HOW HURRICANES SWEEP UP HOUSING MARKETS: EVIDENCE FROM FLORIDA

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Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the authors and do not reflect the position of Zillow Group. We thank Richard Carson, Julie Cullen, and Mark Jacobsen for insightful discussions. We thank Rebecca Fraenkel for initial data extractions. We have also benefited from comments and suggestions by Judd Boomhower, Gordon McCord, and seminar participants at UCSD, Wharton Risk Center, and Camp Resources 2019. All errors are our own. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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ABSTRACT

This paper examines the impacts of hurricanes on the housing market and the associated implications for local population turnover. We first characterize the post-hurricane equilibrium dynamics in local housing markets using microdata from Florida during 2000-2016. Our results show that hurricanes cause an increase in equilibrium prices and a concurrent decrease in transactions in affected areas, both lasting up to three years. Together, these dynamics imply a negative transitory shock to the housing supply as a consequence of the hurricane. Furthermore, we match buyer characteristics from mortgage applications to provide the first buyer-level evidence on population turnover. We find that incoming homeowners in this period have higher incomes, leading to an overall shift in the local economic profile toward higher-income groups. Our findings suggest that market responses to destructive natural disasters can lead to uneven and lasting demographic changes in affected communities, even with a full recovery in physical capital. Joshua S. Graff Zivin University of California, San Diego 9500 Gilman Drive, MC 0519 La Jolla, CA 92093-0519 and NBER jgraffzivin@ucsd.edu Yanjun Liao University of Pennsylvania 3819 Chestnut Street St. Leonard's Court, Suite 130 Philadelphia, PA 19104 yjpenny@wharton.upenn.edu

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1 Introduction

Approximately fifteen tropical cyclones make landfall across the globe each year, including an average of three in the United States where they are concentrated along the Gulf and east coasts. These storms, known as hurricanes in the United States, are characterized by strong winds and heavy rainfall that can generate substantial damage to physical infrastructure. The frequency and intensity of hurricanes, which are fueled by warm ocean temperatures in the tropics, are forecasted to increase substantially under climate change, along with the economic damages that accompany them.

While the initial damage from hurricanes is physical, it can lead to a wide range of behavioral responses that tend to amplify local economic consequences. These include disinvestment from affected regions, diminished employment opportunities, and out-migration, among others.[1] If real estate markets are well functioning, all of these impacts should be capitalized into housing values (Rosen, 1974), thereby providing a succinct measure of total economic damages. This approach has been taken by many studies focused on the impacts of a singular extreme storm, e.g. Hurricanes Andrew, Katrina, and Sandy (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Kousky, 2010; Atreya et al., 2013; Bin and Landry, 2013; Ortega and Taspınar, 2018; Gibson and Mullins, 2020).

In this paper, we estimate the impact of hurricanes on housing values for all storms that make landfall in Florida between 2000 and 2016. Our focus on all storms is substantively important for two reasons. First, we are able to assess the economic impacts of more typical storms that are not complicated by the supply shortages, rebuilding bottlenecks, and philanthropic investments that generally accompany severe events. Second, our larger sample size over a longer period of time allows us to exploit an identification strategy that better captures general equilibrium effects. These are especially important since hurricanes are likely to impact housing supply as a result of destruction as well as housing demand as homeowners and businesses learn more about risks in a particular location.[2]

[1] Past literature has examined household responses (Gagnon and Lopez-Salido, 2014; Bleemer and Van der Klaauw, 2017; Gallagher and Hartley, 2017; McCoy and Zhao, 2018), migration patterns (Paxson and Rouse, 2008; Boustan et al., 2017), industry and labor market consequences (Groen and Polivka, 2008; McIntosh, 2008; Belasen and Polachek, 2009; Deryugina et al., 2018; Seetharam, 2018), macroeconomic growth (Skidmore and Toya, 2002; Hsiang and Jina, 2014; Strobl, 2011), and government spending (Deryugina, 2017).

[2] This paper is also closely related to the small literature that examines the impacts of wars, earthquakes, and flooding on local economic activity through the destruction of capital and infrastructure

Our rich transaction-level data also allow us to examine the implications of these adjustments on local demographics. Even if price effects are transient, changes in the composition of neighborhoods can have long-lasting impacts by altering the distribution of rents associated with locally circumscribed access to economic opportunities and amenities (Kling et al., 2005, 2007; Chetty et al., 2016). To our knowledge, this paper is the first to present micro-evidence directly linking demographic changes to home transactions in response to local environmental shocks.

Our analysis is based on hurricane data from the National Oceanic and Oceanographic Association (NOAA) along with a detailed housing dataset that combines transaction records and county tax assessments. The transaction data include 95% of all housing transactions within the State of Florida. The repeated tax assessments over time provide rich information on hedonic characteristics for each parcel, thereby allowing us to infer characteristics of transacted homes with a high level of accuracy. As such, this dataset allows us to identify and track individual parcels over time, observing most transactions and major renovations that took place between 2000 and 2016.

Our estimation strategy is unique in the literature, combining a staggered difference-in-differences framework that exploits the randomness in the paths and timing of hurricanes with a repeat sales model that ensures credible identification of within-home price changes. Treatment for an individual parcel is defined as being exposed to hurricane-strength wind speed, independent of damage to that particular parcel. We find that home prices increase in exposed areas in the three years following a hurricane. Compared to unexposed areas, home prices in exposed areas are 5% higher on average during this period, with a peak of 10% in the second year. This effect is identified in two models. The first uses variation within census tract while controlling for property characteristics, seasonality, and differential economic growth across counties. The second employs parcel fixed effects and therefore restricts the identifying variation to result from repeated sales of the same property. The estimates are very similar across the two models, providing strong evidence that the price effect is mainly driven by within-home appreciation rather than a shift in the composition of transacted homes.

We also find that the transaction probability of homes in exposed areas falls by 0.6 percentage points or 6% of the baseline probability. The timing of this quantity effect is similar

(Ikle, 1951; Davis and Weinstein, 2002; Miguel and Roland, 2011; Gignoux and Mené ́ndez, 2016; Feigenbaum et al., 2017; Kocornik-Mina et al., 2020).

to that of the price effect: both last around three years before returning to the baseline. Taken together, they suggest that the housing markets within exposed areas experience a temporary negative supply shock. The duration of this effect is consistent with the time it takes for hurricane victims to seek financial aid from insurance companies or federal agencies, and to eventually restore any substantially damaged homes to habitable or sellable conditions.[3]

While the adjustment in the market equilibrium appears to be transitory, our analysis suggests that it generates lasting impacts on local demographics. Using the subset of our housing transactions that can be matched to Home Mortgage Disclosure Act (HMDA) records, we show that the average income of new buyers increases nearly proportionally to the rise in home prices.[4] In subsequent years, transacted prices and buyer incomes return to baseline levels but not below, yielding a long-term stock effect whereby more than 25% of homes are occupied by households with a higher income than before the hurricane arrived. On the other hand, we do not find any major changes to the racial, ethnic, or gender profiles of buyers, suggesting that the socio-demographic characteristics of neighborhoods are quite stable in the face of these housing market shocks. The distributional impacts we measure are of direct relevance to any assessments of the equity impacts of hurricanes, and they provide a unique opportunity to explore the implications of gentrification in a causal framework.

The remainder of the paper is organized as follows. Section 2 describes the data, Section 3 develops our estimation framework, Section 4 reports and interprets the results, and Section 5 concludes.

2 Background and Data

We have two objectives in this paper: first, to examine the equilibrium adjustments in the housing market following a hurricane; second, to understand the implications for population turnover. The first objective requires data that represents the universe of transactions, and the second requires demographic information on the home buyers. We build a comprehensive

[3] Housing shortages of this nature have been increasingly identified by media reporting on recent hurricane events. See, for example, the Wall Street Journal's coverage of the impact of Hurricane Irma in Florida Keys (https://www.wsj.com/articles/hurricane-irma-destroyed-25-of-homes-in-florida-keys) or that of Hurricane Florence in North Carolina (https://www.wsj.com/articles/hurricane-florence-creating-housing-shortage-for-displaced-north-carolinians).

[4] These transactions involve properties with similar home characteristics and price dynamics to the entire market.

dataset that combines Florida hurricane exposure at the parcel level, housing transactions, tax assessments, and mortgage-holder demographics. This section gives an overview of the background and data for this study.

2.1 Florida Housing Market

Florida is the third most populous state in the U.S, and it is home to a large number of seasonal residents and retirees. Racial and ethnic composition varies considerably across locations within the state. South Florida has a large Hispanic population, while the panhandle has the state's highest concentration of Blacks (see Figure A5 for the demographic composition in Florida counties and nearby states based on the 2010 Census). Florida has a similar percentage of family households[5] as surrounding states. Given its prominent tourism industry, the homeowner vacancy rate (2-6%) and the rental vacancy rate are significantly higher than those of nearby states (see Figure A6 for statistics on family and housing in Florida counties).

Our primary source of housing data is the Zillow Transaction and Assessment Dataset (ZTRAX). The data cover Florida housing transactions between 2000 and 2016, accounting for around 95% of all transactions over this period. Each transaction record contains information on the timing of the sale, transaction price, mortgage profile (including loan amount and lender's name), location, as well as buyers' and sellers' names. We exclude three types of transactions where the price likely deviates from the home's market value: (1) non-arm's-length transactions[6]; (2) foreclosure sales[7]; and (3) transactions that involve multiple homes on different parcels.

We also obtain parcel-level[8] assessment records over the same period from ZTRAX, which are originally generated by the county assessor's offices. The assessment data contain

[5] A family household is a household maintained by a householder who is in a family.

[6] An arm's length transaction is one in which the buyers and sellers act independently and do not have any relationship to each other. An example of a non-arm's-length transaction is one between family members, where the price is often lower than market value. We rely on a combination of Zillow's internal code and the type of deed to determine the nature of the transaction.

[7] Foreclosed properties are often sold at substantially lower prices than comparable non-foreclosure sales, partly because lenders have an incentive to sell them quickly. For example, Campbell et al. (2011) finds an average foreclosure discount of 27% in Massachusetts.

[8] A parcel is also known as a lot or a plot. It is a defined piece of real estate, usually resulting from the division of a large area of land.

an essential set of hedonic characteristics for each parcel, including square footage, year built and remodeled, lot size, number of rooms, number of bathrooms, number of units, and land use codes. We use land use codes to group homes into three property types based on land use classifications in county tax assessments: single-family residence (69.7% of all sample transactions), condominium (24.1%), townhouse (6.2%).[9] Importantly, we observe multiple assessments for a single parcel and hence can track changes in these characteristics over time. The transaction and assessment datasets are matched by parcel and assessment year to ensure the condition of each property at the time of transaction is accurately reflected in the data.

The data contain precise geographic coordinates for each parcel.[10] This has two major advantages. First, it allows us to determine the hurricane exposure of any home by directly calculating its distance from a hurricane track, as described below. Second, we can use the coordinates in conjunction with detailed shapefiles[11] to accurately identify the census tract[12] for each parcel. This in turn allows us to match housing transactions to mortgage records from HMDA with high accuracy, ultimately enabling us to exploit fine geographic variation in our estimation.

Figure A1 plots the monthly median price by home type in the top panel. Median home prices experienced large fluctuations during our study period – starting around $100,000 in 2000, rising to a peak of more than $200,000 in 2007, declining back to $100,000 in 2010-2012, before gradually climbing upward as the economy recovered from the financial crisis. The lower panel shows that, conversely, the composition of transacted property types remained stable over time. Since we match buyers with mortgages (henceforth "borrowers") to HMDA records, we also report median prices for the subset of all Zillow borrowers and the share of such sales (see Figure A2 in the Appendix). The pattern of prices closely resembles that for all buyers, but the share of sales with a mortgage decreased from 75% in 2007 to 50% in 2010 as the financial crisis unfolded.

[9] Other common terminology for these are respectively single-family detached, multi-family, and single-family attached.

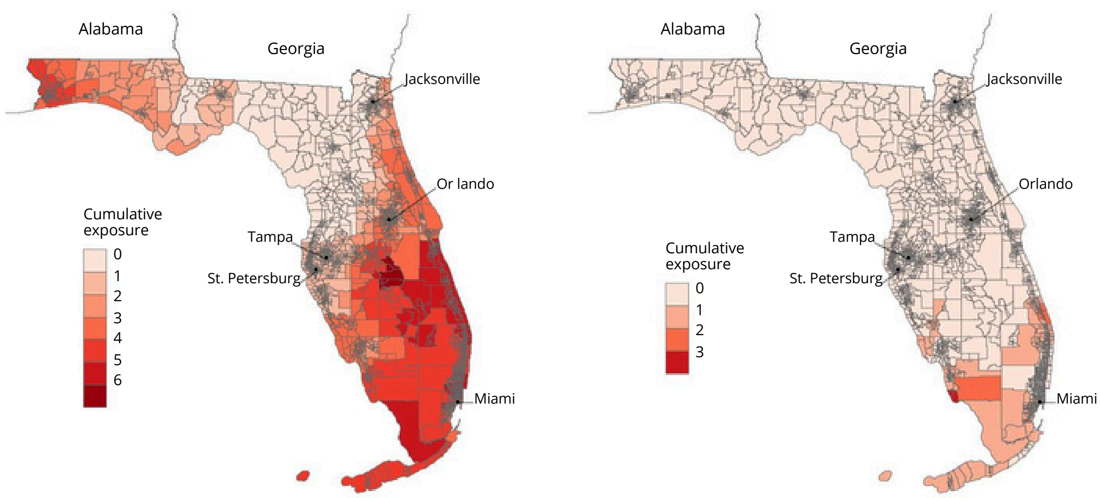
[10] The longitude and latitude measures are reported with a precision of five decimal places (or 1.11 meter at the equator).

[11] Source: TIGER/Line Shapefiles, Census Bureau. Available at https://www.census.gov/geo/maps-data/data/tiger-line.html.

[12] Florida's 67 counties are comprised of more than 4200 census tracts.

