

# Chapter 2: Hurricane Irma and Rental Housing in Florida

Matthew Varkony<sup>1</sup>

<sup>1</sup>*Rosenstiel School of Earth, Marine, and Atmospheric Science, University of Miami, Miami,  
Florida*

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Corresponding author: [mvarkony@miami.edu](mailto:mvarkony@miami.edu)

# 1 Introduction

Rental housing represents a significant form of shelter in the United States, accommodating over 44 million households in the country<sup>1</sup>. Throughout Florida, a large number of these rental units are located in counties with high exposure to hurricanes and other climate stressors such as flooding and sea level rise (Joint Center for Housing Studies, 2022). High hazard exposure compounds housing challenges for renters, making this tenure status a particularly vulnerable group to the consequences of extreme climate events (Fothergill and Peek, 2004). Therefore, understanding how and to what extent hurricanes affect the market for rental housing is an important step towards increasing the climate resilience of renter households.

In this paper, I analyze the impact of Hurricane Irma on the market for rental housing. My data set includes rental listings for the whole state of Florida between the year 2014 and 2019, transaction values of homes throughout Florida's coastal counties, and high-resolution measures of wind speed from Hurricane Irma. I use a difference in differences research design to identify hurricane induced changes throughout the rental market described by increasing prices and reduced supply of rental units. My analysis contributes 2 main findings to the existing climate and housing literature. First, I show that hurricane impacted units observe increased rental listings following storm exposure. Second, I provide insight into the supply-side mechanisms contributing to the observed increase in rental prices and decrease in available rental units.

In this analysis, I ask how the price of rental housing is affected by exposure to high-

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<sup>1</sup>This number represents more than one third of all US households

intensity hurricane winds. Graff Zivin et al. (2023) find evidence that hurricanes increase the transaction price of homes driven by a shock in the supply of available housing. In line with previous research and building off the complimentary nature of homeownership and renting, I find that rental prices increase in the aftermath of hurricane exposure. The reductions in the supply of rental housing due to hurricane exposure and an increased demand for rentals stemming from a spike in temporary housing contributes to the increasing price of rentals in the short term.

In addition, I also document how Hurricane Irma affected the supply of rental housing by quantifying changes in household tenure decisions following hurricane exposure. Sheldon and Zhan (2019) provide evidence of changing tenure decisions for households migrating into disaster impacted areas. The authors suggest that rising ownership costs from increasing insurance premiums (or lack of insurance access) contribute to higher rental rates for in-migrating households. In my analysis, I show that single family rental units exposed to Hurricane Irma exit the renter market with a higher likelihood than non-impacted units, reducing the availability of single family rental units. These results justify the possibility of increasing ownership rates proposed by Sheldon and Zhan (2019) while also taking advantage of the transaction premium on hurricane impacted households demonstrated by Graff Zivin et al. (2023).

A number of methodological challenges create obstacles for the empirical analysis of hurricane impacts on the rental market. First, the informal nature of renting and lack of available, high resolution rental data inhibits a finer level of nuance needed to understand changes in the rental market (Boeing and Waddell, 2017; Smith et al., 2006). In this study, I overcome previous limitations to high resolution rental analysis by using a novel data set of

weekly, unit level rental listings throughout the state of Florida. This rental data provides listing information for units as portrayed on rental listing websites and represents the best opportunity to capture changing listing values after Hurricane Irma.

Second, a lack of easily available storm intensity data complicates the accurate categorization of treatment versus control units. I address this challenge by implementing high resolution wind speed data for Hurricane Irma. Through this high resolution wind speed data I am able to implement a finer level of treatment assignment based on a unit's location within an impacted or non-impacted census block (Hendricks et al., 2021). The increased accuracy of this assignment sets the stage for a difference in differences research design that can identify the causal effect of high intensity hurricane winds on rental prices.

Finally, identifying which channels affect the price of rental housing depends, in part, on the response of landlords. I investigate changes to landlord tenure choices, and thus the supply of rental housing, using the following approach. I combine the novel rental data set with housing transactions data to analyze whether impacted rental units are more likely to leave the rental market via transaction following a hurricane. While both single family and apartment units are available in the rental market, I focus specifically on transactions in the single family market due to challenges in identifying transacted apartment units.

The main data set used in this analysis<sup>2</sup> provides weekly listing values for rental units throughout the state of Florida from 2014-2019. The weekly listings data set captures listing prices for each unit, within each year, until the unit is presumably rented and taken off the market. I assume that a unit's closing price is captured by the final listing observed within

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<sup>2</sup>The rental data used in this analysis is purchased from the real-estate research firm Altos Research: <https://altosresearch.com>

a data set during a given year. This assumption provides over 1.1 million data points for my analysis. Included in the rental listing for each unit is a set of geographic coordinates representing a point geometry. Each point geometry is then categorized within a given census block, the lowest level of geographic grouping provided by the United States Census. Each census block is assigned a level of exposed wind speed from Hurricane Irma based on the geographic coordinates of its centroid. From here, I assign this level of wind speed exposure to the corresponding rental unit in the census block.

