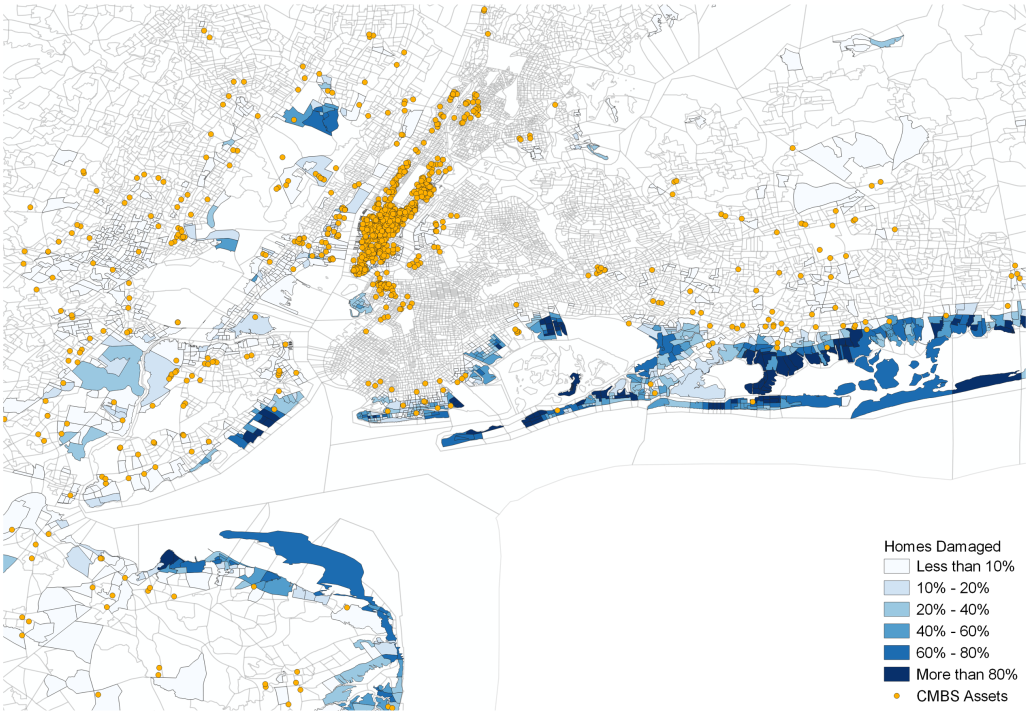
Panel B: FEMA 100-year Floodplain



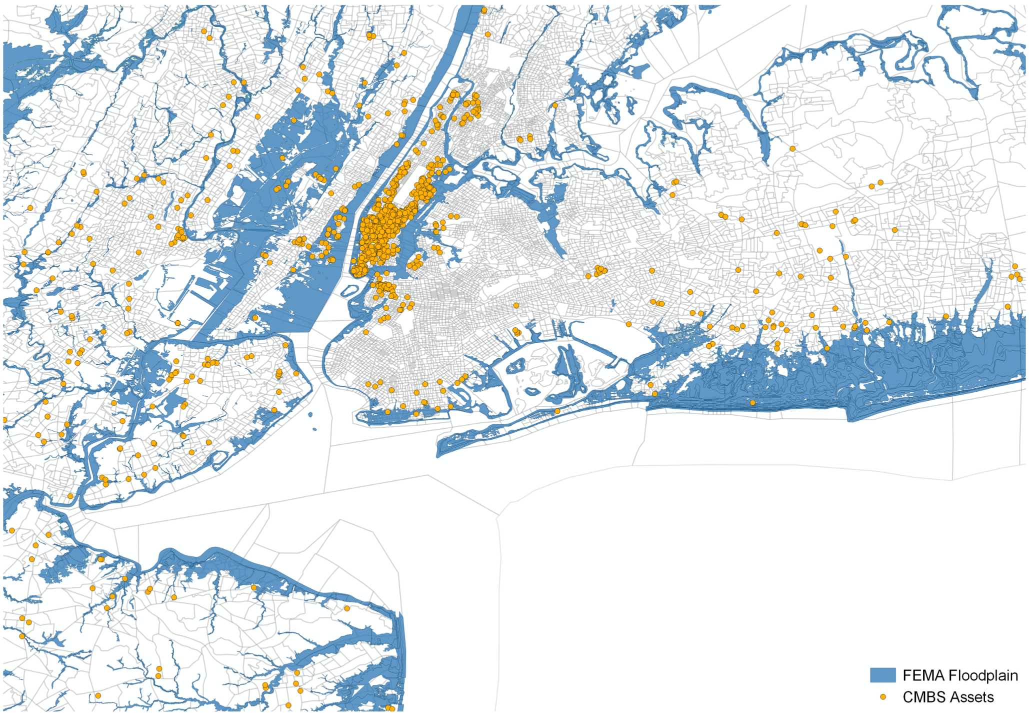
Notes: The impact area of Hurricane Harvey was much larger than the geographic area depicted in Panel A of Figure 1. The displayed area in Figure 1 is selected to illustrate the location of the majority of the assets in our sample in relation to both the impact area of Harvey and FEMA's 100-year floodplain.

Figure 2
Hurricane Sandy

Panel A: Spatial Distribution of Damaged Homes by Census Block Group



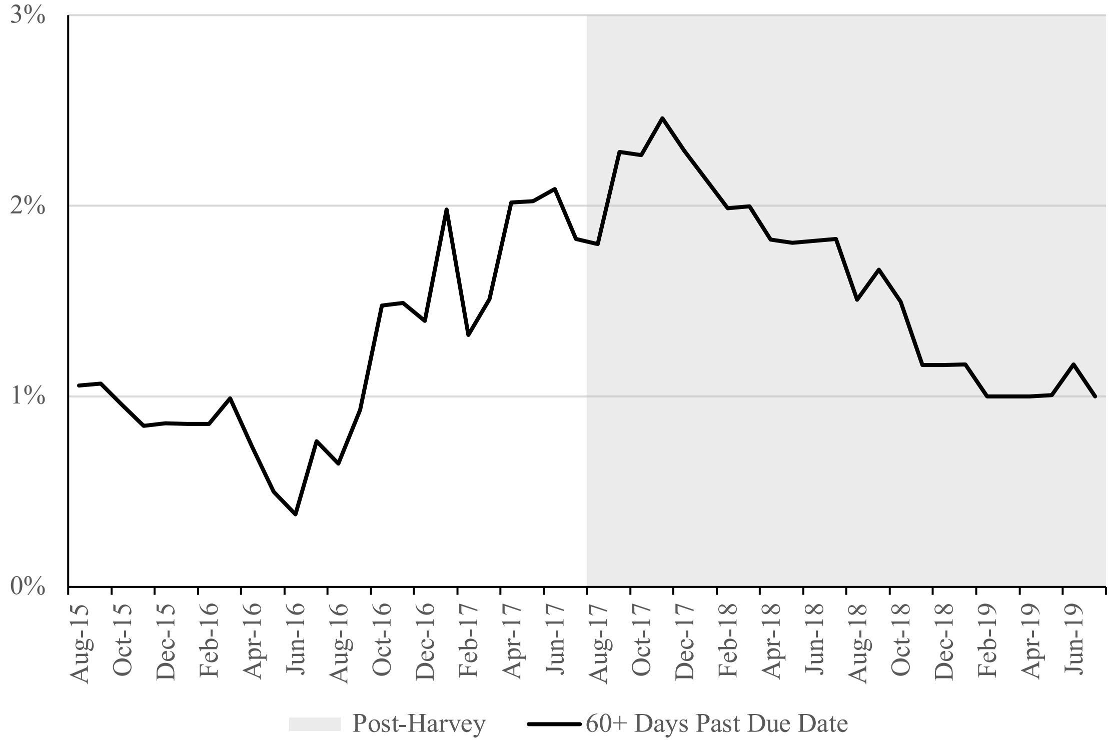
Panel B: FEMA 100-year Floodplain



Notes: The impact area of Hurricane Sandy was much larger than the geographic area depicted in Panel A. The displayed area in Figure 2 is selected to illustrate the location of the majority of the assets in our sample in relation to both the impact area of Sandy and FEMA's 100-year floodplain.