Figure 1: Florida Hurricane Exposure by Census Tract, 1992-2017

(a) All hurricanes (b) Category 3+



Notes: these figures depict hurricane exposure by census tract across Florida. Panel (a) shows the number of times each census tract was exposed to hurricane-strength wind speed (64 nautical miles per hour and above) and Panel (b) shows the number of times each was exposed to category 3 wind speed (96 nautical miles per hour and above) between 1992 and 2017. Calculations are based on hurricane track point measurements and census tract population centroids.

2.2 HurricaneHistoryandExposure

Florida is located on the peninsula between the Gulf of Mexico and the North Atlantic, and its unique geography has exposed it to more hurricanes than any other U.S. state. A tropical cyclone is classified as a hurricane when the 1-minute sustained wind speeds reach 64 nautical miles (kn) per hour (or 74 mph). Between 1992 and 2017, a total of fifteen hurricanes swept past parts of Florida. Of these, five reached wind speeds corresponding to Category 3 and above within Florida.[13]

Each hurricane is recorded in six-hour intervals in the Tropical Cyclone Extended Best Track dataset.[14] Each observation consists of the geographic coordinates of the center, maximum sustained wind speed, and maximum radial extent of 34, 50, and 64 kn wind speeds.

[13] Thresholds for the Saffir–Simpson hurricane wind scale are: Category 1, 74-95 mph; Category 2, 96–110 mph; Category 3, 111–129 mph; Category 4, 130–156 mph; Category 5, 157+ mph.

[14] Data source: Demuth et al. (2006). Available at http://rammb.cira.colostate.edu/research/tropical-cyclones/tc-extended-best-track-dataset/.

Following the approach in Deryugina (2017), we approximate the full hurricane path by linear interpolation between consecutive observations.[15] Since the maximal reach radius of 96 kn is not provided in the dataset, we construct a measure by estimating a nonlinear relationship between wind speed and its reach radius (see Appendix B.1 for details on this procedure).

Throughout this paper, we define hurricane exposure by whether a location was ever within the reach of a 64 kn wind speed radius along a hurricane path. Severe exposure is similarly defined but with a 96 kn wind speed.[16] This requires proximity to the hurricane path as well as high sustained wind speed at that stretch of the path. In our hurricane sample, the average radius of 64kn wind speed is 95 miles, and that of 96 kn wind is 45 miles. It is important to note that our exposure measure does not directly indicate actual damage to a house. Homes lying outside of the hurricane-strength wind speed radius, for example, might also be affected by heavy precipitation, while some homes inside might sustain little damage due to factors such as advantageous topography or more resilient building materials. Our estimates therefore capture the combined impacts of the damage to a subset of housing and the general equilibrium effect from the ensuing housing shortage.

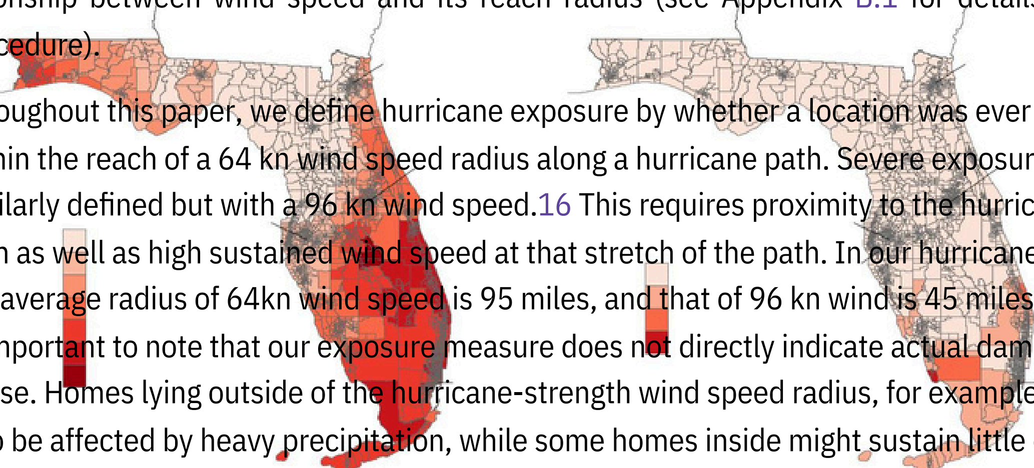


Figure 1 shows the geographic distribution of hurricane events by census tract, defining exposure using their population-weighted centroids. In Panel (a), we see that approximately 90% of tracts experience at least one hurricane event between 1992 and 2017, with high variation in frequency across locations. We plot the distribution of severe exposure events separately in panel (b). This set of locations is much more limited (16%) and concentrated in south Florida. The average census tract experiences 2.6 hurricane events and 0.16 severe exposure events between 1992 to 2017.

[15] We also assume the hurricane center travels with constant speed between two consecutive observations, while wind speed and radii change linearly with time. See Appendix B.2 for more details on the interpolation procedure.

[16] We use the category 3 speed threshold both to be in line with previous literature, and because we do not believe the difference between the categories 1 and 2 thresholds is sufficient to produce measurable differences in outcomes. Category 4 wind speeds, on the other hand, almost never reach Florida shores over our hurricane time period.

2.3 HomeMortgageDisclosureAct

The Home Mortgage Disclosure Act (HMDA), enacted by Congress in late 1975, requires all large financial institutions[17] to disclose all of their home lending activity every year. The loans reported were estimated to represent approximately 90 percent of closed-end home lending nationwide in 2016 (Dietrich et al., 2018). These records are made publicly available to promote mortgage market transparency.[18] The HMDA data provide the date, property location (census tract), mortgage loan amount, application purpose (purchase, improvement, or refinancing), mortgage lender's name, and applicant demographics including annual income, gender, and race.

We merge the subset of successful loan applications for purchases from HMDA to our transaction data. Similarly to Bayer et al. (2016), matches are based on the year of each transaction, the census tract of the home, the loan amount (in 1000s), and the lender name.[19] The full procedure ultimately matches a little more than half of the original Zillow transactions with a mortgage, with no significant yearly variation in pairing success.[20] This match rate is similar to Bayer et al. (2016), who merge HMDA data to the universe of housing transactions in the Bay Area. The merged data enable us to look at the evolution of borrower demographic characteristics following hurricane events.

3 Econometric Framework

This section describes our research design. The first part of our analysis concerns post-hurricane adjustments in the housing market. We study two main outcomes that characterize the equilibrium: housing price and transaction probability. We model each separately with different units of analysis, but both specifications ultimately rely on the randomness of hurricane paths and their timing as the identifying variation. In the second part of the analysis,

[17] By 2020 definition, a large financial institution is one with more than $47 million in assets. This threshold is subject to yearly revision.

[18] See http://www.ffiec.gov/hmda for more details.

[19] See Appendix C for detail on the matching procedure.

[20] There are two main reasons why the match rate is not closer to 80%. First, because we cannot distinguish between mortgages of the same amount issued by the same lender in the same census tract in a given year, we drop all such observations. Second, we keep only high-quality matches based on lender names.

we use the framework from the housing price model to examine population turnover.

3.1 Housing Price Model

We model the transaction price of a home as follows:

$$\log(Price_{imy}) = \sum_{\tau=-6}^{10} \beta_\tau Hurr^{\tau}_{imy} + \gamma' HouseChar_{iy} + \delta_{ht} + \delta_{hm} + \delta_{hcy} + \varepsilon_{imy} \quad (1)$$

where i denotes an individual transaction, m is the month and y the year of the transaction, h is the type of the transacted property, and t is the census tract and c the county of the property.[21] The unit of analysis is an individual transaction. $\log(Price_{imy})$ is the log of the price in transaction i occurring in month m of year y.[22] $Hurr^{\tau}_{imy}$ is a set of indicators specifying whether the transaction occurs τ years after the house was exposed to a hurricane ($\tau = 0$ refers to transactions in the first twelve months after a hurricane, $\tau = 1$ the next twelve months, and so on; a negative τ indicates the transaction happens before the hurricane). $HouseChar_{iy}$ is a set of house characteristics commonly used in hedonic models, including lot size, structural age, effective age,[23] number of stories and number of bathrooms. We control for the latter two characteristics flexibly using a set of value bins. Remodels can lead these variables to change over time for a given parcel, and we assign characteristics from the latest assessment that precedes the transaction.

We also account for both fixed and time-varying regional differences in housing attributes and local amenities by using a set of geographic and temporal fixed effects. δ_{ht} denote census tract fixed effects, which absorb cross-sectional correlations in the likelihood of being hit by a hurricane and time-invariant local amenities, such as proximity to the coast. δ_{hm} denote month-of-year fixed effects that control for the seasonality in both home prices and the timing of hurricanes. It is also important to account for housing market booms and busts during our sample period, especially given their uneven impacts across markets (Ferreira and Gyourko, 2012). We use county-by-year fixed effects (δ_{hcy}) to control for changing macroeconomic

[21]Census tracts and counties are defined according to the 2000 census definition throughout to maintain geographic consistency across time.

[22]Similarly to most of the hedonic pricing literature, we use the log of the transaction price to address the skewed distribution of prices, as well as to obtain plausible effects over a wide range of price levels.

[23]The time (in years) since the last major remodel.

conditions at the county level. Finally, all fixed effects are also interacted with the property type (h).

The key variables of interest are the hurricane indicators. They are constructed based on the definition of hurricane exposure for individual parcels as described in Section 2.2.[24] The identification of the causal effect of hurricanes on the housing market relies on the exogeneity of storm paths and timing. Specifically, the identifying assumption is that, conditional on the set of controls, these indicators are orthogonal to any idiosyncratic shocks to transaction prices:

$$E[\varepsilon_{imy} \times Hurr\tau i \,|HouseChar_{i}, \delta_{ht}, \delta_{hm}, \delta_{hcy}] = 0 \quad \forall \tau.$$

Our estimation is thus based on a staggered difference-in-differences (DD) framework with many hurricane treatments at different times.[25] Areas exposed to a hurricane are compared to unexposed areas before and after the hurricane in a repeated cross-section of housing transactions.

There are two main advantages to using this set of event time indicators rather than a single indicator as in a standard DD specification. First, the post-hurricane indicators estimate dynamics flexibly rather than imposing any restrictions on the trend or duration of the market adjustments. These dynamics provide important insights into the adjustment process. Second, this approach allows us to assess the credibility of our DD design by estimating and comparing pre-hurricane trends directly.

Throughout this paper, we cluster standard errors at the county level to allow for correlations in the idiosyncratic shocks to all transactions occurring in the same county over the entire sample period. Furthermore, we estimate the following four variants of our main specification.

Repeat sales. Hurricanes may change the composition of transacted homes. Equation (1) used an exhaustive set of controls to greatly limit the extent to which our estimates could be driven by compositional shifts, but to fully eliminate within-tract selection of transacted

[24] Specifically, we calculate exposure to each of the 15 hurricanes for each transacted property. We then construct the hurricane indicators based on the transaction timing relative to all hurricane events the house is exposed to.

[25] This design has been used by several studies of the economic impacts of natural disasters such as Belasen and Polachek (2009), Strobl (2011), Gallagher (2014), Hsiang and Jina (2014), Deryugina (2017), and Boustan et al. (2017)

attributes, we replace the census tract fixed effects (δ_{ht}) with parcel-level ones (δ_p):

$$\log(Price_{imy}) = \sum_{\tau=-10}^{36} \beta_\tau Hurr^{\tau}_{imy} + \gamma' HouseChar_{iy} + \delta_p + \delta_{hm} + \delta_{hcy} + \varepsilon_{imy} \quad (2)$$

This approach restricts the identifying variation to sales of properties that transact more than once over our time period, and holds all time-invariant characteristics fixed (Cannaday et al., 2005; Hallstrom and Smith, 2005; Harding et al., 2007).[26]

Wind intensity heterogeneity. We explore the heterogeneous effects of different wind intensities, as we expect stronger winds to result in more severe damages to the housing stock. Specifically, we split the sample into areas exposed to Category 1-2 wind speeds and those exposed to the faster winds of Category 3 and above storms, as discussed in Section 2.2. We estimate the dynamics of both groups simultaneously using interactions of pooled category indicators with event time indicators.

Other outcome variables. Understanding any systematic shift in housing or buyer characteristics after a hurricane is important for us to assess the nature of market responses to the disasters. To do so, we replace the outcome variable in equation (1) with other characteristics of interest, including lot size and buyer income.

Standard DD. To summarize our results, we also estimate a standard DD model, defining treatment as exposure to a hurricane in the 36 months preceding a sale. The identifying assumption for this specification is the same as that for the event study specification, but we rely on the evidence from the results of the event study to determine the length of the housing market adjustments.

3.2 Transaction Probability Model

Market equilibria are characterized by both prevailing prices and quantities. At the individual home level, transacted quantity is either zero or one. Formally, let $1(Transacted)_{py}$ be an indicator of whether a transaction record exists for parcel p in year y. We model its

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[26] This approach is used to generate several major house price indices, including the Case-Shiller Index, Federal Housing Finance Agency's (FHFA) monthly House Price Index, and CoreLogic's LoanPerformance Home Price Index.

relationship to hurricane events as follows:

$$1(Transacted)_{py} = \sum_{\tau=-6}^{10} \beta_\tau Hurr^{\tau}_{py} + \gamma' HouseChar_{py} + \delta_p + \delta_{hy} + \delta_{cy} + \varepsilon_{py}. \quad (3)$$

where p, h, y, and c denote parcel, property type, year, and county as before. Here, the unit of analysis is a parcel-year. We construct a balanced panel of parcels that have ever been transacted during our sample period.[27] We treat all parcel-year observations without a transaction record as having no transaction. This approach introduces measurement error if there are unreported transactions, which could lead to biased estimates if the missing pattern is endogenous to or correlated with hurricane events. In our analysis, we drop all observations for counties that did not start reporting transactions until after the beginning of our sample period.[28] We exclude all parcels with structures built after 2000, so that this panel consists of the transacted housing stock that was present since the beginning of the study period. Note that because Florida is subject to tight land supply due to land use and geographic constraints (Saiz, 2010), new developments are relatively scarce, especially in densely populated urban areas.