Results demonstrate an increase in the rental listing price of exposed units relative to the rental trend they would have experienced without hurricane exposure. I find that Irma exposed units experience an increased rental value of \$64.08. This increase in the rental listing value is consistent for Irma exposure Category 1 and 2 wind intensities. The increased rental prices for hurricane impacted regions align with general housing market outcomes observed in other hurricane and housing studies which find increased transaction values of impacted households (Vigdor, 2008; Graff Zivin et al., 2023). Further investigation of the heterogenous timing effects of hurricane induced rental increases suggests that price increases are most pronounced in the 12 – 24 months post Irma exposure.

Further investigation of the mechanisms contributing to the increased rental prices suggest that shrinking supply contributes to the price changes within the rental market. In the single family rental market, impacted block groups see an average reduction in the count of available (and new) rental units. This reduction in the availability of single family rental units coincides with an increased likelihood of impacted units being transacted. I find that single family properties in impacted block groups have 0.3% greater chance of being transacted than non-impacted housing units. Additionally, there is a steep decrease in the rental

rate for impacted block groups suggesting a switch in tenure decision for these households. The increased propensity for housing units to transition from renter to owner occupied units, combined with increasing household wealth of home purchasers observed in Graff Zivin et al. (2023), suggests that wealthier households are buying up single family rental stock resulting in a supply-side shift for increased rental prices.

The results of this study provide important empirical evidence to support a growing recognition of distorted rental markets following hurricane exposure in Florida (Liebson, 2022). Additionally, this analysis investigates possible mechanisms contributing to the experienced rental increases including short-term supply shifts in the market equilibrium. The observed increases in rental prices will have an impact on the type of households that can afford to live in coastal locations, suggesting that state and local governments will need to explore solutions to increase the availability of affordable housing in these locations.

In the following section I present a summary of the current literature on hurricane impacts to housing markets and the impact this has for more vulnerable populations within these markets. The rest of the paper is laid out as follows; Section 3 described the data while Section 4 provides the empirical methods used to answer my research questions. Section 5 presents and discuss the results of this analysis. Section 6 concludes with major take-aways and caveats for future research.

## **2 Disasters, Housing Tenure, and Rental Vulnerability**

Previous research on the relationship between disasters and housing markets suggests that supply reductions due to capital damages drive the observed transaction price increases

in the literature (Graff Zivin et al., 2023; Vigdor, 2008). Vigdor (2008) and Graff Zivin et al. (2023) both suggest that reductions in housing supply outweigh changes in demand. Yet, Graff Zivin et al. (2023) find that price increases taper off 2 to 3 years following a hurricane event, a departure from the permanent price increase reported by Vigdor (2008). One likely reason for the different findings is rebuilding efforts after hurricane exposure. Vigdor (2008)'s study of Hurricane Katrina captured a city in decline, while Graff Zivin et al. (2023) analyze general hurricane impacts in Florida between 2000-2016. Elliott and Clement (2017) provide support for the attenuating housing price increases with evidence of increased land development in the years following a natural disaster. The increased rate of land development for impacted areas provides the initial process for an increase in the production of housing and the replenishment of damaged homes. Another potential reason for attenuating price increases can be attributed to the timing of access to aid and other financing opportunities for rebuilding and renovations (Sutley and Hamideh, 2018). Rental housing can serve as a temporary means of shelter for homeowners in the midst of a disaster rebuilding process. Given that owner occupied housing suffers less damage and recovers more quickly than rental housing following a disaster (Zhang and Peacock, 2010; Peacock et al., 2014), it is important to understand how shifts in the supply and demand of rental housing impacts rental prices following a disaster. This work contributes to the disaster literature on housing markets by analyzing the effect of Hurricane Irma on rental listings throughout Florida.

Disaster effects on demand may also play an important role in the shifting equilibrium price of impacted housing. Changes to insurance rates, updates in risk awareness, and changing socio-demographics all influence the demand for housing in disaster prone areas. Sheldon

and Zhan (2019) suggest that increasing ownership costs lead to the observed reductions in homeownership rates for households moving to locations recently affected by a disaster. Additionally, Sheldon and Zhan (2019) build on results from Bakkensen et al. (2019) who find that risk updating from disaster exposure influences ownership decisions. In general, as Bakkensen et al. (2019) suggests, disasters may change the socio-demographics of households looking to own and rent housing. One potential reason for a shifting demographic of households may be a shift towards a smaller, less diverse labor market with increased wages relative to pre-disaster conditions (Pais and Elliott, 2008; Belasen and Polachek, 2009; Groen et al., 2020). Graff Zivin et al. (2023) find that households purchasing units are wealthier in the post-disaster environment, a result that compliments evidence of wage increase for laborers in disaster effected regions. This paper contributes to the literature on disaster influenced socio-demographic changes by further investigating the impact hurricane exposure has on household tenure decisions.