Figure 3
Average Delinquency Rate over Time

Panel A: Hurricane Harvey



Panel B: Hurricane Sandy

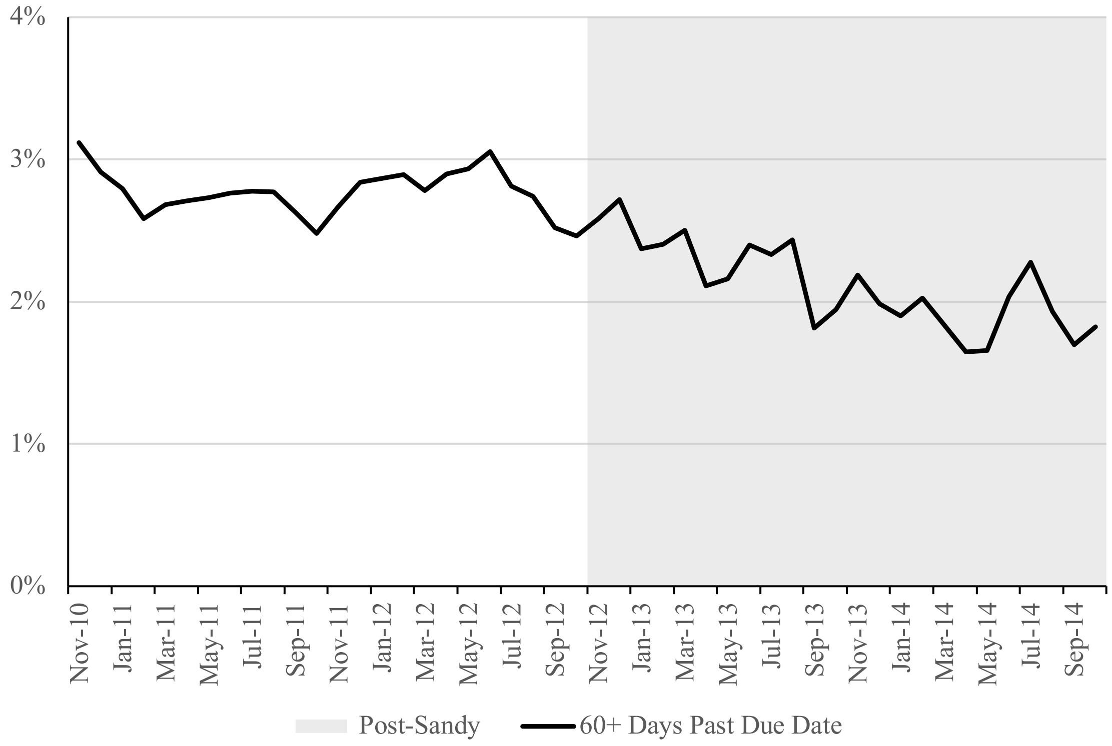


Figure 4
Home Damage Ratio and Probability of Delinquency – CMBS Loans in Retail

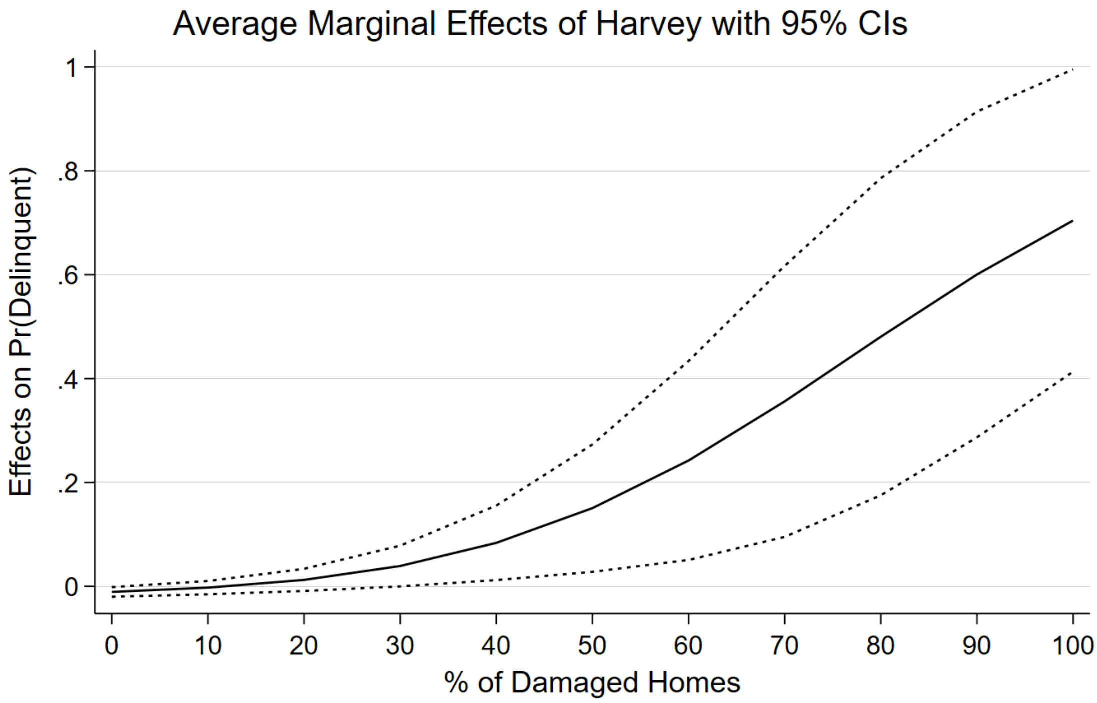


Figure 5
Home Damage Ratio and Probability of Delinquency – CMBS Loans in Multifamily