We construct the panel by year rather than by month because of computational constraints. As most hurricanes between 2000 and 2016 occurred in August, we set event years to begin in August and end in July. For example, a transaction in an area exposed to Katrina (August 2005) has its year 0 indicator turned on only if it occurs between August 2005 and July 2006. This ensures a correct event year classification for the vast majority of transactions, an uncontaminated event year -1 indicator, and a small and predictable downward bias in the estimate of the event year 0 indicator.[29]

Despite the differences in the data structure, this model shares many similarities to the previous one on housing prices. We deploy the same event-study specification, which also controls for time-varying property characteristics observed from repeated assessments. Be-

[27] As discussed in Section 2, we also exclude three types of transactions that might not reflect market conditions.

[28] These counties drive an insignificant fraction of Florida's housing market activity, with combined sales accounting for less than 1% of total sales over the period in which we observe sales in all counties (2005-2016).

[29] The year 0 indicator is slightly attenuated because it captures some transactions in areas affected by four hurricanes in the couple months before these actually took place. These are Wilma (October 2005), Frances and Jeanne (September 2004), and Matthew (September 2016).

cause the threat to identification is similar to that from the previous model, we include parcel fixed effects, county-by-year fixed effects, and type-by-year fixed effects. As such, our identification assumption is also similar to that of our prior model and requires that:

$$E[\varepsilon_{py} \times Hurr^{\tau}_{p} | HouseChar_{py}, \delta_{p}, \delta_{ty}, \delta_{cy}] = 0 \quad \forall \tau.$$

Our dataset includes three main parcel types: single-family residence, condominium, and townhouse. Since substitutability between these may be limited, we also estimate this transaction probability model separately for each type. The type-by-year fixed effects are eliminated in these estimations. Standard errors are clustered at the county level throughout.

3.3 Variation in Hurricane Exposure

Figure 1 shows that hurricane exposure in Florida is quite dispersed geographically. In this section, we take a closer look at variation over time as well as the relative contribution by individual hurricanes.

In our regression models, we use a set of event time treatment indicators to estimate dynamics of various outcome variables. In Table A9, we tabulate the means of these indicators in the price model and show the contribution of each hurricane to treatment saturation. The share of treated transactions fluctuates between 8 and 12% across event years. In Table A10, we generate a similar variation profile for the transaction probability model as specified in equation (3). Again, the total treated share is relatively stable at around 10%. Together, these patterns underscore the similarities in the identifying variation used in the two models.

Lastly, we examine variation in exposure to severe storms, which we define as experiencing category 3 or greater wind speeds (Table A11). The fraction of transactions having been exposed to high wind speeds is small, less than 1% across all years. This greatly limits the statistical power available to estimate the heterogeneous effects of higher wind speeds. Further considering that the landfall of these storms is geographically clustered within south Florida[30] for which the parallel trends assumption is less likely to hold, these results will ultimately be interpreted more cautiously.

[30] See Figure 1.

4 Results

This section reports our results. We begin by estimating the post-hurricane dynamics in housing prices for areas affected by hurricanes while addressing potential composition effects in Section 4.1. Likewise, we estimate how transaction probabilities are impacted for parcels in these areas in Section 4.2. Together, these two outcomes characterize equilibrium shifts in the housing market as it recovers from hurricanes, and we further consider mechanisms in Section 4.3. In Section 4.4, we examine the implications of these market adjustments on local population turnover. In Section 4.5, we explore potential heterogeneity by hurricane intensity.

4.1 Post-Hurricane Price Dynamics

We begin by estimating the post-hurricane dynamics of housing prices following the event study specification in equation (1). This analysis is based on all valid transactions (henceforth "full sample") regardless of whether a mortgage is involved. The first two columns of Table A1 summarize the average price and home attributes in these transactions.

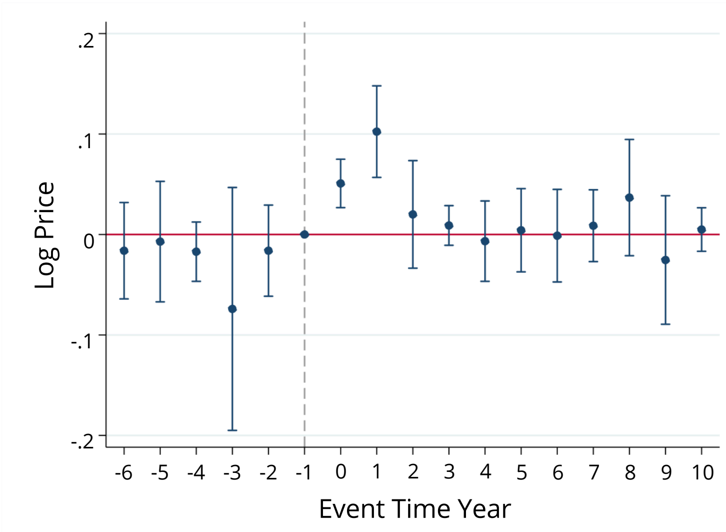
The estimated coefficients of event year indicators are plotted along with their 95% confidence intervals in Figure 2, and full results are reported in the first column of Table A12. None of the estimates for pre-hurricane indicators are statistically different from zero, supporting our choice of fixed effects to control for preexisting differences in average census tract prices, seasonality, and county-specific dynamics. Our event year 0 and 1 estimates suggest that hurricanes result in increases in home prices of 5% in the first and 10% in the second twelve-month periods after the strike. This surge in prices appears to end sometime in the next twelve-month period (event year 2) as the estimated increase relative to unaffected homes drops to 2% and is no longer statistically significant. All later event year estimates are small and not statistically distinguishable from zero. Together, these suggest a temporary surge in prices in the three years immediately following a hurricane in exposed areas. In Table A3, we provide additional estimates using a standard difference-in-differences specification, where we define a transaction as treated when it occurred in event year 0-2. Consistent with the event study, the estimate suggests an average three-year price increase of 5% for the entire market. When we estimate the price change separately for each of our three property type (single-family residence, condominium, townhouse) we find that the increase is the largest for condominia, at 8.5%.

A possible reason for this price increase could be a shift in the distribution of transacted homes: in the aftermath of a hurricane, homes with greater hurricane resistance or desirability based on any characteristics which are unobserved in the data, may be more likely to be transacted. In the extreme, the price surge could be entirely driven by such compositional shifts without reflecting changes in any individual home's price. To investigate this further, we re-estimate our price model with the inclusion of parcel fixed effects and restrict the sample to only include homes that were transacted at least once both before and after a hurricane. Results are plotted in Figure 3 and reported in the second column of Table A12. Standard errors are larger because of the smaller sample size, possibly as well as the more exhaustive set of fixed effects. On the other hand, this specification produces more stable parallel trends, and more importantly, the previous patterns are closely reproduced and of larger magnitude. Our point estimates imply that properties on average sold at 5% higher prices in the event year immediately following the hurricane, as much as 14% in the next event year, and 8% in the third event year. These results again suggest that homes sold in the first two to three years after a hurricane in exposed areas appreciated relative to when they were sold outside of this post-hurricane window.

We next perform robustness checks using different subsets of the full sample to address several concerns. First, comparing home price dynamics across the exposure boundary could be problematic if the boundary is measured with noise or if there are large spillover effects from the more exposed areas to nearby areas. To address this concern, we drop transactions that are within 10 miles of either side of an exposure boundary and estimate the standard DD specification. Results are reported in column (1) of Table A4. The estimate suggests an average price increase of 7.7% in the three years after a hurricane, which is larger than the main results. This shows our finding of a price increase is robust to excluding the comparison of transactions near the boundary.

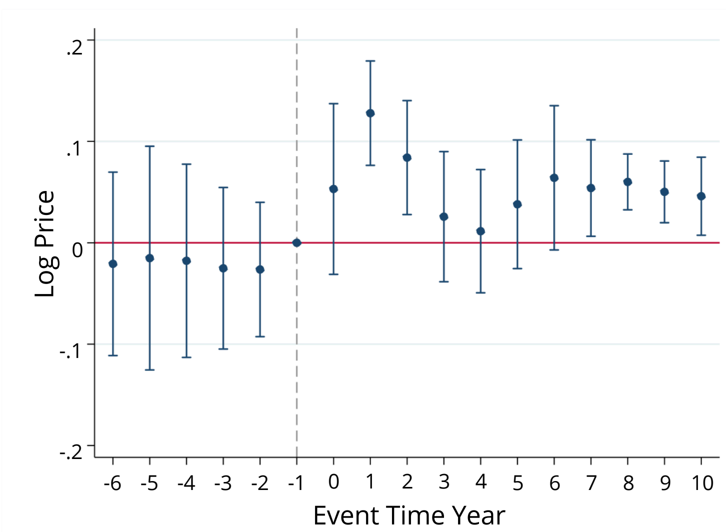
Another concern is that our sample contains hurricanes that occurred within three years of each other. Some places were hit a second time while they were still adjusting from a first hurricane hit. In all previously discussed specifications, we let the event time indicators capture all events for transactions affected by multiple hurricanes. However, this could result in misspecification if the composite effects of the two events are not the linear combination of their respective dynamics. To determine whether our results are affected, we re-estimate the main price regression but drop all transactions of properties which experi-

Figure 2: Hurricane Effects on House Prices – Full Sample



Notes: estimates from equation (1) are plotted with their 95% confidence intervals. The results are based on the full sample of Florida home sales (N = 7,216,109). The model controls for standard hedonic variables and census tract, month, and county-year fixed effects. Standard errors are clustered by county.

Figure 3: Hurricane Effects on House Prices – Repeat Sales



Notes: estimates from equation (2) are plotted with their 95% confidence intervals. The results are based on only parcels with repeated transactions appearing in both pre- and post-hurricane periods (N = 1,338,384). The model also controls for age and effective age at time of sale, and parcel, month, and county-year fixed effects. Standard errors are clustered by county.

enced more than one hurricane within three years.[31] As shown in column (2) of Table A4, the estimate is very similar to the main estimates. Finally, we conduct a last robustness check to address a broader concern regarding the property of our multi-way fixed-effect estimator under dynamic treatment effects (see, for example, Goodman-Bacon (2018)). Specifically, we construct a sample based on all transacted properties that were either never affected by a hurricane or affected by a subset of hurricanes not occurring in three consecutive years.[32] This ensures that the three-year dynamic responses to earlier hurricanes are not used as part of the control for later hurricanes. The estimates based on this sample are reported in column (3) of Table A4. We find an average increase in home prices of 6.5% in the three years post-hurricane. This also suggests that biases from overlapping treatment dynamics are not likely to be the main driver of our results.

4.2 Post-Hurricane Dynamics of Transaction Probability

We now turn our attention to transaction probabilities to better understand the mechanisms behind the increase in home prices. We estimate these post-hurricane dynamics using equation (3). As described in Section 3, we construct a balanced panel of parcels where each observation is a parcel-year with an associated indicator for whether or not a transaction occurred in that year. The balanced panel approach requires that our analysis focus only on parcels with structures built before 2000. We report summary statistics for this panel in Table A2.

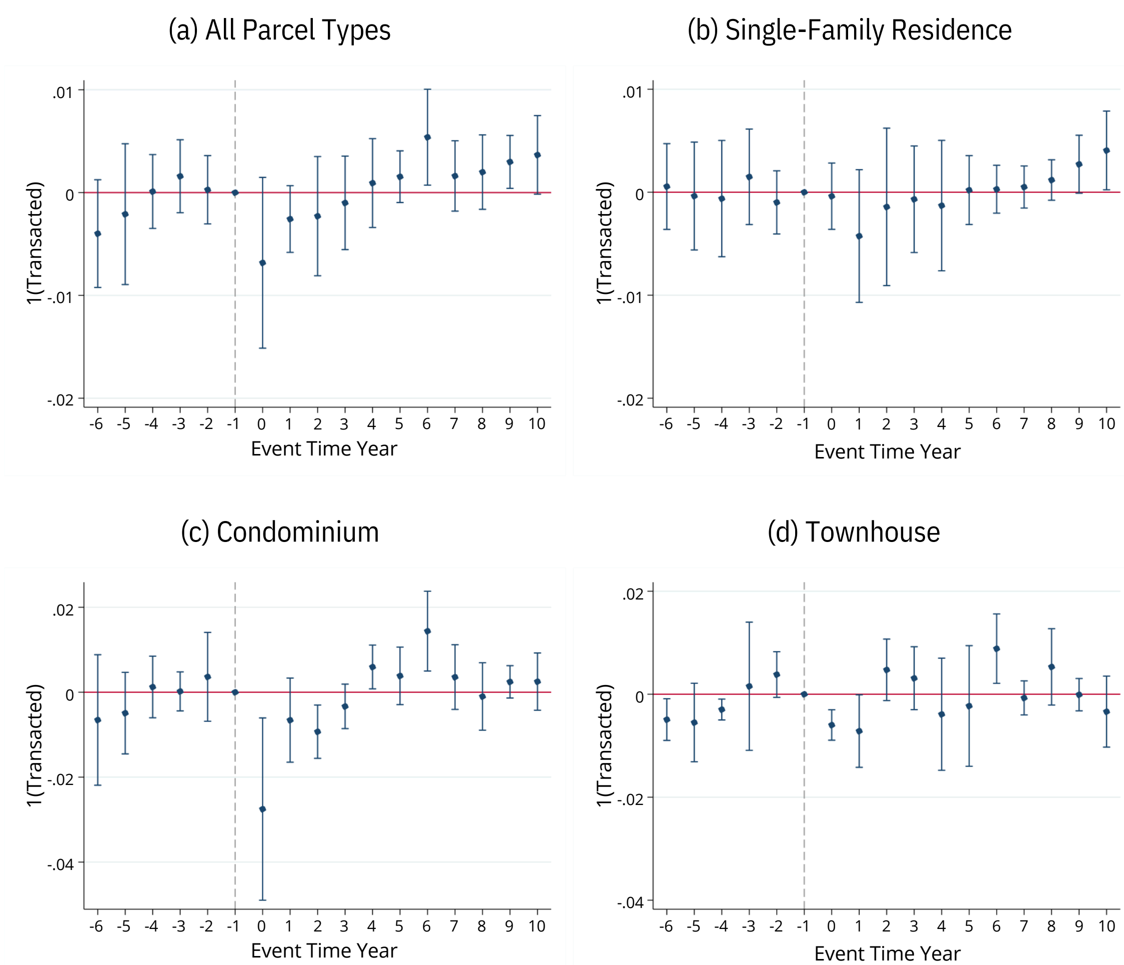
The estimates from the full sample are plotted along with their 95% confidence intervals in Panel (a) of Figure 4 (and are also reported in the third column of Table A12). The baseline probability of transaction is around 10%. Again, we see a stable pre-trend with all pre-hurricane indicators being statistically indistinguishable from zero. In event year 0, the estimate indicates a drop of 0.7 percentage points, or seven percent of the baseline probability. The effect shrinks in the next two event years and gradually returns to the baseline.

As shown in Table A2, the characteristics of the three property types are quite different and substitutability between them may be limited. Considering the wide confidence intervals for these estimates, each property type likely experiences different equilibrium dynamics.

[31] Transactions that occurred before the consecutive hurricanes are also dropped to avoid substantial geographic imbalance in the remaining sample of transactions.

[32] These hurricanes are Andrew, Opal, Irene, Dennis, Katrina, Wilma, and Irma.

Figure 4: Hurricane Effects on Transaction Probability by House Type



Notes: estimates from equation (3) are plotted with their 95% confidence intervals. Panel (a) plots the results based on all parcel types (N = 49,302,345), Panels (b)-(d) are based on single-family residence (N = 33,560,908), condominium (N = 12,832,339), and townhouse (N = 2,909,058), respectively. The model controls for effective age, parcel and county-year fixed effects. In Panel (a), the model also includes type-year fixed effects. Standard errors are clustered by county.

Therefore, we also estimate the model for each type separately, and report these results in Panels (b)-(d) in Figure 4.[33]

For single-family residences, which make up around 70% of Florida housing market transactions, we observe a small but negative effect that peaks at 5 percentage points in event year 1. None of the event year indicators are statistically significant at the 5% level, but the negative effects are significant at the 10% level in the first two years post-hurricane. In contrast, the changes in transaction probability we observe for the other two property types are statistically significant at conventional levels. Condominia, representing around 20% of transactions, are nearly 3 percentage points less likely to be transacted in event year 0, and still around 1 percentage point less likely to transact in the following two event years. Townhouses, which make up the smallest share of the market at under 10%, experience a transaction probability drop of just under 1 percentage point in the first two event years.

The standard DD estimates for all parcels and by property type are provided in Table A5. Aggregated over the three years immediately following a hurricane, our results reveal a 6.8% market-wide decrease in transaction probability. The heterogeneous effects range from a 23% decrease for condominia to a 3% decline for single-family residences, relative to the baseline. The large drop in transaction probability in the condominium market is particularly informative because it coincides with the largest increase in transaction prices, as we showed previously.

4.3 Mechanisms for Price and Transaction Probability Dynamics

In the previous sections, we show that areas hit by a hurricane see an increase in housing prices and a concurrent fall in transactions. These dynamics together are consistent with a negative supply shock. We further find that this shock is temporary, as both price and probability appear to respond for two to three years and eventually return to the baseline. It is worth noting that this does not imply that hurricanes only induce supply-side adjustments. In fact, localities exposed to hurricanes are likely to experience changes in housing demand through mechanisms such as people updating their beliefs about local disaster risks (Bin and Polasky, 2004; Hallstrom and Smith, 2005; Bin et al., 2008; Gibson and Mullins, 2020) as well as disruptions to local industries and labor markets (Belasen and Polachek, 2009; Seetharam, 2018). Our results should be viewed as net of these demand-side effects,

[33] This specification drops the property-type-by-year fixed effects, but is otherwise identical.

illustrating a general equilibrium adjustment. In this section, we further discuss the nature of the negative supply shock and consider a number of alternative explanations.

Hurricanes generate extreme winds and major flooding that can cause severe damage to buildings. As a result, part of the housing stock in exposed areas may become uninhabitable in the short run, driving part of the negative supply shock. But severe damage is also likely to lower transaction volume by making it very difficult to sell devastated property. At the same time, displaced homeowners may need to temporarily rent in unaffected neighboring regions (the costs of which are often eligible for insurance coverage and federal assistance). This increase in rental market demand could result in upward pressure on housing prices, in particular on condominia if a larger share of these are used as rental properties.

The timing of our measured impacts is also consistent with that of reconstruction. It takes time for homeowners to restore their homes to pre-disaster conditions. If their homes are properly insured, homeowners can obtain payouts relatively quickly. However, claim disputes and delays in damage assessment are common when insurance companies are overwhelmed by many claims.[34] Moreover, many homeowners seek financial relief from the government when their insurance coverage is insufficient.[35] This requires homeowners to navigate a highly complex and interlinked system of federal programs and bureaucratic processes that can take months and sometimes more than a year to result in some form of compensation.[36]

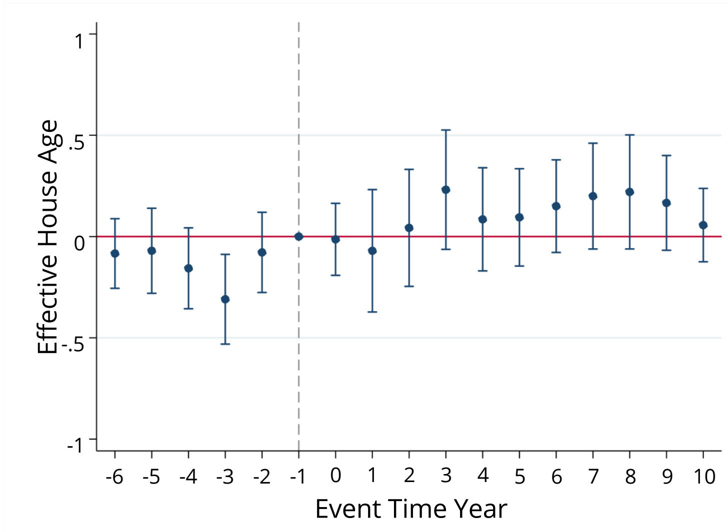
Even after financial disbursement from insurers and federal programs, the repairing and rebuilding process can take a long time. Anecdotal evidence suggests that post-disaster recovery is often hindered by a shortage of construction labor, with many finding that it takes at least 18-24 months to repair or rebuild their significantly damaged homes after a large loss. Notably, this duration is consistent with our observed effects on transaction probability and price, thus destruction and reconstruction provide a highly plausible explanation for the

[34] Assessing damage can be particularly difficult after a hurricane because wind damage is covered by homeowners' insurance, but flood damage is not, and hurricanes can cause both types of damages. After Hurricane Katrina, for example, there were multiple lawsuits over the extent to which damages should be covered.

[35] CoreLogic (2017) estimated that about 60% of homeowners do not insure their homes up to the full replacement value. Moreover, only 47% of homeowners living in 100-year floodplains have flood insurance.

[36] These include FEMA's Individual Assistance and SBA's Disaster Loan programs, and other state and local government programs (Kutz and Ryan, 2006; Hoople, 2013; Deryugina et al., 2018; Kousky et al., 2018).

Figure 5: Changes in Characteristics of Transacted Homes – Effective Age



Notes: estimates from a variant of equation (1) are plotted with their 95% confidence intervals. The dependent variable is effective house age, which is the number of years since last remodeled (if applicable). The results are based on the full sample of Florida home sales. The specification controls for census tract, month, and county-year fixed effects. Standard errors are clustered by county.

dynamics we observe. Below, we consider three additional potential mechanisms. Additional mechanism 1: quality improvement through rebuilding

The rebuilding process may not only restore, but actually improve the condition of a damaged home, thereby driving up its value. This could happen for a number of reasons. First, the rebuilding project is often subject to stricter building codes than prevailed during original construction.[37] Second, communities that participate in the National Flood Insurance Program (NFIP) must follow program rules regarding floodplain management that could also lead to substantial improvements in housing quality.[38] Lastly, hurricanes could fully destroy some structures in the poorest of conditions, sparing homeowners some of the demolition costs, and setting in motion a new construction process that would have eventually taken place anyway. The same could be true of more modest renovations, whereby an insurance

[37] Florida building codes have been updated multiples times over the sample period. A 2018 report on new residential building codes and enforcement systems by the Insurance Institute for Business & Home Safety gave Florida a rating of 95/100, the highest score among all the states it evaluated.

[38] In particular, all substantially damaged properties in 100-year floodplains must be elevated (Kousky, 2019).

payout provides an extra incentive for a remodeling that was already being considered.

We explore this possibility by examining whether the effective age of houses transacted after a hurricane is systematically different from other years. Effective age is defined as the number of years since the last remodel, which we calculate by constructing a history of home renovations using repeated assessment records over the sample period.[39] If remodeling drives price increases, we would expect the houses transacted in this period to have a smaller effective age, because we would observe a recent renovation. In Figure 5, we plot the event study coefficients from a specification identical to equation (1) but with effective age as the dependent variable. The estimates do not reveal any significant changes in the effective age of transacted homes in hurricane-exposed areas.

Of course, we do not observe all renovations. However, most major remodeling projects require a permit, which would trigger an observable reassessment. These include structural or electrical projects and others that cost more than a few thousand dollars (though thresholds vary across counties). Smaller projects (such as repainting or new flooring) do not require a permit, but they are also less likely to materially move prices. Moreover, while compliance with the permitting process is imperfect, it is harder to evade for larger projects, and far riskier for projects funded by insurance payouts or FEMA assistance. For all of these reasons, we conclude that non-observed remodels are unlikely to play a significant role in explaining the overall market dynamics revealed by our analysis.

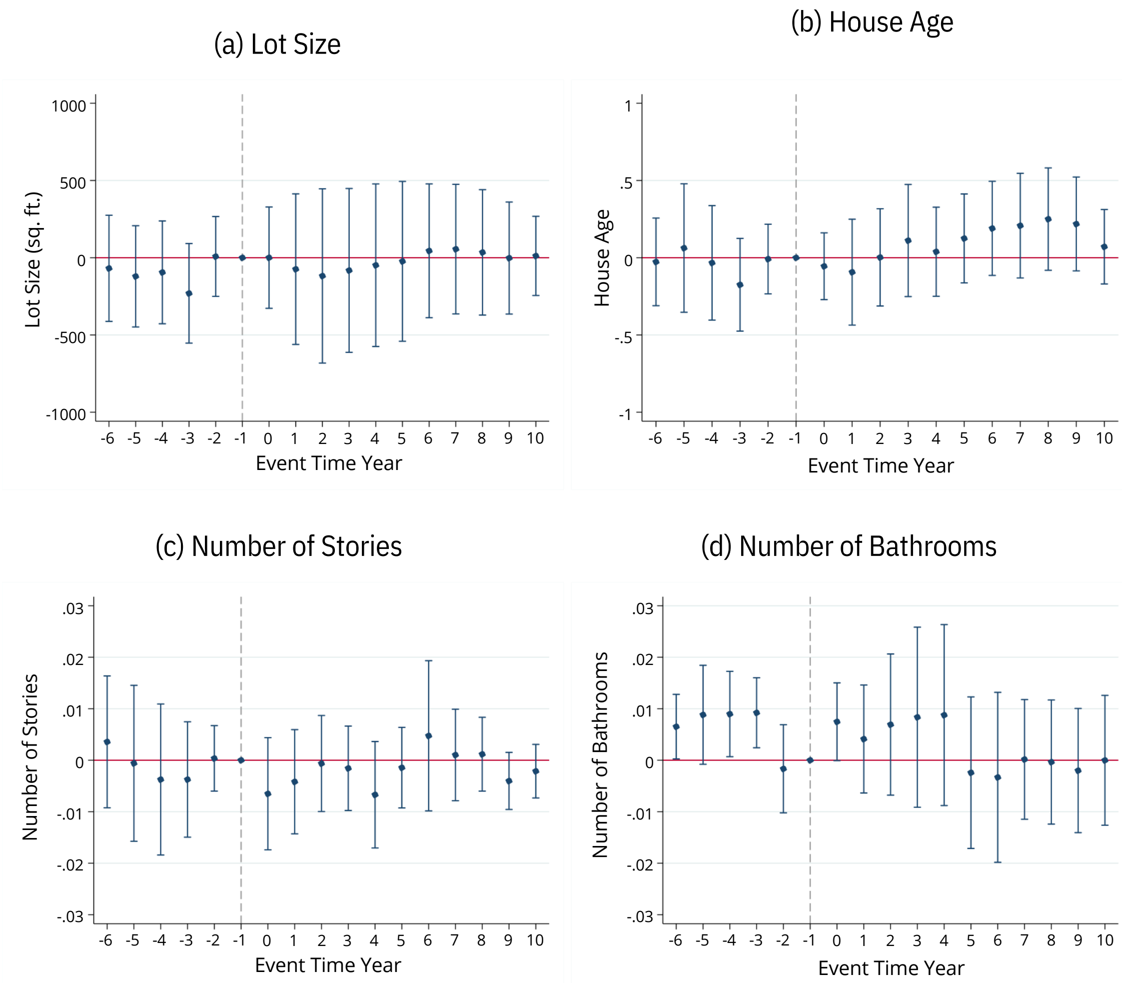
Additional mechanism 2: composition shift through information revelation

As discussed in Section 4.1, we first control for major hedonic characteristics and subsequently include parcel fixed effects to address most types of compositional shifts in housing transactions. Nevertheless, we cannot completely rule out all compositional effects. Some homes may be more hurricane-resistant due to structural factors and material resiliency. If this is difficult for potential buyers to observe (or sellers to credibly signal), hurricanes could provide an opportunity to overcome the information asymmetry problem. This type of information revelation would be consistent with our price appreciation results.

This mechanism has two testable implications. First, hurricanes are likely to lead buyers

[39] Most parcels are not assessed annually. A parcel is likely to be re-assessed when a major improvement (which requires permitting from the local housing authority) or transaction happens. For each parcel, we pull together all available assessment records and fill in the missing years using the previous assessment observation.