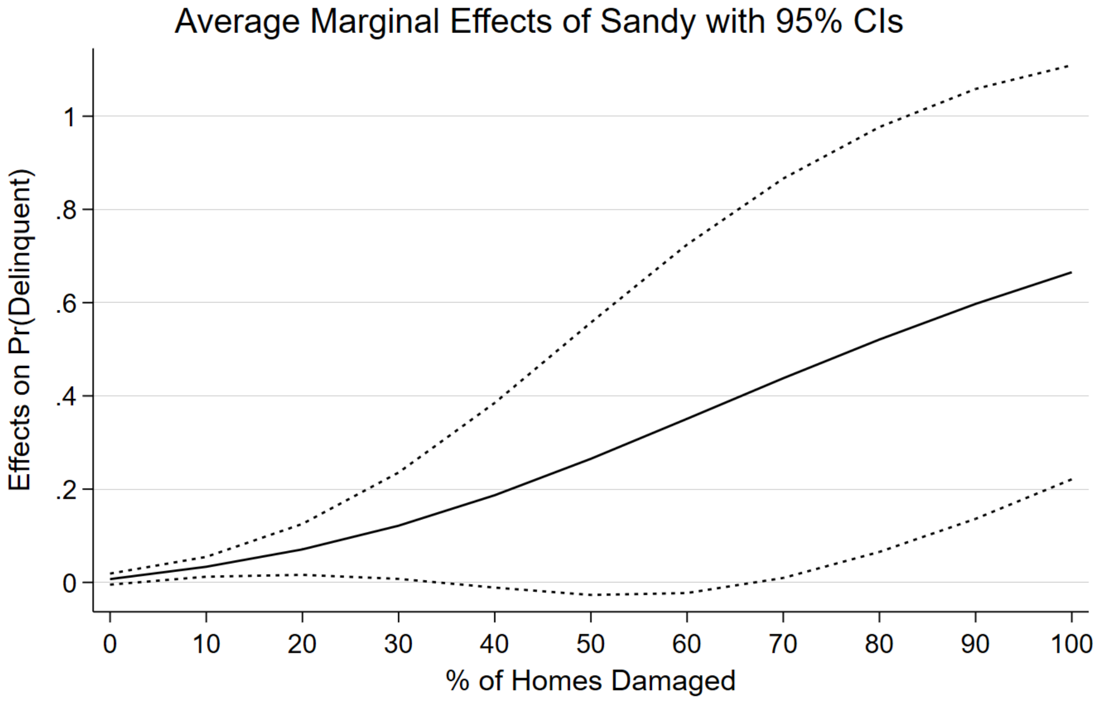
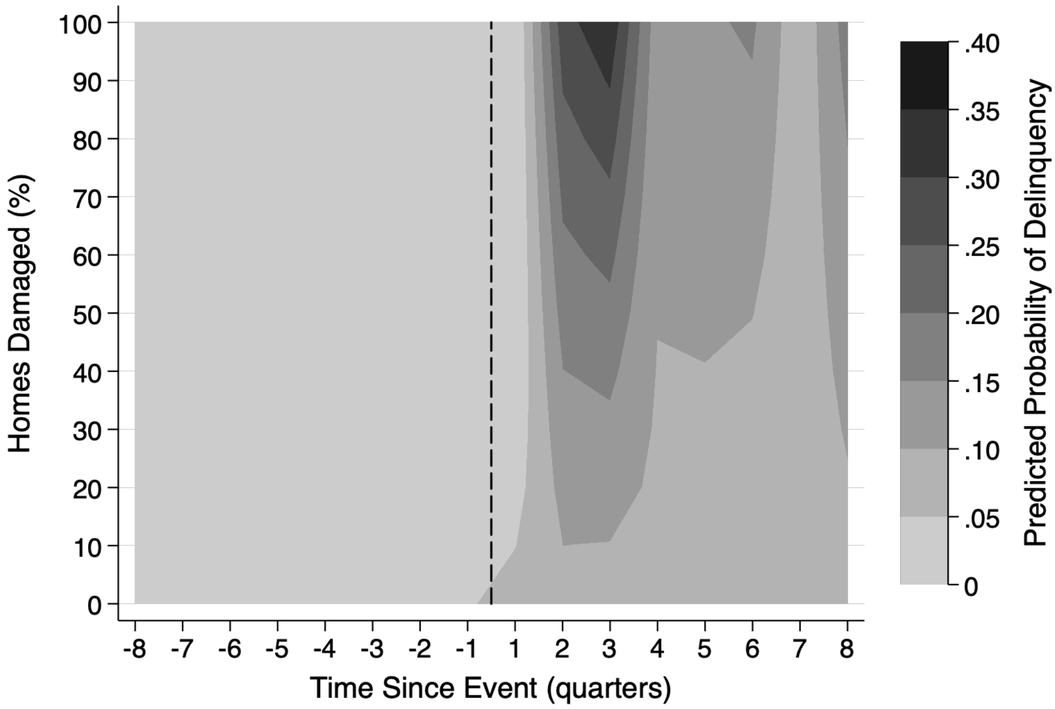


Figure 6
Hurricane Harvey – Probability of Delinquency over Time

Panel A: Full Sample



Panel B: Retail Buildings

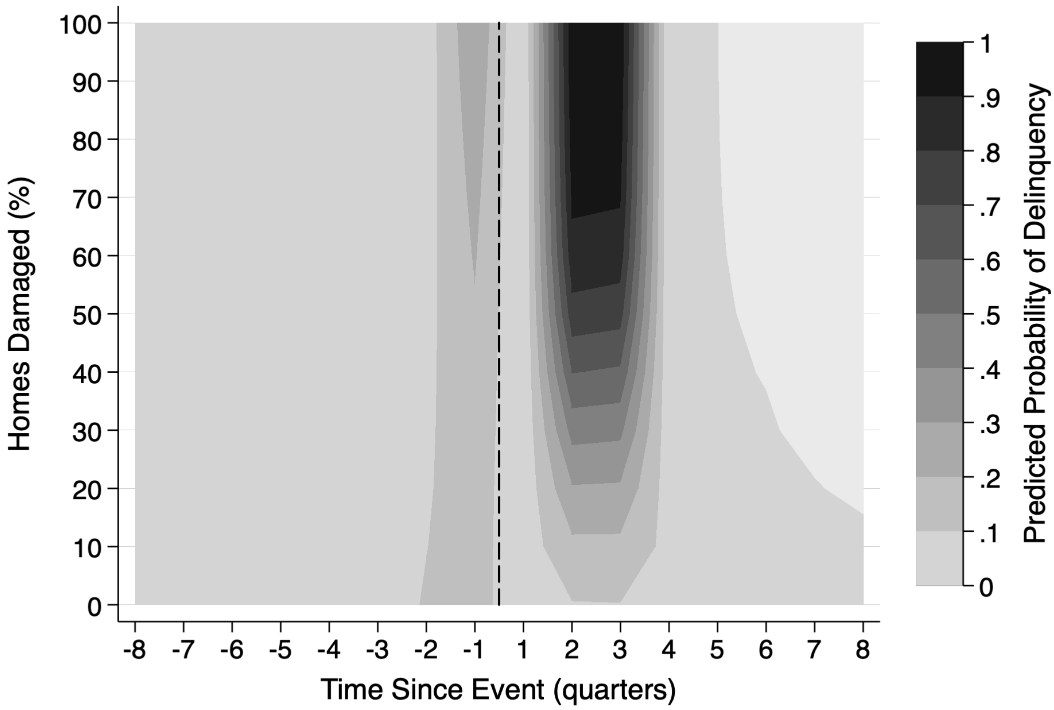
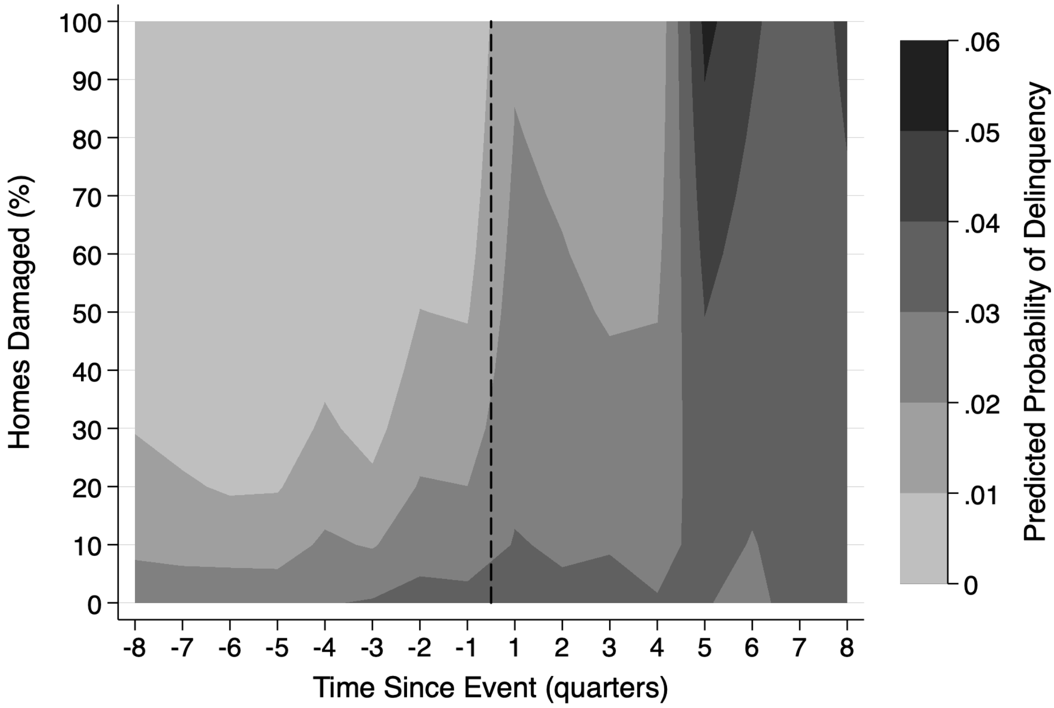