Figure 6: Changes in Characteristics of Transacted Homes



Notes: estimates from a variant of equation (1) are plotted with their 95% confidence intervals. The dependent variable in each panel is indicated in the caption above the graph. The results are based on the full sample of Florida home sales. The specification controls for census tract, month, and county-year fixed effects. Standard errors are clustered by county.

to more highly value the characteristics that are associated with hurricane resistance. Second, if so valued, hurricanes should induce a compositional shift toward these characteristics in transacted homes. Unfortunately, such characteristics – building and roof materials, etc. – are not easily observable in our data.[40] Here, we provide a partial test of these impli- cations using observed characteristics that are predictors of disaster resistance. One such characteristic is the house's age: newer homes are more resistant to hurricanes because of improvements in building technology and more stringent building codes. Effective age may also play a role, particularly if the triggering event involved major structural modifications. Another characteristic is the number of stories, as taller buildings are more prone to wind damage, all else equal.

To test for differential capitalization, we estimate the following equation:

$$\log(Price_{imy}) = \beta_1 Hurr_{imy} + \gamma' HouseChar_{iy} + \eta' Hurr_{imy} \times HouseChar_{iy} + \delta_{ht} + \delta_{hm} + \delta_{hcy} + \varepsilon_{imy}. \quad (4)$$

Here, we augment the standard DD specification with an interaction between the treatment indicator (Hurrimg) and each of the home characteristics. η captures the differential capitalization effect during the adjustment period. Results are reported in Table A6, and we find no differential capitalization effect for house age or for being a one-story building. We also find a smaller price effect for being recently renovated, in contrast to the expectation that such homes could be more resistant to hurricanes.

We also test for any systematic changes in these variables among transacted homes, as predicted by the second testable implication. As shown in Figure 6, none of these characteristics experience detectable changes after hurricane exposure. If anything, there is a gradual rise in average house age, which is likely a mechanical effect due to the aging of the housing stock.

Additional mechanism 3: speculative buyers or investors

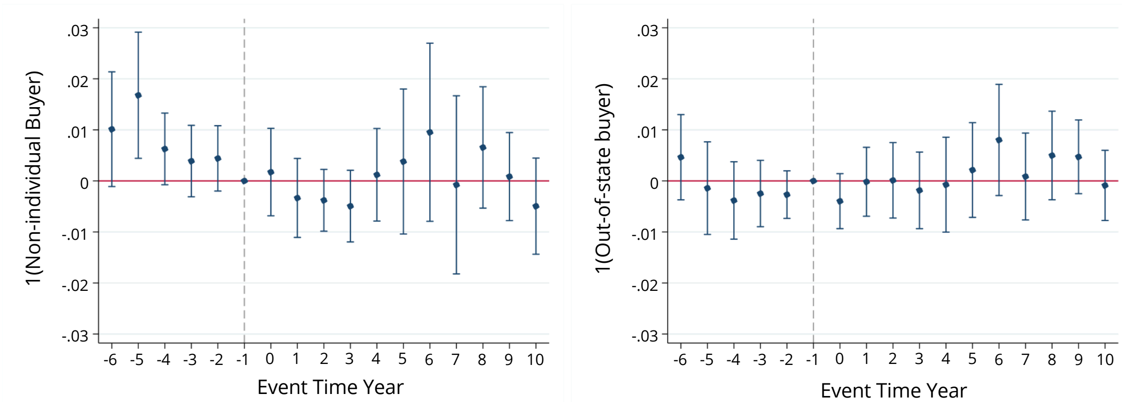
The last alternative mechanism that we explore is speculation. Disasters may open up opportunities for developers and other risk-neutral agents to buy properties in damaged areas and renovate them for profit, as suggested by anecdotal evidence.[41] To test for this mechanism,

[40] The assessment data contains flags for building quality and roof material. However, our exploration revealed serious inconsistencies across these measures, in addition to patchy coverage.

[41] For example, see City Lab, https://www.citylab.com/equity/2020/03/nashville-tornado-real-

Figure 7: Testing for Speculative Buyers

(a) Non-individual Buyers (b) Out-of-state Buyers



Notes: estimates from a variant of equation (1) are plotted with their 95% confidence intervals. The dependent variable is an indicator for non-individual buyer in Panel (a) (N = 7,216,109), and an indicator for out-of-state buyer in Panel (b) (N = 6,859,171). The models control for census tract, month, and county-year fixed effects. Standard errors are clustered by county.

we examine the composition of sales in terms of (1) individuals versus non-individuals and (2) in-state versus out-of-state buyers.

In our data, we observe which transactions involve any non-individual buyers, and these account for 13.2% of all transactions in the sample. We again employ the event study specification but with an indicator for the involvement of non-individual buyers as the dependent variable. Results are plotted in Panel (a) of Figure 7. While we observe a slightly decreasing trend in non-individual buyers, this trend is not only statistically insignificant in the three post-hurricane event years (after which it reverses), but it also appears to predate the hurricane. Overall, the pattern is not indicative of any consistent change in investor purchases in the immediate aftermath of a hurricane, and we conclude that institutional investing therefore cannot explain the housing market dynamics in our setting.

To determine which buyers live out-of-state, we use the buyer address recorded in the transaction data. Approximately 54% of buyers use the address of the transacted property as their corresponding address, reflecting their intention to immediately inhabit the property. Among the remaining buyers, an out-of-state address likely reflects purchases by investors or those acquiring a second home. These buyers account for 15.1% of all purchases in our

estate-speculators-opportunity-zone/607558/, or the Wall Street Journal, https://www.wsj.com/articles/the-new-storm-chasers-real-estate-disaster-investors-11564498767.

sample. We again estimate a variant of equation (1), with an indicator for being out-of-state on the left hand side. The results, plotted in Panel (b) of Figure 7, show no movement in the fraction of transactions that are made by out-of-state buyers, providing further evidence that our market dynamics are very unlikely to be driven by an increase in speculative buying.

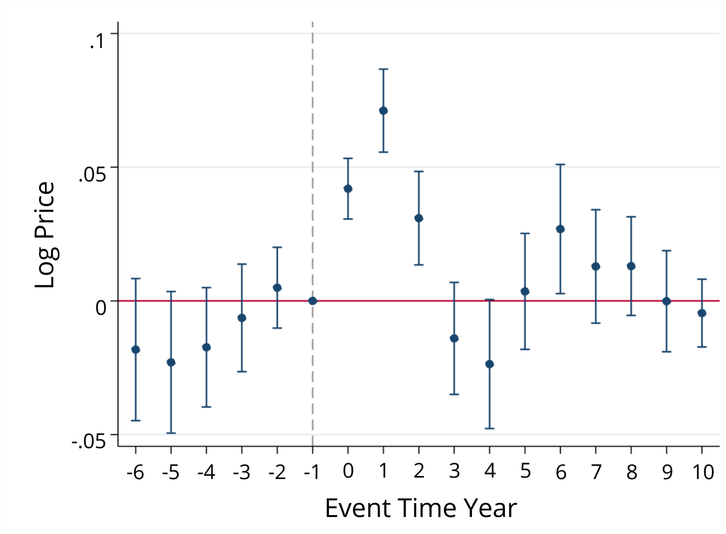
4.4 Implications for Population Turnover

The equilibrium shifts in the housing market we documented in the previous section may affect the income and wealth distributions of impacted regions, and these could have associated demographic consequences for hurricane-battered communities. In this section, we turn our attention to buyer income. In this analysis, we focus on the subsample of home buyers for whom we obtained a high-quality match in HMDA records ("HMDA sample" henceforth), where we observe buyer income. The HMDA sample is therefore a subset of all transactions with a mortgage ("borrower sample" henceforth). In this section, we begin by comparing samples to gauge the representativeness of the HMDA sample relative to both the borrower and full samples, and then proceed in estimating the equilibrium effect of hurricane exposure on income and other demographic characteristics.

Table A1 reports the mean and median of characteristics of transacted homes in the three samples. The full sample contains more outlier homes which are expensive and have larger lot sizes than typical homes. Since these are likely to be estates of the wealthy, these purchases would be less likely to be financed by mortgages. Most property characteristics are otherwise comparable at both the mean and median of their values across the three samples. We also confirm that the borrower and HMDA samples have similar post-hurricane price dynamics by re-estimating equation (1) in both of these samples. Results are plotted in Figure 8 for the HMDA sample and Appendix Figure A4 for the borrower sample, and both resemble the pattern estimated in the full sample. We also examine whether hurricanes affect the distribution of cash buyers versus borrowers (Appendix Figure A3), and find no evidence of a significant change. Overall, the transactions in the HMDA sample appear to be quite comparable to the two larger samples based on observable characteristics. Nevertheless, we caution that there may be important differences between cash buyers and borrowers, and also between those borrowing from large lenders covered by HMDA and those borrowing from smaller ones.

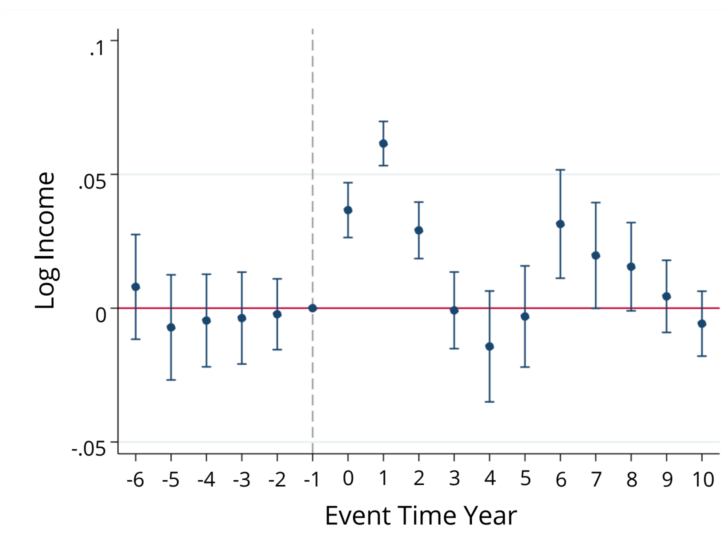
Using the HMDA sample, we now estimate the effect of hurricanes on the average in-

Figure 8: Hurricane Effects on House Prices – HMDA Sample



Notes: estimates from equation (1) are plotted with their 95% confidence intervals. The results are based on the HMDA sample (N = 1,928,142). The model includes standard hedonic variables and census tract, month, and county-year fixed effects. Standard errors are clustered by county.

Figure 9: Hurricane Effects on Buyer Income – HMDA Sample



Notes: estimates from a variant of equation (1) are plotted with their 95% confidence intervals. The dependent variable is buyer income. The results are based on the HMDA subsample (N = 1,846,467). The model includes standard hedonic variables and census tract, month, and county-year fixed effects. Standard errors are clustered by county.

come of new buyers by replacing the outcome variable in equation (1) with buyer income (Figure 9). We find the dynamics of post-hurricane income to be strikingly similar to those of prices: the average income increases by around 4% in the first event year, nearly 7% in the second, and reverts to 4% in the third before returning to its pre-hurricane baseline in later years. Table A7 reports the standard DD coefficients for each property type, where we find a similar increase in buyer income across-the-board. Combined with our previous finding that homes transacted post-hurricane are similar to those transacted before, these results suggest that comparable homes are being transferred to buyers of higher income levels.

There are several plausible reasons why post-hurricane buyers could have higher incomes. First, high-income households generally have a higher willingness-to-pay for housing in any location.[42] In an impacted market after a storm, higher-income households are thus more likely to outbid others. Second, financial institutions may become more cautious about lending in hurricane-struck locations. For example, they could be less willing to issue larger loans to accommodate a higher home price.[43] Our results suggest that hurricanes may exacerbate pre-existing constraints and further limit location choices for lower-income households.

To put these findings in context, approximately 28% of local homes changed hands during the three-year adjustment period. If our results on HMDA buyers generalize to the non-borrower side of the market, the implications for local communities are profound. Given that homeownership is often a long-term decision, this pattern may result in a lasting change in the economic profile of affected communities toward higher income, and likely higher wealth. In turn, the influx of higher-income households could trigger further gentrification in these neighborhoods, as the new residents demand (and are able to pay for) new local amenities (Card et al., 2008; Guerrieri et al., 2013). In most cases, gentrification eventually produce winners and losers, largely depending on who the incumbent homeowners are, and who rents.

In addition to income, we also examine the race and gender profiles of buyers from the HMDA sample. Based on the race of the mortgage applicant and co-applicant (when

[42] This is a common feature in models of locational choice with heterogeneous income levels, e.g. Banzhaf and Walsh (2008).

[43] A recent study finds that lenders securitize a larger fraction of their loans after a hurricane to transfer risks to government-sponsored enterprises such as Fannie Mae and Freddie Mac (Ouazad and Kahn, 2019). Conforming loans must not exceed certain loan limits. This requirement could further tighten credit constraints facing lower-income households.

applicable)[44], we classify each application into three categories: (1) the applicant(s) is non-Hispanic white; (2) the applicant(s) is a racial or ethnic minority; (3) one applicant is non-Hispanic white while the other is a minority. We estimate the changes in these outcomes in three years post-hurricane using a standard DD specification and report the results in Table A8. The estimates are all very small. We find a 0.2 percentage points decrease in the fraction of non-Hispanic white applicants from a 60.5% baseline, which is both economically small and statistically insignificant. We also find a marginally significant increase of 0.5 percentage points for minority applicants and a compensating 0.3 percentage points decrease for pairs of applicants with mixed minority status. Similarly, we classify applications into two categories based on whether all applicants are female and estimate a 0.4 percentage points increase in the fraction of female applicants out of a 29.6% baseline. We conclude that there is no meaningful change to the overall racial or gender profile of buyers post-hurricane.

4.5 HeterogeneousEffects

In this section, we explore the heterogeneous effects of differential wind speed exposure. As described in Section 2.2, we further classify exposure as either low intensity (64-95 kn wind speed) or high intensity (96 kn and above). In our sample, high-intensity exposure is limited because we determine exposure for each point within the path of the hurricane winds. If a category 3 or higher hurricane passes through a location at lower than 96 kn wind speeds, we do not consider this location to have been exposed to high-intensity winds. Nevertheless, exploring this heterogeneity helps bridge our results to the existing literature, which largely focuses on the information content of a single, high-intensity hurricane.