Figure 7
Hurricane Sandy – Probability of Delinquency over Time

Panel A: Full Sample



Panel B: Multifamily Buildings

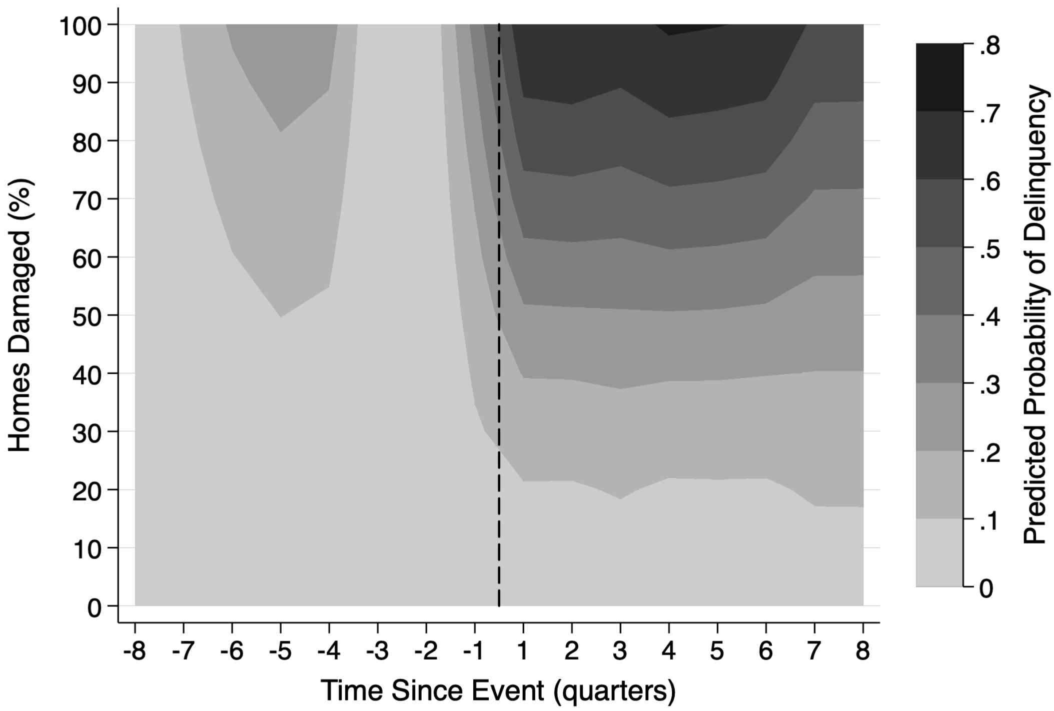


Table 1
Descriptive Statistics

	Panel A – Harvey				*Panel B – Sandy*			
	All	Undamaged	Damaged	Diff.	All	Undamaged	Damaged	Diff.
	(1)	(2)	(3)		(4)	(5)	(6)	
Homes damaged	4.25		8.15		1.66		9.77	
(% by Block Group)	[0.055]		[0.096]		[0.033]		[0.167]	
FEMA floodplain	8.10	5.85	10.17	***	5.94	2.01	25.10	***
(%)	[0.151]	[0.188]	[0.232]		[0.105]	[0.068]	[0.466]	
Property Type (%)								
Multifamily	39.95	42.90	37.24		25.10	26.74	17.12	
Retail	40.29	31.56	48.50		31.41	29.52	40.64	
Office	19.66	25.55	14.26		43.49	43.74	42.24	
Year of construction	1988	1984	1991	***	1956	1953	1967	***
Construction vintage (%)								
Before 1970	8.70	11.16	6.43		54.50	58.27	36.17	
1970-1979	22.54	27.96	17.57		10.46	10.19	11.78	
1980-1989	27.25	29.12	25.53		12.16	11.18	16.91	
1990-1999	8.63	9.18	8.12		9.01	7.94	14.22	
2000 or after	32.88	22.58	42.35		13.87	12.42	20.93	
Loan balance	12,112	13,131	11,176	***	31,938	31,138	35,834	***
($000s)	[104.76]	[148.69]	[147.09]		[280.18]	[306.49]	[689.10]	
Interest rate	5.10	5.11	5.09	**	5.85	5.84	5.88	***
(%)	[0.005]	[0.007]	[0.006]		[0.003]	[0.004]	[0.009]	
Loan-to-Value ratio	69.29	69.20	69.37	**	63.47	62.65	67.42	***
(at securitization %)	[0.045]	[0.072]	[0.056]		[0.070]	[0.080]	[0.134]	
Debt service coverage ratio	1.85	1.91	1.80	***	1.88	1.92	1.64	***
(DSCR)	[0.007]	[0.005]	[0.004]		[0.007]	[0.009]	[0.010]	
Term	122.70	122.67	122.72		126.57	126.42	127.27	**
(months)	[0.327]	[0.237]	[0.225]		[0.144]	[0.154]	[0.387]	
Amortization term	343.75	338.67	348.42	***	294.16	291.66	306.33	***
(months)	[0.870]	[0.676]	[0.547]		[0.502]	[0.557]	[1.152]	
Interest-only (IO) periods	22.84	25.50	20.40	***	37.76	38.38	34.71	***
(months)	[0.184]	[0.290]	[0.230]		[0.213]	[0.238]	[0.479]	
Occupancy rate	92.50	92.27	92.72	***	94.86	94.88	94.77	
(%)	[0.052]	[0.069]	[0.076]		[0.040]	[0.045]	[0.086]	
Origination year	2012	2012	2012	***	2005	2005	2005	*
Number of loan-months	32,603	15,614	16,989		50,749	42,104	8,645	
Number of loans	1,119	544	575		1,525	1,265	260	

Notes: Standard errors in brackets. Significant differences between the "Undamaged" and "Damaged" samples at the 0.10, 0.05, and 0.01 level are indicated by *, **, and *** respectively.