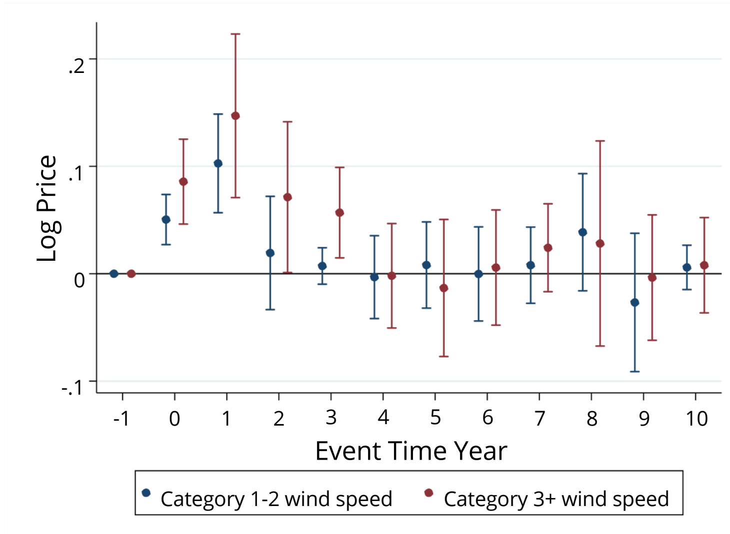
To examine heterogeneity, we estimate a variant of equation (1) which allows for separate post-hurricane dynamics for each of the two levels of exposure, and we plot the post-period coefficients in Figure 10.[45] Since most instances of exposure are of low intensity, the price dynamics generated by low-intensity exposure are very similar to the overall pattern shown in Figure 2. The high-intensity exposure estimates, on the other hand, suffer from wider errors because of the significantly lower treatment saturation.[46] The general pattern is very

[44] 40.55% of the mortgage applications in HMDA have a co-applicant.

[45] We pool the pre-hurricane indicators for the two types of exposure to enhance power, and as before, the pre-period indicators are both flat and statistically zero.

[46] At most 1% of homes are ever sold from areas affected by category 3 and above wind speeds in any year before or after a hurricane, as such wind speeds rarely affected Florida over our sample

Figure 10: Heterogeneous Effects by Hurricane Intensity – Full Sample



Notes: estimates for separate wind categories are plotted with their 95% confidence intervals. The results are based on the full sample of Florida home buyers (N = 7,216,109). The model includes standard hedonic variables and census tract, month, and county-year fixed effects. Standard errors are clustered by county.

similar: the average price jumps up in event year 0, peaks at event year 1, and tapers down in subsequent years. The point estimates are larger for the high-intensity storms, with a peak of 15% compared to 10% for low intensity. The effect also appears to be more persistent: the fourth year after high-intensity exposure still experiences a statistically significant 5% increase in housing prices, whereas the corresponding estimate is small and insignificant for low-intensity exposure. The lack of power, however, ultimately constrains our ability to detect statistically differential effects.

5 Conclusion

This paper provides two sets of findings. First, we estimate the equilibrium dynamics occurring in the Florida housing market in the wake of a hurricane. We find an increase in housing prices and a concurrent decrease in transaction probability, both lasting up to three years. The direction and duration of these effects are consistent with the underlying mech-

period (see the right panel of Figure 1, but recall that it depicts tract-centroid and not individual home category 3 hurricane exposure).

anism whereby a part of the housing stock is first damaged by hurricanes, and eventually restored. We find little empirical support for alternative explanations. Second, we examine demographic changes in local communities associated with these market adjustments and find that incoming home buyers during the recovery period have higher average income conditional on the characteristics of transacted homes, resulting in an enduring increase in the distribution of income, and likely wealth in these communities.

Several interesting implications emerge from these findings. First, our results suggest that there is a limited demand response from any updated beliefs about the riskiness of an affected location. In the short run, any behavioral response on the demand side of the market is dominated by the effect of the supply shock. Since potential home buyers are likely well informed about the general risk of hurricane exposure in Florida, the realization of a hurricane conveys little information beyond the very local effect on homes located in flood zones, as identified in previous studies. Moreover, we remarkably find no evidence that hurricanes fundamentally change the long-run demand for housing in affected areas. Whether this is due to the scarcity of desirable regions with warm winter weather – an important urban amenity (Glaeser and Gyourko, 2005) – or the resilience of local businesses and economic opportunity remains an open question.

In addition, our transaction probability findings imply a close-to-full recovery in the housing market after three years. Such timeline for the recuperation of physical capital is in line with past studies on capital destruction by natural disasters (Gignoux and Mené ´ndez, 2016; Kocornik-Mina et al., 2020). Since the incentive to rebuild is governed by the comparison between construction costs and housing prices (Gyourko and Saiz, 2004), higher housing prices during the adjustment period provide a strong price signal for the recovery, even for areas with high-intensity exposure. This stands in contrast to the evidence from New Orleans after Hurricane Katrina, where recovery was slow. Due to unexpected levee failures, Katrina's impacts in New Orleans were much more severe than other hurricanes. The widespread damage there likely affected local amenities and industries so much that it fundamentally altered the long-run housing market equilibrium. While New Orleans is undoubtedly an outlier, an important question for future research will be to understand the sensitivity of market outcomes and long-run welfare consequences to different levels of damage.

Finally, we return to the increase in the average income of home buyers. To the extent that higher income residents bring along more expensive assets and spur more economic development in these areas, this could result in more expensive future hurricane damage claims. For the privately insured, these risks should be reflected in higher premiums. But for publicly funded insurance and disaster relief programs under FEMA, HUD, and other government agencies, these risks could come at the expense of taxpayers (Dinan, 2016). As of 2019, the National Flood Insurance Program was over 20 billion dollars in debt even after Congress cancelled an additional 16 billion in 2017. To the extent that homeowners are counting on public assistance or insurance rates not reflective of actual risks, some of this gentrification may be the result of moral hazard, highlighting the need for program reform as advocated for by many researchers (Congressional Budget Office, 2017; Kousky et al., 2018).

The empirical relationship between housing supply and buyer income is interesting in and of itself. Our model highlights the important role of financial constraints as a driver of post-hurricane housing market dynamics. As such, reforms to lending practices in the recovery period could play an important role in ensuring an equitable recovery from natural disasters. Clearly, such reforms would need to account for the usual information asymmetries that shape lending programs. Whether the scope for adverse selection and the tools available to combat it are sufficient to address these distributional concerns is a rich area for future research.

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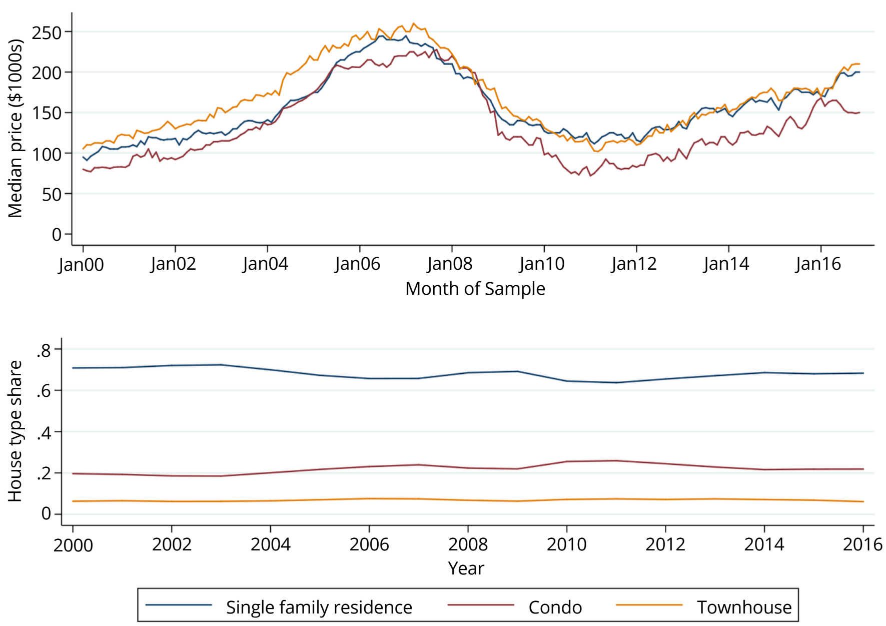
Appendix

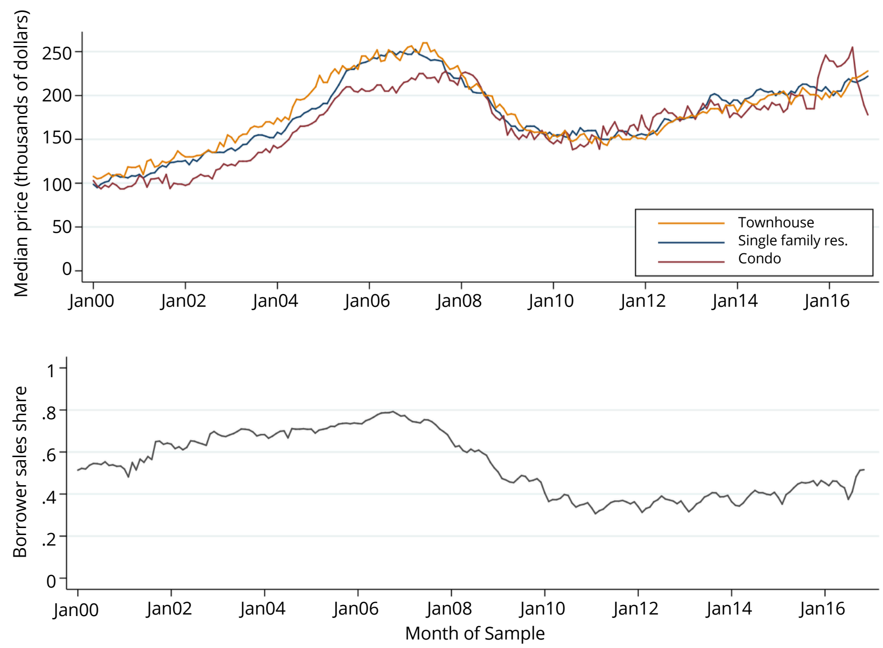
Figures

Figure A1: Florida Housing Market Sales and Composition



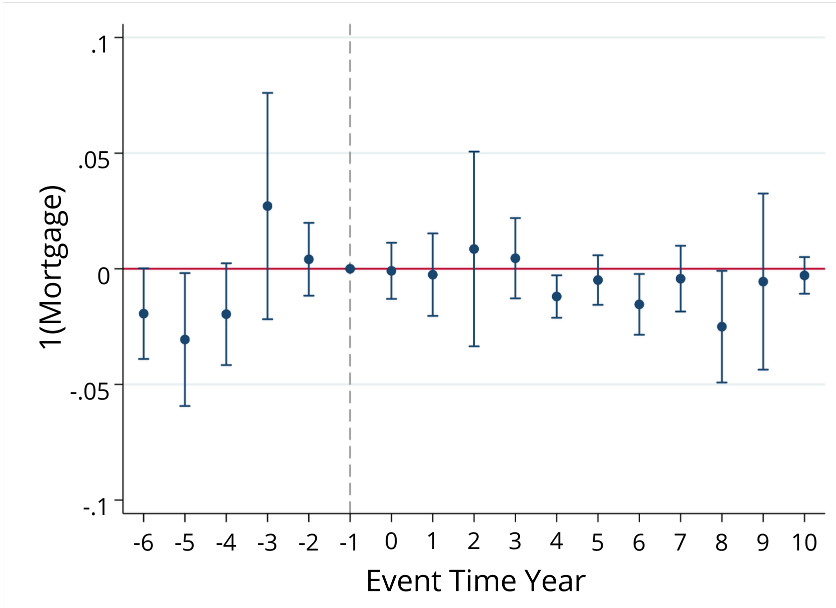
Source: authors' calculation based on ZTRAX data. Notes: the top panel plots the monthly median prices for the three major home types. The bottom panel plots the annual sales percentages of each home type. These time series are based on the full sample of Florida home buyers.

Figure A2: Florida Borrowers Market Price and Sales Share



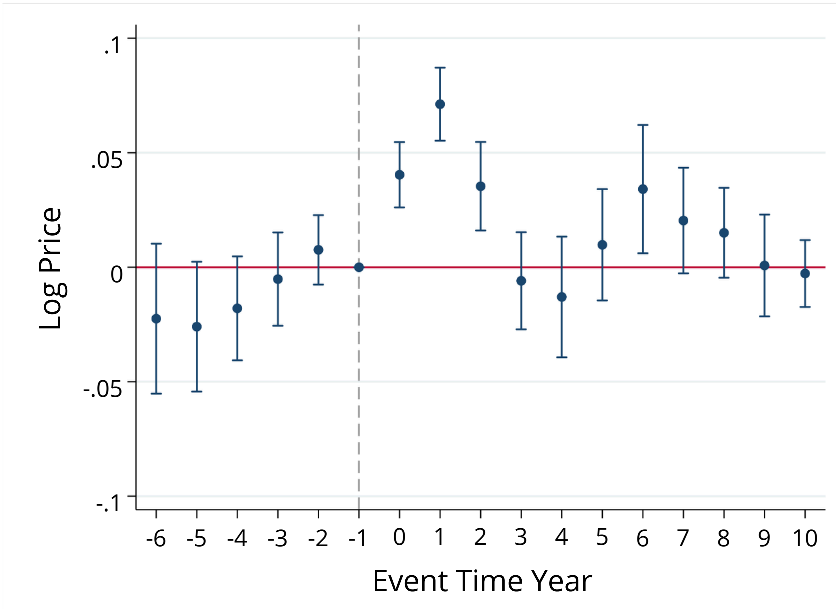
Source: authors' calculation based on ZTRAX data. Notes: the top panel plots the median price in the borrower subsample. The bottom panel plots the share of borrower sales among all sales. All time series are monthly.