Table 2
Hurricane Harvey and Probability of Delinquency

	Full Sample (1)	Multifamily (2)	Retail (3)	Office (4)
Harvey (1=yes)	1.204***	-1.206	-1.428**	2.502***
	[0.366]	[1.366]	[0.722]	[0.518]
Homes damaged	-0.044*	-0.890	-0.010	-0.032
(% by Block Group)	[0.024]	[0.950]	[0.018]	[0.051]
Harvey*Homes damaged	0.062*	0.810	0.118***	-0.077
	[0.035]	[0.888]	[0.024]	[0.083]
Log(interest rate)	-3.394	7.345*	2.830	-22.525***
	[2.897]	[4.340]	[5.320]	[7.958]
Log(original loan balance)	0.058	-0.379	-0.017	0.031
	[0.164]	[0.583]	[0.301]	[0.296]
LTV at origination	0.019	0.224	-0.029	-0.050
	[0.030]	[0.180]	[0.051]	[0.043]
LTV at origination over 70%	-0.013	-0.447	1.225**	0.426
	[0.460]	[1.211]	[0.624]	[0.911]
Current DSCR	-0.908***	-1.298	-1.316	-0.842*
	[0.318]	[0.907]	[1.046]	[0.433]
Occupancy rate	-0.053***	-0.083**	-0.036***	-0.061***
	[0.011]	[0.038]	[0.013]	[0.019]
Term	-0.059***	-0.021	-0.131***	-0.032
(months)	[0.013]	[0.018]	[0.021]	[0.025]
Amortization term	0.003*	-0.001	0.004	0.002
(months)	[0.002]	[0.012]	[0.005]	[0.003]
Construction vintage (1=yes)				
1970-1979	0.484	0.513	1.773	1.021
	[0.730]	[1.234]	[1.899]	[1.237]
1980-1989	-0.131	0.158	2.264	0.731
	[0.681]	[1.063]	[1.946]	[0.721]
1990-1999	-2.256*		0.178	-1.179
	[1.349]		[2.015]	[2.106]
2000 or after	0.138	-0.826	2.129	2.230***
	[0.681]	[2.038]	[2.010]	[0.734]
Constant	2.968	-16.696	5.923	39.345***
	[6.099]	[16.625]	[13.064]	[13.432]
Property type fixed-effects	yes	N/A	N/A	N/A
MSA fixed-effects	yes	yes	yes	yes
Vintage fixed-effects	yes	yes	yes	yes
Year fixed-effects	yes	yes	yes	yes
Number of loan-months	25,896	9,964	6,750	2,944
Number of loans	882	317	300	118
Pseudo R-squared	0.53	0.46	0.55	0.62

Notes: Robust standard errors clustered at the loan level in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and *** respectively.

Table 3
Hurricane Sandy and Probability of Delinquency

	Full Sample	Multifamily	Retail	Office
	(1)	(2)	(3)	(4)
Sandy (1=yes)	0.043	0.301	0.091	-0.003
	[0.126]	[0.277]	[0.298]	[0.173]
Homes damaged	-0.045**	-0.012	-0.030	-0.088*
(% by Block Group)	[0.022]	[0.054]	[0.024]	[0.050]
Sandy*Homes damaged	0.041	0.089**	-0.016	-0.008
	[0.027]	[0.040]	[0.013]	[0.074]
Log(interest rate)	6.670***	12.508**	7.159*	8.670*
	[2.325]	[5.150]	[3.735]	[4.473]
Log(original loan balance)	0.144	1.062***	0.530*	-0.074
	[0.122]	[0.344]	[0.277]	[0.141]
LTV at origination	0.032	0.072	-0.018	0.104**
	[0.034]	[0.070]	[0.038]	[0.048]
LTV at origination over 70%	0.051	-0.214	0.114	-0.622
	[0.543]	[1.418]	[0.724]	[0.624]
Current DSCR	-0.456	-1.071**	-0.092	-0.542
	[0.341]	[0.488]	[0.469]	[0.691]
Occupancy rate	-0.037***	0.007	-0.020	-0.061***
	[0.009]	[0.032]	[0.015]	[0.014]
Term	-0.044***	-0.057***	-0.029***	-0.049***
(months)	[0.008]	[0.022]	[0.010]	[0.016]
Amortization term	-0.000	0.005	-0.000	-0.001
(months)	[0.001]	[0.004]	[0.002]	[0.003]
Construction vintage (1=yes)				
1970-1979	0.263	-2.395***	1.082	0.741
	[0.490]	[0.799]	[0.811]	[0.771]
1980-1989	0.875**		1.661*	1.057*
	[0.446]		[0.947]	[0.613]
1990-1999	0.184	-1.998*	0.401	0.292
	[0.591]	[1.205]	[1.038]	[0.850]
2000 or after	0.340	-2.456**	0.370	0.539
	[0.468]	[1.179]	[0.809]	[0.864]
Constant	-9.377	-37.346**	-16.942	-12.206
	[6.296]	[15.573]	[10.482]	[11.718]
Property type fixed-effects	yes	N/A	N/A	N/A
MSA fixed-effects	yes	yes	yes	yes
Vintage fixed-effects	yes	yes	yes	yes
Year fixed-effects	yes	yes	yes	yes
Number of loan-months	44,411	8,286	13,028	19,330
Number of loans	1,241	226	349	507
Pseudo R-squared	0.27	0.45	0.19	0.38

Notes: Robust standard errors clustered at the loan level in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and *** respectively.