Figure A3: Hurricane Effects on the Share of Transactions Involving a Mortgage



Notes: estimates from a variant of equation (1) are plotted with their 95% confidence intervals. The dependent variable is an indicator of whether the transaction involves a mortgage. The results are based on the full sample (N = 7,226,845). The model includes standard hedonic variables and census tract, month, and county-year fixed effects. Standard errors are clustered by county.

Figure A4: Hurricane Effects on House Prices – Borrower Sample



Notes: estimates from Equation (1) are plotted with their 95% confidence intervals. The results are based on the borrower sample (N = 4,083,298). The model controls for standard hedonic variables and census tract, month, and county-year fixed effects. Standard errors are clustered by county.

Tables

Table A1: Summary Statistics of Housing Transactions

Variable	FullSample Mean	FullSample Median	BorrowerSample Mean	BorrowerSample Median	HMDASample Mean	HMDASample Median
Price	272,775	155,000	238,031	178,000	252,401	187,900
AssessedValue	149,678	103,326	149,064	110,640	159,264	117,914
No.ofBuildings	0.939	1	0.947	1	0.942	1
No.ofStories	1.25	1	1.23	1	1.24	1
No.ofBathrooms	1.79	2	1.86	2	1.86	2
LotSize(sq.ft.)	11,605	7,143	11,708	7,500	11,906	7,700
HouseAge	22.1	19	19.7	16	20.9	17
EffectiveHouseAge	17.7	15	15.3	12	16.3	13
LoanAmount	–	–	194,797	150,000	198,277	157,250
BuyerIncome	–	–	–	–	113,116	72,000
N	7,414,454		4,207,160		1,972,728	
%SingleFamily	69.7		76.1		76.9	
%Condo	24.1		17.4		16.9	
%Townhouse	6.2		6.6		6.2	

Notes: The unit of observation is a transaction. The full sample contains all transactions. The borrower sample contains all transactions with a mortgage. The HMDA sample contains all transactions that have a valid match to the HMDA records.

Table A2: Summary Statistics of the Parcel-Year Panel

	Statistic	All	SingleFamily	Condominium	Townhouse
Transacted ⋆	Mean	0.102	0.103	0.101	0.103
AssessedValue	Mean	149,437	154,697	136,827	132,850
	Median	105,450	110,500	84,222	107,650
No.ofBuildings	Mean	0.963	0.993	0.880	0.967
	Median	1	1	1	1
No.ofStories	Mean	1.22	1.11	2.06	1.26
	Median	1	1	1	1
No.ofBathrooms	Mean	1.67	1.75	1.37	1.98
	Median	2	2	2	2
LotSize(sq.ft.)	Mean	16,876	16,093	29,732	4,164
	Median	9,027	9,500	8,802	3,485
HouseAge	Mean	30.1	31.8	27.7	21.2
	Median	28	28	28	21
EffectiveHouseAge	Mean	23.8	23.9	25.1	18.0
	Median	22	21	26	18
N(parcel-year)		49,363,437	33,619,163	12,834,600	2,909,674
Share(%)		100	68.11	26.00	5.89

⋆ "Transacted" is an indicator of whether the parcel has been involved in a transaction in the given year.

Table A3: The Effect of Hurricanes on Housing Prices

Log(Price)	(1) All	(2) SingleFamily	(3) Condominium	(4) Townhouse
EventYear0-2	0.0505∗∗∗	0.0536∗∗∗	0.0850∗∗∗	0.0491∗∗∗
	(0.0147)	(0.0118)	(0.00727)	(0.0158)
Age	-0.00436∗∗∗	-0.00353∗∗∗	-0.0159∗∗∗	-0.00779∗∗∗
	(0.000730)	(0.000405)	(0.00531)	(0.00107)
EffectiveAge	-0.00808∗∗∗	-0.00722∗∗∗	-0.00253	-0.0136∗∗∗
	(0.000819)	(0.000890)	(0.00430)	(0.00456)
LotSize(1,000sq.ft.)	0.00272∗∗∗	0.00337∗∗∗	-0.000309	0.0325∗∗
	(0.000473)	(0.000258)	(0.000295)	(0.0150)
N	7,216,109	5,029,557	1,741,743	444,809
R2	0.571	0.556	0.611	0.604
County-Year-TypeFEs	Yes	Yes	Yes	Yes
Month-TypeFEs	Yes	Yes	Yes	Yes
Tract-TypeFEs	Yes	Yes	Yes	Yes

Notes: this table reports estimates from a variant of equation (1), where the set of event indicators are replaced by a single indicator of whether the transaction occurs in year 0-2 following exposure to a hurricane. The dependent variable is the log of transaction price. The unit of analysis is a transaction. The regressions also control for the number of stories and the number of bathrooms in bins, and an indicator for event year 3-10. Standard errors (in parentheses) are clustered at the county level. ∗ $p < 0.1$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$

Table A4: Robustness Checks on Housing Price Results

	(1) BoundaryObs.	(2) RepeatHits	(3) OverlappingEvents
EventYear0-2	0.0765∗∗∗	0.0492∗∗∗	0.0651∗∗∗
	(0.0120)	(0.00990)	(0.0123)
N	3,031,677	5,739,937	3,128,012
R2	0.590	0.563	0.600
County-Year-TypeFEs	Yes	Yes	Yes
Month-TypeFEs	Yes	Yes	Yes
Tract-TypeFEs	Yes	Yes	Yes

Notes: this table reports estimates from a version of equation (1), where the set of event indicators are replaced by a single indicator of whether the transaction occurs in year 0-2 following exposure to a hurricane. The unit of analysis is a transactions. Each column corresponds to a different subset of the full sample. Column (1) drops all observations within 10 miles to the boundary of hurricane-scale wind exposure. Column (2) drops all observations that have been exposed to two hurricanes within three years through out the sample period. Column (3) is based on a subset of hurricanes, selected so that they either coincide with another hurricane in the set or are not within three years of any other hurricanes. The observations associated with hurricanes outside of this set are dropped. The regressions also control for the number of stories and the number of bathrooms in bins, and an indicator for event year 3-10. Standard errors (in parentheses) are clustered at the county level. ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$

Table A5: The Effect of Hurricanes on Transaction Probability

1(Transacted)	(1) All	(2) SingleFamily	(3) Condominium	(4) Townhouse
EventYear0-2	-0.00679 * *	-0.00308	-0.0230 * *	-0.00387
	(0.00326)	(0.00332)	(0.0105)	(0.00241)
N	49,302,345	33,560,908	12,832,339	2,909,058
R2	0.0856	0.0866	0.0832	0.0977
County-YearFEs	Yes	Yes	Yes	Yes
Type-YearFEs	Yes	Yes	Yes	Yes
ParcelFEs	Yes	Yes	Yes	Yes

Notes: this table reports estimates from a version of equation (3), where the set of event indicators are replaced by a single indicator of whether the transaction occurs in year 0-2 following exposure to a hurricane. The dependent variable is an indicator of whether a transaction takes place that involves the given parcel in a given year. The unit of analysis is a parcel-year. The regressions also control for effective age, lot size, and an indicator for event year 3-10. Standard errors (in parentheses) are clustered at the county level. * $p < 0.1$, * * $p < 0.05$, * * * $p < 001$

Table A6: Differential Capitalization

Log(Price)	(1a) MainEffect	(1b) InteractionEffect
Event Year 0-2	0.0874 ⋆	
	(0.0441)	
House Age	-0.0060 ⋆ ⋆ ⋆	0.0006
	(0.0009)	(0.0008)
Effec. House Age	-0.0091 ⋆ ⋆ ⋆	0.0023 ⋆ ⋆
	(0.0008)	(0.0010)
One-Story	-0.0692 ⋆ ⋆ ⋆	0.0180
	(0.0206)	(0.0200)
N	7,216,109	
R^2	0.560	

Notes: this table reports estimates from equation (4). Column (1a) reports the coefficients associated with the treatment indicator and home characteristics, and column (1b) reports the coefficients of the interaction term of each of the characteristics with the treatment indicator. The model also controls for lot size and number of bathrooms and their interaction with the event indicator, an indicator for event year 3-10, as well as tract-type, month-type, and county-year-type FEs. Standard errors (in parentheses) are clustered by county. ⋆ $p < 0.1$, ⋆ ⋆ $p < 0.05$, ⋆ ⋆ ⋆ $p < 0.01$.

Table A7: The Effect of Hurricanes on Housing Prices and Buyer Income (HMDA Sample)

	(1) All	(2) SingleFamily	(3) Condominium	(4) Townhouse
	Dependent variable: log price			
EventYear0-2	0.0588***	0.0598***	0.0589***	0.0557***
	(0.00454)	(0.00508)	(0.00821)	(0.00976)
N	1,928,142	1,482,160	326,189	119,793
R2	0.720	0.711	0.765	0.786
	Dependent variable: log income			
EventYear0-2	0.0460***	0.0480***	0.0426***	0.0400***
	(0.00504)	(0.00699)	(0.0104)	(0.0110)
N	1,846,467	1,421,677	309,904	114,885
R2	0.417	0.404	0.456	0.362
County-YearFEs	Yes	Yes	Yes	Yes
MonthFEs	Yes	Yes	Yes	Yes
TractFEs	Yes	Yes	Yes	Yes

Notes: this table reports estimates from a version of equation (1), where the set of event indicators are replaced by a single indicator of whether the transaction occurs in year 0-2 following exposure to a hurricane. The dependent variable is the log of transaction price in the top panel and the log of buyer income in the bottom panel. The unit of analysis is a transaction. The sample contains all transactions that have a match with the HMDA records. The regressions also control for home characteristics and an indicator for event year 3-10. Standard errors (in parentheses) are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: The Effect of Hurricanes on Additional Buyer Demographics (HMDA Sample)

	(1) White	(2) Minority	(3) Mixed	(4) Female
EventYear0-2	-0.00205	0.00503	-0.00297 * * *	0.00412 * *
	(0.00342)	(0.00348)	(0.00105)	(0.00206)
N	1,928,142	1,928,142	1,928,142	1,928,142
R2	0.225	0.240	0.009	0.034
MeanD.V.	0.605	0.364	0.031	0.296
County-Year-TypeFEs	Yes	Yes	Yes	Yes
Month-TypeFEs	Yes	Yes	Yes	Yes
Tract-TypeFEs	Yes	Yes	Yes	Yes

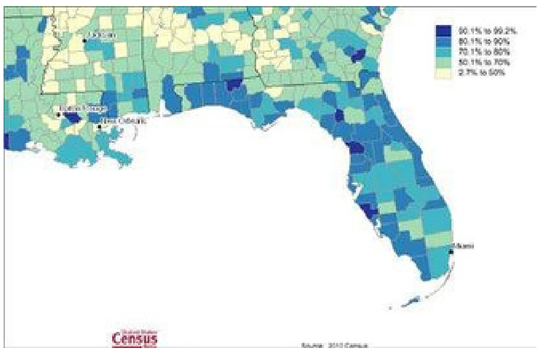
Notes: this table reports estimates from a version of equation (1), where the set of event indicators are replaced by a single indicator of whether the transaction occurs in year 0-2 following exposure to a hurricane. The dependent variables in columns (1)-(3) represent the race and ethnicity combination of the applicant and co-applicant (when applicable). Respectively, they are an indicator of the applicant(s) being non-Hispanic white, an indicator of the applicant(s) being a racial or ethnic minority, and an indicator of one applicant being non-Hispanic white while the other is a minority. The dependent variable in column (4) is an indicator of the applicant(s) being female. The unit of analysis is a transaction. The regressions also control for home characteristics and an indicator for event year 3-10. Standard errors (in parentheses) are clustered at the county level. * $p < 0.10$, * * $p < 0.05$, * * * $p < 0.01$.

Online Appendices

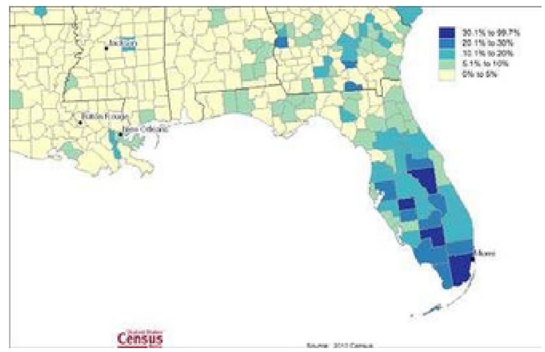
A AdditionalFiguresandTables

Figure A5: Demographics in Florida Counties

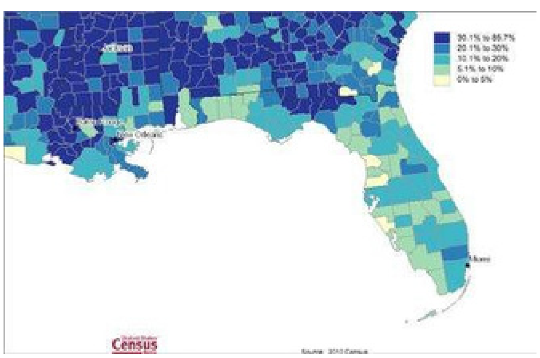
(a) Percent White



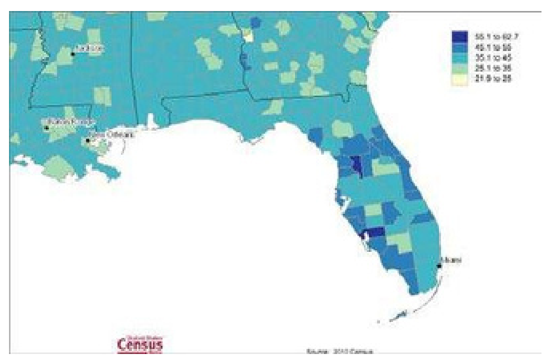
(b) Percent Hispanic or Latino



(c) Percent Black



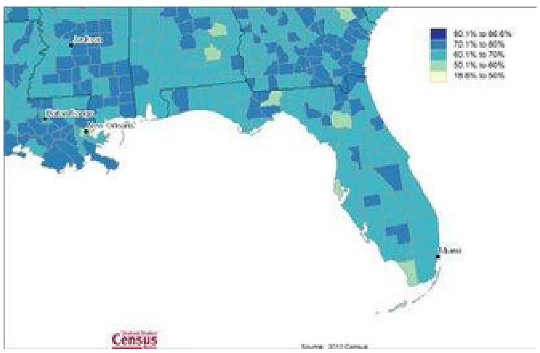
(d) Median Age



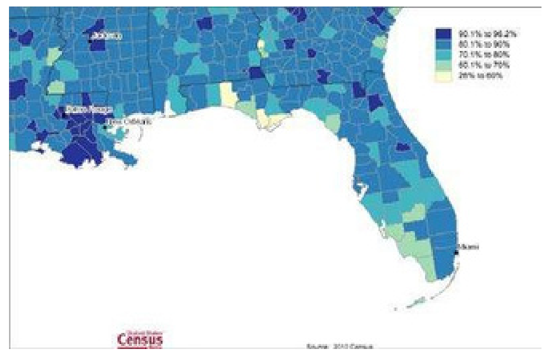
Source: Census Data Mapper based on data from the 2010 Census.

Figure A6: Family and Housing Statistics in Florida Counties

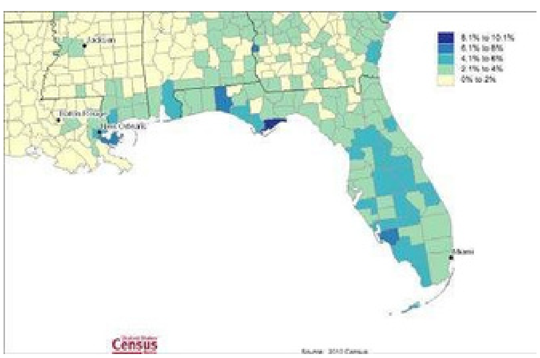
(a) Percent Family Households



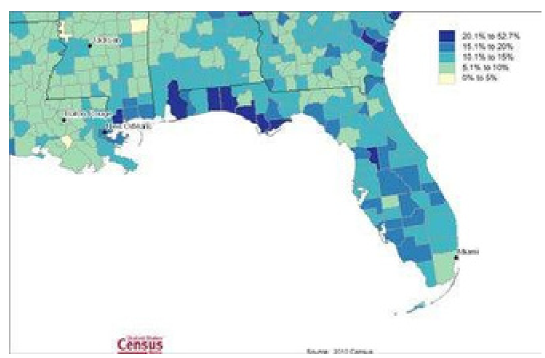
(b) Percent Occupied Housing Units



(c) Homeowner Vacancy Rate



(d) Rental Vacancy Rate



Source: Census Data Mapper based on data from the 2010 Census.

Table A9: Variation in hurricane event time indicators (housing price model)

Event Time

Matthew16

Irma17

Andrew92

Total

Notes: all numbers in percentage points. Definition of exposure given in Section 2.2.

Table A10: Variation in hurricane event time indicators (transaction probability model)

Event Time

Andrew92
Earl98
Georges98
Irene99
Charley04
Frances04
Dennis05
Katrina05
Wilma05
Hermine16
Matthew16
Irene17

Total

Notes: all numbers in percentage points. Definition of exposure given in Section 2.2.

Table A11: Variation in category 3+ hurricane event time indicators (housing price model)

Event Time

Andrew92

Dennis05

Katrina05

Wilma05

Hermine16

Matthew16

Irma17

Earl98

Georges98

Irene99

Charley04

Total

Notes: all numbers in percentage points. Definition of exposure given in Section 2.2.

Table A12: The Impacts of Hurricanes on Prices and Transaction Probability (Event Study)

	(1) Price–FullSample	(2) Price–RepeatSales	(3) Probability–FullSample
EventYear-6	-0.0162	-0.0208	-0.00399
	(0.0240)	(0.0447)	(0.00261)
EventYear-5	-0.00710	-0.0151	-0.00210
	(0.0300)	(0.0546)	(0.00341)
EventYear-4	-0.0171	-0.0178	0.000104
	(0.0148)	(0.0471)	(0.00179)
EventYear-3	-0.0741	-0.0252	0.00159
	(0.0605)	(0.0394)	(0.00177)
EventYear-2	-0.0161	-0.0263	0.000274
	(0.0227)	(0.0328)	(0.00166)
Event Year 0	0.0508***	0.0531	-0.00683
	(0.0121)	(0.0416)	(0.00414)
Event Year 1	0.102***	0.128***	-0.00257
	(0.0228)	(0.0255)	(0.00162)
Event Year 2	0.0200	0.0840***	-0.00229
	(0.0268)	(0.0278)	(0.00289)
Event Year 3	0.00897	0.0257	-0.00100
	(0.00988)	(0.0317)	(0.00227)
Event Year 4	-0.00664	0.0114	0.000927
	(0.0200)	(0.0301)	(0.00215)
Event Year 5	0.00421	0.0380	0.00154
	(0.0208)	(0.0314)	(0.00125)
Event Year 6	-0.00119	0.0641*	0.00539**
	(0.0231)	(0.0352)	(0.00233)
Event Year 7	0.00873	0.0540**	0.00162
	(0.0179)	(0.0235)	(0.00171)
Event Year 8	0.0367	0.0600***	0.00199
	(0.0290)	(0.0136)	(0.00180)
Event Year 9	-0.0254	0.0502***	0.00298**
	(0.0320)	(0.0150)	(0.00128)
EventYear10	0.00492	0.0459**	0.00366*
	(0.0109)	(0.0190)	(0.00191)
	Yes	Yes	Yes
County-Year-Type FEs	Yes	Yes	Yes
Month-Type FEs	Yes		
Tract FEs			
Parcel FEs		Yes	Yes
Hedonic Variables	Yes	Yes	Yes
N	7,216,109	1,338,384	49,302,345
R^2	0.571	0.778	0.0856

Notes: estimates from equations (1)-(3) are reported in columns (1)-(3), respectively. The unit of analysis is a transaction in columns (1)-(2), and a parcel-year in column (3). The hedonic variables include bins of number of stories and number of bathrooms, lot size, house age, and effective age. Standard errors (in parentheses) are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B Determining Hurricane Exposure

B.1 Imputing Maximal Reach Radius of 96 Knots Wind Speed

In this section, we describe how we calculate the maximal reach radius associated with a wind speed of 96 nautical miles per hour (kn). For each hurricane track point, we observe the radii associated with a wind speed of 34, 50, and 64 kn. We estimate the relationship between the maximal reach radii and wind speed using the following model:

$$\log(Maxradius_{sht}) = \alpha_{ht} + \beta_1 Speed + \beta_2 Speed^2 + \varepsilon_{sht} \quad (5)$$

where α_{ht} are hurricane-track-point fixed effects and Speed (s) takes one of the three speed values available. Note that instead of specifying the minimum pressure and maximum wind speed, we choose to employ a set of fixed effects which absorb their variations. The relationship between a wind speed threshold and its associated maximal radius is very well captured by this model as suggested by its estimation's R^2 of 0.93 (0.90 within track-point fixed effects). The estimated function is negative and concave, suggesting the radius decreases at an increasing rate as wind speed increases. Full results are reported in Table B1.

Table B1: Wind Speed and Maximal Reach Radius Model

	log(Maxradius)
Speed	-0.0224***
	(0.004)
$Speed^2$	-0.0002***
	(0.00004)
Hurricane-track-point FEs	Yes
N	1188
R^2	0.93
Within-R^2	0.90

Notes: Standard errors in parentheses (clustered at the hurricane-track-point level). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We use the estimates (including the track-point fixed effect) to predict the maximum radii for 96 kn wind speeds at track points where the maximum sustained wind speed is actually above 96 kn. This procedure raises the typical concerns regarding out-of-sample predictions since 96 kn is not within the support of wind speeds used in the estimation. To address this concern, we check the validity of our predictions by comparing them to the observed radius of the maximum speed, which is provided in the Extended Best Track dataset. In particular, because the radius is strictly decreasing in wind speed, our imputed radius should always be greater than (or equal to) the radius associated with a 96 kn and above maximum speed in the cases when such speeds are observed. Our prediction satisfies this condition for over

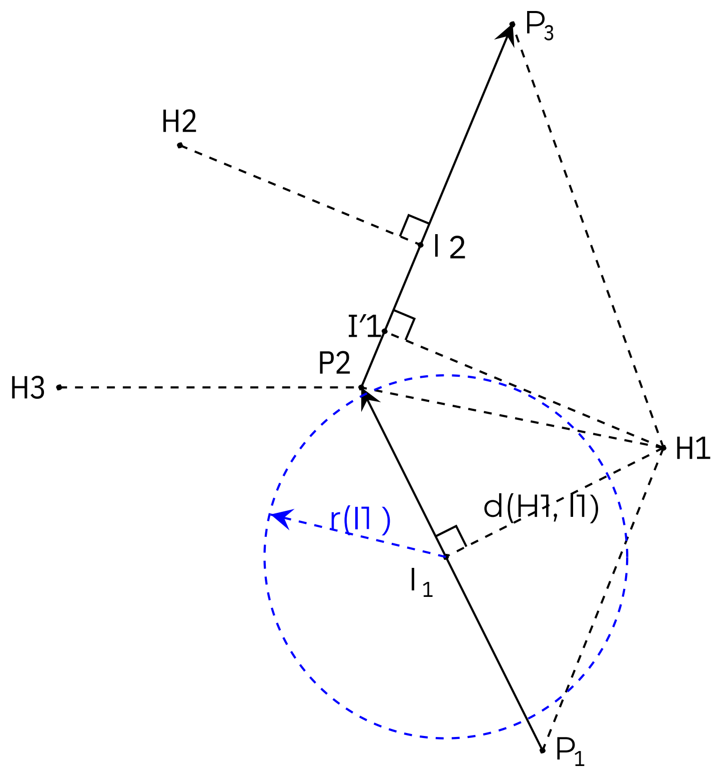


Figure B1: Hurricane Track Interpolation

90% of imputations and is within rounding error[47] for 10 of the 13 extrapolations for which it fails. In these 13 cases, we replace the model's predicted maximal radius for 96 kn speeds with the wider observed radius of the maximum speed reached.

B.2 Hurricane Track Interpolation and Exposure Calculation

In this section, we describe the procedure used to assign the exposure status of a home to a hurricane, with the geometric relationships illustrated in Figure B1. Suppose we want to determine the exposure status of a home H1 to a hurricane, whose track is recorded by three observations, P1, P2, and P3. At each track point, we observe the maximal reach radius $r(\cdot)$ associated with 64 kn wind speed and the maximum wind speed $v(\cdot)$ at the center.

We take the following steps to calculate exposure:

1. We interpolate linearly between neighboring track points (P1 → P2, P2 → P3), and calculate the distance from the home H1 to each linear segment. For instance, the distance between H1 and P1–P2 is d(H1, I1), or the distance between H1 and its projection point I1.

[47] All radii measurements in the dataset are rounded to the nearest 5 kn.

2. We calculate key variables for each projection point by interpolating between the observed track points. These variables are the 64 kn wind speed radius (denoted $r(\cdot)$) and the center wind speed (denoted $v(\cdot)$). We assume these values change linearly from one observation to another along the track segment. For example, the 64 kn wind speed radius for I1 is calculated using the observed 64 kn radii of P1 and P2 as follows:

$$r(I1) = \frac{d(I1,P2)}{d(P1,P2)} r(P1) + \frac{d(I1,P1)}{d(P1,P2)} r(P2).$$

Similarly, $v(I1)$ is calculated using $v(P1)$ and $v(P2)$:

$$v(I1) = \frac{d(I1,P2)}{d(P1,P2)} v(P1) + \frac{d(I1,P1)}{d(P1,P2)} v(P2)$$

3. We also calculate the distance of the home to each track point: $d(H1, P1)$, $d(H1, P2)$, and d(H1, P3). We thus have a collection of points representing the potential exposure set $S_{H1} = \{P1, I1, P2, P3\}$ with corresponding distances to H1, 64 kn wind speed radii, and center wind speeds.

4. For each point in SH1, we check two conditions: (1) whether the center wind speed is above 64 kn (e.g. $v(I1) \geq 64$)); (2) whether H1 is within the 64 kn wind speed radius (e.g. d(H1, I1) < r(I1)). If both are satisfied for any point in SH1, H1 is considered to be exposed to the hurricane.[48]

Our approach takes care of two other general cases where the path of a hurricane does not curve around a home the way it does with H1: the potential exposure set of H2 consists of {P1, P2, I2, P3}, while that of H3 consists of {P1, P2, P3}. In practice, a hurricane track is observed in many more segments. We pre-select the four segments closest to each home Hi and determine exposure by checking the above conditions for each point in the full set S_{Hi} generated by these segments.

[48] Generally, the interpolated radius is either zero or very close to zero at any point where the center wind speed does not reach 64 kn, in which case exposure is not triggered as the first condition is not satisfied.

C Zillow-HMDAMatchingProcedure

We use the following procedure to match the HMDA data to transactions:

1. We first select the subset of HMDA loan applications that are (1) successful and (2) whose purpose is a home purchase.

2. We create all possible pairs of observations from Zillow and HMDA with the same year, census tract, and loan amount (in 1000s) using the "joinby" command in Stata. A small percentage of lenders make multiple loans of the same amount in a single census tract every year. If there also exist multiple Zillow records with these same characteristics, we drop all such matches because we cannot infer the exact mapping between the multiple observations on the two sides.

3. Lendernamesmayberecordeddifferentlyacrossandevenwithin ZillowandHMDA. Extensive manual inspection revealed general patterns of mismatch, and we apply corresponding corrections to both datasets. For example, we replace acronyms such as "FCU" and "NB" with their full forms ("Federal Credit Union" and "National Bank").

4. WecalculatetheJaccardsimilarityindexforeverypairofHMDA-Zillowobservations using the "matchit" command in Stata. This index indicates the extent of the overlap between the strings containing the lenders' names from both datasets.

5. WekeepallpairswithaJaccardsimilarityindexaboveanacceptablethreshold,except for those joining a single HMDA record to multiple Zillow transactions each with an index above this threshold. The threshold is chosen so that we observe it to produce the correct pairing in large random subsamples chosen from every year in our data.