Table 4
FEMA Floodplains and Probability of Delinquency

	Harvey		Sandy	
	(1)	(2)	(3)	(4)
Pre-Hurricane FEMA Zone	1.618***	1.736***	0.120	0.431
	[0.536]	[0.593]	[0.616]	[0.670]
Post-Hurricane	1.649***	1.393***	0.137	0.066
	[0.341]	[0.364]	[0.135]	[0.130]
Post-Hurricane FEMA Zone	1.100	1.285*	-0.302	0.166
	[1.131]	[0.718]	[0.883]	[0.997]
Homes damaged		-0.046**		-0.056*
(% by Block Group)		[0.022]		[0.030]
Post-Hurricane*Homes Damaged		0.074**		0.069*
		[0.033]		[0.035]
Post-Hurricane FEMA Zone*Homes Damaged		0.038		-0.026
		[0.065]		[0.066]
Log(interest rate)	-3.635	-3.582	6.640***	6.819***
	[2.849]	[3.054]	[2.312]	[2.321]
Log(original loan balance)	0.073	0.069	0.143	0.138
	[0.155]	[0.172]	[0.122]	[0.122]
LTV at origination	0.013	0.013	0.033	0.034
	[0.030]	[0.031]	[0.033]	[0.033]
LTV at origination over 70%	-0.032	0.024	0.032	0.009
	[0.469]	[0.485]	[0.543]	[0.541]
Current DSCR	-0.965***	-0.934***	-0.463	-0.476
	[0.345]	[0.337]	[0.343]	[0.342]
Occupancy rate	-0.055***	-0.055***	-0.038***	-0.037***
	[0.011]	[0.012]	[0.009]	[0.009]
Term	-0.054***	-0.056***	-0.045***	-0.045***
(months)	[0.012]	[0.013]	[0.008]	[0.008]
Amortization term	0.003	0.003	-0.000	-0.000
(months)	[0.002]	[0.002]	[0.001]	[0.001]
Construction vintage (1=yes)				
1970-1979	0.367	0.419	0.256	0.225
	[0.786]	[0.680]	[0.498]	[0.514]
1980-1989	-0.290	-0.267	0.862**	0.912**
	[0.728]	[0.644]	[0.432]	[0.434]
1990-1999	-2.168	-2.110	0.219	0.204
	[1.391]	[1.299]	[0.587]	[0.599]
2000 or after	0.117	0.193	0.382	0.349
	[0.745]	[0.638]	[0.467]	[0.472]
Constant	3.984	4.407	-9.343	-9.458
	[5.727]	[6.047]	[6.268]	[6.328]
Property type fixed-effects	yes	yes	yes	yes
MSA fixed-effects	yes	yes	yes	yes
Vintage fixed-effects	yes	yes	yes	yes
Year fixed-effects	yes	yes	yes	yes
Number of loan-months	25,896	25,896	44,411	44,411
Number of loans	882	882	1,241	1,241
Pseudo R-squared	0.53	0.54	0.27	0.28

Notes: Robust standard errors clustered at the loan level in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and *** respectively.

Appendix

Table A1
Descriptive Statistics – Hurricane Harvey

	Multifamily				Retail				Office			
	All	Undamaged	Damaged	Diff.	All	Undamaged	Damaged	Diff.	All	Undamaged	Damaged	Diff.
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
Loan balance	10,268	10,526	9,995	***	11,031	11,528	10,735	**	18,080	19,483	15,767	***
($000s)	[61.83]	[89.59]	[84.76]		[194.03]	[260.96]	[267.87]		[319.78]	[445.54]	[417.80]	
Interest rate	4.99	4.95	5.04	***	5.21	5.33	5.14	***	5.07	5.10	5.03	***
(%)	[0.007]	[0.009]	[0.010]		[0.008]	[0.014]	[0.009]		[0.009]	[0.012]	[0.013]	
Loan-to-Value ratio	70.87	70.59	71.17	***	67.68	67.52	67.78	*	69.38	68.96	70.07	***
(at securitization %)	[0.062]	[0.092]	[0.082]		[0.082]	[0.156]	[0.089]		[0.082]	[0.118]	[0.092]	
Debt service coverage ratio	1.95	2.01	1.90	***	1.76	1.81	1.73	***	1.83	1.87	1.76	***
(DSCR)	[0.005]	[0.007]	[0.007]		[0.005]	[0.009]	[0.006]		[0.008]	[0.010]	[0.011]	
Term	116.83	116.69	116.97		130.97	134.99	128.56	***	117.63	117.49	117.86	
(months)	[0.227]	[0.296]	[0.347]		[0.313]	[0.567]	[0.364]		[0.167]	[0.236]	[0.212]	
Amortization term	358.21	354.09	362.57	***	328.19	319.32	333.50	***	346.33	336.69	362.21	***
(months)	[0.565]	[0.822]	[0.768]		[0.757]	[1.395]	[0.871]		[0.975]	[1.379]	[1.157]	
Interest-only (IO) periods	23.16	22.56	23.80	***	22.24	29.06	18.17	***	23.43	26.05	19.11	***
(months)	[0.264]	[0.386]	[0.359]		[0.308]	[0.577]	[0.344]		[0.431]	[0.593]	[0.582]	
Occupancy rate	92.25	93.07	91.37	***	94.93	94.74	95.04	**	88.03	87.85	88.31	*
(%)	[0.066]	[0.065]	[0.117]		[0.071]	[0.110]	[0.093]		[0.156]	[0.187]	[0.275]	
Origination year	2013	2013	2013	***	2011	2010	2011	***	2012	2012	2012	
Year of construction	1981	1979	1984	***	1996	1993	1998	***	1985	1983	1989	
Construction vintage (%)												
Before 1970	13.84	16.27	11.27		5.20	6.49	4.43		5.41	8.35	0.58	
1970-1979	34.33	40.31	28.01		11.05	16.26	7.94		22.20	21.66	23.08	
1980-1989	34.08	31.37	36.95		11.75	11.10	12.14		45.22	47.61	41.29	
1990-1999	3.70	4.24	3.13		15.07	17.70	13.50		5.41	6.94	2.89	
2000 or after	14.04	7.81	20.64		56.93	48.45	62.00		21.76	15.44	32.16	
Homes damaged	3.92		8.08		5.02		8.02		3.31		8.77	
(% by Block Group)	[0.080]		[0.148]		[0.096]		[0.144]		[8.88]		[12.68]	
FEMA floodplain	11.83	10.48	13.26	***	5.38	2.58	7.06	***	6.08	2.11	12.63	***
(%)	[0.283]	[0.374]	[0.426]		[0.197]	[0.226]	[0.282]		[0.299]	[0.227]	[0.675]	
Number of loan-months	13,025	6,698	6,327		13,167	4,927	8,240		6,411	3,989	2,422	
Number of loans	429	219	210		479	185	294		211	140	71	

Notes: Standard errors in brackets. Significant differences between the "Undamaged" and "Damaged" samples at the 0.10, 0.05, and 0.01 level are indicated by *, **, and *** respectively.

Table A2
Descriptive Statistics – Hurricane Sandy

	Multifamily				Retail				Office			
	All	Undamaged	Damaged	Diff.	All	Undamaged	Damaged	Diff.	All	Undamaged	Damaged	Diff.
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)	
Loan balance	11,534	11,542	11,473		16,139	16,768	13,913	***	55,127	52,813	66,794	***
($000s)	[173.75]	[191.59]	[335.26]		[255.63]	[274.30]	[634.20]		[572.27]	[630.18]	[1,347.49]	
Interest rate	5.91	5.89	6.06	***	5.87	5.85	5.92	***	5.79	5.80	5.76	***
(%)	[0.008]	[0.008]	[0.026]		[0.006]	[0.007]	[0.014]		[0.005]	[0.005]	[0.012]	
Loan-to-Value ratio	59.22	58.43	65.21	***	68.13	67.70	69.67	***	62.55	61.83	66.15	***
(at securitization %)	[0.164]	[0.176]	[0.425]		[0.094]	[0.108]	[0.186]		[0.107]	[0.122]	[0.192]	
Debt service coverage ratio	2.11	2.17	1.65	***	1.54	1.56	1.47	***	1.98	2.02	1.81	***
(DSCR)	[0.023]	[0.026]	[0.029]		[0.005]	[0.006]	[0.007]		[0.010]	[0.011]	[0.018]	
Term	132.00	131.16	138.40	***	127.48	126.43	131.21	***	122.77	123.52	118.97	***
(months)	[0.338]	[0.347]	[1.226]		[0.275]	[0.294]	[0.687]		[0.174]	[0.196]	[0.347]	
Amortization term	279.83	276.66	304.00	***	312.55	312.11	314.11		289.14	287.03	299.79	***
(months)	[1.006]	[1.086]	[2.519]		[0.803]	[0.921]	[1.631]		[0.802]	[0.877]	[1.978]	
Interest-only (IO) periods	37.18	38.42	27.77	***	28.88	28.88	28.88		44.50	44.77	43.14	**
(months)	[0.442]	[0.475]	[1.156]		[0.341]	[0.385]	[0.739]		[0.332]	[0.371]	[0.725]	
Occupancy rate	96.30	96.35	95.93	***	96.32	96.31	96.35		92.97	93.01	92.79	*
(%)	[0.050]	[0.055]	[0.112]		[0.076]	[0.091]	[0.120]		[0.066]	[0.073]	[0.157]	
Origination year	2004	2004	2004	***	2005	2005	2005	***	2005	2005	2006	***
Year of construction	1949	1947	1965	***	1974	1971	1985	***	1947	1946	1954	***
Construction vintage (%)												
Before 1970	65.97	68.17	49.26		33.84	37.35	21.41		62.81	66.33	45.07	
1970-1979	8.78	8.28	12.57		11.39	11.80	9.91		10.77	10.28	13.25	
1980-1989	8.13	8.15	7.91		9.35	8.60	12.01		16.51	14.77	25.27	
1990-1999	6.89	5.67	16.22		17.76	16.10	23.65		3.90	3.82	4.33	
2000 or after	10.23	9.73	14.05		27.66	26.15	33.02		6.01	4.81	12.08	
Homes damaged	1.16		9.97		2.61		11.84		1.27		7.69	
(% by Block Group)	[0.061]		[0.463]		[0.078]		[0.310]		[0.035]		[0.174]	
FEMA floodplain	5.57	1.87	33.65	***	5.92	1.94	20.01	***	6.17	2.13	26.53	***
(%)	[0.203]	[0.128]	[1.229]		[0.187]	[0.124]	[0.675]		[0.162]	[0.106]	[0.731]	
Number of loan-months	12,737	11,257	1,480		15,942	12,429	3,513		22,070	18,418	3,652	
Number of loans	405	359	46		473	376	97		648	531	117	

Notes: Standard errors in brackets. Significant differences between the "Undamaged" and "Damaged" samples at the 0.10, 0.05, and 0.01 level are indicated by *, **, and *** respectively.

Table B1
Hurricane Harvey – Probability of Delinquency by Quarter

	Full Sample (1)	Multifamily (2)	Retail (3)	Office (4)
Quarters since Harvey (1=yes)				
-8 quarters	-3.344***	0.181	-6.507***	-3.238***
	[0.618]	[1.186]	[1.284]	[0.881]
-7 quarters	-3.037***	0.019	-5.207***	-3.493***
	[0.559]	[1.174]	[1.092]	[0.818]
-6 quarters	-2.778***		-4.219***	-3.295***
	[0.564]		[0.979]	[0.961]
-5 quarters	-3.215***	-0.980	-4.963***	-4.108***
	[0.585]	[1.002]	[1.049]	[0.859]
-4 quarters	-1.948***	1.144	-3.206***	-3.216***
	[0.483]	[0.936]	[1.126]	[0.866]
-3 quarters	-0.948**	3.250***	-1.657	-2.342***
	[0.407]	[0.784]	[1.041]	[0.684]
-2 quarters	-0.502*	1.838	-0.373	-1.088**
	[0.298]	[1.180]	[0.697]	[0.497]
1 quarter	0.921***	1.062**	-1.592	1.795***
	[0.339]	[0.464]	[1.159]	[0.547]
2 quarters	1.326***	1.374**	-0.677	2.482***
	[0.414]	[0.624]	[1.152]	[0.721]
3 quarters	1.212**	0.975**	-0.608	3.001***
	[0.501]	[0.430]	[1.058]	[0.826]
4 quarters	1.297**	0.993**	-0.774	2.983***
	[0.520]	[0.485]	[1.119]	[0.834]
5 quarters	1.050**	0.610	-0.598	2.967***
	[0.462]	[0.777]	[1.217]	[1.042]
6 quarters	0.528	-1.125		3.521**
	[0.609]	[0.796]		[1.404]
7 quarters	1.096*	-0.311		3.974***
	[0.624]	[0.244]		[1.217]
8 quarters	1.189*			3.681***
	[0.612]			[1.157]
Homes damaged	-0.002	-0.118	0.033	0.083
(% by Block Group)	[0.028]	[0.142]	[0.029]	[0.075]
Harvey*Homes damaged				
-8 quarters	-0.073		-0.167*	-0.142*
	[0.048]		[0.092]	[0.079]
-7 quarters	-0.102		-0.307*	-0.142*
	[0.076]		[0.168]	[0.077]
-6 quarters	-0.044		-0.084*	-0.149**
	[0.039]		[0.050]	[0.073]
-5 quarters	-0.001	-0.206**	-0.004	-0.090
	[0.034]	[0.099]	[0.037]	[0.079]
-4 quarters	-0.062**	-0.249***	-0.176	-0.100
	[0.032]	[0.090]	[0.125]	[0.089]
-3 quarters	-0.116**		-0.303***	0.108*
	[0.053]		[0.117]	[0.061]
-2 quarters	-0.057***		-0.053**	0.035
	[0.017]		[0.026]	[0.052]
1 quarter	-0.073*	-0.249***	-0.123	-0.096**
	[0.044]	[0.069]	[0.131]	[0.045]
2 quarters	0.036	-0.085*	0.170***	-0.215***
	[0.033]	[0.045]	[0.052]	[0.072]
3 quarters	0.045	-0.026	0.163***	-0.251***
	[0.041]	[0.062]	[0.047]	[0.069]

Table B1 (continued)
Hurricane Harvey – Probability of Delinquency by Quarter

	Full Sample (1)	Multifamily (2)	Retail (3)	Office (4)
4 quarters	0.010	0.002	-0.102	-0.256***
	[0.052]	[0.038]	[0.097]	[0.069]
5 quarters	0.017	0.008	-0.133	-0.281***
	[0.051]	[0.041]	[0.140]	[0.096]
6 quarters	0.025	0.052		-1.044*
	[0.054]	[0.041]		[0.583]
7 quarters	-0.002	0.006		-0.326***
	[0.065]	[0.010]		[0.100]
8 quarters	0.021			-0.048
	[0.053]			[0.133]
Log(interest rate)	-3.067	6.988	8.655	-24.025***
	[2.933]	[5.464]	[6.825]	[8.990]
Log(original loan balance)	0.097	-0.444	0.167	-0.026
	[0.175]	[0.725]	[0.268]	[0.296]
LTV at origination	0.018	0.369	0.028	-0.053
	[0.031]	[0.292]	[0.075]	[0.046]
LTV at origination over 70%	-0.043	-0.857	0.424	0.527
	[0.472]	[1.962]	[0.728]	[0.949]
Current DSCR	-0.915***	-1.618*	-1.113	-0.854*
	[0.316]	[0.891]	[1.083]	[0.474]
Occupancy rate	-0.054***	-0.104**	-0.047***	-0.064***
	[0.012]	[0.042]	[0.012]	[0.019]
Term	-0.061***	-0.026	-0.172***	-0.032
(months)	[0.014]	[0.031]	[0.023]	[0.025]
Amortization term	0.004*	-0.003	0.004	0.002
(months)	[0.002]	[0.015]	[0.006]	[0.003]
Construction vintage (1=yes)				
1970-1979	0.469	1.157	0.617	1.069
	[0.748]	[1.332]	[1.539]	[1.216]
1980-1989	-0.174	0.590	1.074	0.724
	[0.715]	[1.009]	[1.621]	[0.725]
1990-1999	-2.313		-0.195	-1.217
	[1.428]		[1.724]	[2.347]
2000 or after	0.120	0.781	1.453	2.370***
	[0.717]	[1.681]	[1.601]	[0.714]
Constant	5.726	-22.627	2.576	45.952***
	[6.191]	[25.363]	[15.194]	[15.242]
Property type fixed-effects	yes	N/A	N/A	N/A
MSA fixed-effects	yes	yes	yes	yes
Vintage fixed-effects	yes	yes	yes	yes
Number of loan-months	25,245	7,019	6,339	2,860
Number of loans	882	299	300	118
Pseudo R-squared	0.50	0.47	0.58	0.59

Notes: Robust standard errors clustered at the loan level in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and *** respectively.

Table B2
Hurricane Sandy – Probability of Delinquency by Quarter

	Full Sample	Multifamily	Retail	Office
	(1)	(2)	(3)	(4)
Quarters since Sandy (1=yes)				
-8 quarters	-0.336	-1.371**	0.245	-0.426
	[0.252]	[0.689]	[0.453]	[0.373]
-7 quarters	-0.309	-0.778	0.174	-0.416
	[0.237]	[0.576]	[0.469]	[0.350]
-6 quarters	-0.246	-0.626	0.240	-0.343
	[0.209]	[0.523]	[0.394]	[0.317]
-5 quarters	-0.279	-0.656	0.177	-0.366
	[0.202]	[0.520]	[0.410]	[0.265]
-4 quarters	-0.131	-0.822*	0.140	-0.026
	[0.184]	[0.431]	[0.424]	[0.234]
-3 quarters	-0.068	-0.710*	0.006	0.117
	[0.164]	[0.406]	[0.398]	[0.194]
-2 quarters	0.021	-0.151	0.184	-0.038
	[0.118]	[0.286]	[0.312]	[0.140]
1 quarter	-0.018	-0.241	0.051	0.048
	[0.081]	[0.162]	[0.194]	[0.125]
2 quarters	-0.053	-0.290	-0.051	0.064
	[0.146]	[0.296]	[0.333]	[0.220]
3 quarters	0.006	0.103	-0.449	0.234
	[0.173]	[0.430]	[0.396]	[0.263]
4 quarters	-0.087	-0.420	-0.176	0.190
	[0.197]	[0.538]	[0.418]	[0.289]
5 quarters	-0.093	-0.347	0.151	-0.121
	[0.234]	[0.606]	[0.430]	[0.357]
6 quarters	-0.168	-0.323	0.128	-0.227
	[0.264]	[0.664]	[0.430]	[0.431]
7 quarters	-0.016	0.414	0.246	-0.112
	[0.284]	[0.645]	[0.436]	[0.539]
8 quarters	-0.072	0.428	0.009	-0.080
	[0.301]	[0.684]	[0.440]	[0.574]
Homes damaged	-0.030	0.043	-0.025	-0.162
(% by Block Group)	[0.026]	[0.031]	[0.027]	[0.139]
Sandy*Homes damaged				
-8 quarters	-0.008	-0.657*	-0.030	0.159
	[0.033]	[0.392]	[0.025]	[0.135]
-7 quarters	-0.021		-0.013	0.124
	[0.037]		[0.017]	[0.145]
-6 quarters	-0.036		-0.003	
	[0.038]		[0.012]	
-5 quarters	-0.033		-0.002	
	[0.035]		[0.012]	
-4 quarters	-0.008	-0.001	-0.001	
	[0.025]	[0.036]	[0.012]	
-3 quarters	-0.029	-0.090	0.002	
	[0.030]	[0.101]	[0.011]	
-2 quarters	0.001	-0.373	-0.004	0.136
	[0.024]	[0.378]	[0.010]	[0.128]
1 quarter	0.023**	0.037***	-0.004	-0.004
	[0.010]	[0.014]	[0.007]	[0.018]
2 quarters	0.022*	0.039**	-0.011	-0.006
	[0.013]	[0.016]	[0.013]	[0.034]
3 quarters	0.017	0.032*	-0.016	-0.092
	[0.016]	[0.018]	[0.020]	[0.148]

Table B2 (continued)
Hurricane Sandy – Probability of Delinquency by Quarter

	Full Sample (1)	Multifamily (2)	Retail (3)	Office (4)
4 quarters	0.020	0.043**	-0.032	-0.476
	[0.018]	[0.020]	[0.023]	[0.483]
5 quarters	0.038*	0.041**	-0.035	0.164
	[0.020]	[0.019]	[0.023]	[0.132]
6 quarters	0.035**	0.039*	-0.032	0.127
	[0.017]	[0.020]	[0.021]	[0.132]
7 quarters	0.030	0.019	-0.029	
	[0.019]	[0.018]	[0.018]	
8 quarters	0.035*	0.019	-0.043	
	[0.021]	[0.018]	[0.029]	
Log(interest rate)	6.648***	14.241**	7.166*	8.355*
	[2.323]	[5.917]	[3.752]	[4.446]
Log(original loan balance)	0.147	1.004***	0.541**	-0.080
	[0.121]	[0.336]	[0.276]	[0.147]
LTV at origination	0.032	0.077	-0.018	0.105**
	[0.033]	[0.071]	[0.038]	[0.047]
LTV at origination over 70%	0.066	-0.314	0.120	-0.662
	[0.541]	[1.404]	[0.722]	[0.616]
Current DSCR	-0.454	-1.106**	-0.095	-0.512
	[0.340]	[0.506]	[0.472]	[0.728]
Occupancy rate	-0.037***	0.009	-0.020	-0.061***
	[0.009]	[0.031]	[0.015]	[0.015]
Term	-0.045***	-0.057***	-0.030***	-0.049***
(months)	[0.009]	[0.022]	[0.011]	[0.016]
Amortization term	-0.000	0.004	-0.000	-0.001
(months)	[0.001]	[0.003]	[0.002]	[0.003]
Construction vintage (1=yes)				
1970-1979	0.265	-2.362***	1.107	0.761
	[0.491]	[0.799]	[0.805]	[0.786]
1980-1989	0.881**		1.689*	1.044*
	[0.444]		[0.943]	[0.618]
1990-1999	0.183	-2.511**	0.398	0.320
	[0.585]	[1.170]	[1.031]	[0.849]
2000 or after	0.338	-2.619**	0.373	0.598
	[0.467]	[1.171]	[0.804]	[0.856]
Constant	0.265	-2.362***	1.107	0.761
	[6.327]	[15.971]	[10.506]	[11.665]
Property type fixed-effects	yes	N/A	N/A	N/A
MSA fixed-effects	yes	yes	yes	yes
Vintage fixed-effects	yes	yes	yes	yes
Number of loan-months	43,311	7,879	12,716	17,723
Number of loans	1,241	226	349	506
Pseudo R-squared	0.27	0.46	0.19	0.38

Notes: Robust standard errors clustered at the loan level in brackets. Significance at the 0.10, 0.05, and 0.01 level is indicated by *, **, and *** respectively.