Finally, rental housing plays an important role in providing affordable shelter for lower income households. Throughout the disaster literature there is a well developed understanding that low income households, in particular low-income renters, suffer the most from disaster exposure (Fothergill and Peek, 2004; Peacock et al., 2014). Areas with high social vulnerability tend to recover more slowly and less robustly from hurricanes due in part to less aid and financing access (Pais and Elliott, 2008; van Zandt et al., 2012; Wyczalkowski et al., 2019). As Elliott and Howell (2017) and Fussell and Harris (2014) demonstrate, low income and households of color are less housing stable, with renters for each of these groups the most prone to becoming unhoused. One reason renters are the most vulnerable is because aid tends to favor homeowners leaving renters at the mercy of their landlords (Peacock et al.,



2014; Howell and Elliott, 2019; Brennan et al., 2022) . Brennan et al. (2022) find evidence of increased eviction rates following disaster events, in part due to an inability to keep up with increasing rent prices from raising housing costs. This papers focus on changes in the price of rental housing contributes to the literature on climate vulnerable households in coastal states.

### **3 Data**

In this paper, I study how hurricane exposure affects the market for rental housing. This section describes the data sets used, including wind speed data from Hurricane Irma, rental unit listing prices throughout Florida, and transaction-level data used in the tenure analysis.

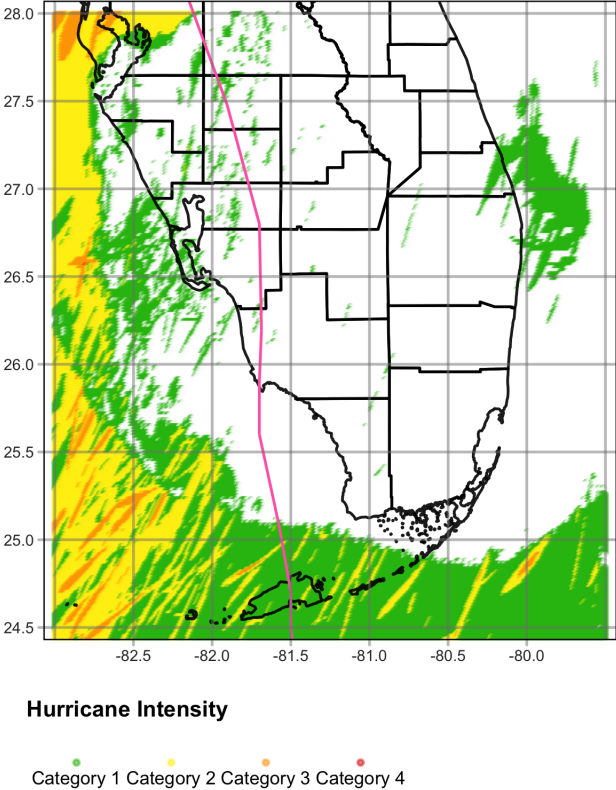
#### **3.1 Hurricane Irma**

Irma, a Category 4 hurricane, first made landfall in Florida on the afternoon of September 10, 2017. After passing through the Florida Keys, Irma tracked northwest along the Florida Strait, gaining strength before crossing over Marco Island back into Florida. Irma’s path through the center of Florida resulted in a drop in intensity; however, due to the original size and strength of Irma, the wind field remained large, with tropical storm-force winds extending out 360 nautical miles from the eye (Cangialosi et al., 2018).

I use wind swaths from Hurricane Irma, created with a high-resolution parametric hurricane model (Hendricks et al., 2021), to associate wind speed intensities with each rental unit in the wind swath study window (Strobl, 2011; Elliott et al., 2015; Esnard et al., 2018). Wind swaths are defined as a continuous surface of peak winds experienced at any location

during a hurricane event. I assign wind speeds to census block centroids based on their geographic overlap with the generated wind swaths. Rental units are then linked to a given level of wind speed exposure based on their location within a census block<sup>3</sup>. Figure 1 presents Irma’s wind swath along with the path of Irma’s eye through Florida.

**Figure 1: Irma Map**



This map presents Irma’s wind swath overlay on Florida with Hurricane Irma’s track in pink. The level of maximum wind speed intensity observed for each location in the wind swath window is categorized in either Low-Intensity, Category 1, Category 2, Category 3, or Category 4. Certain location in the Florida Keys and along Florida’s West Coast experience wind intensities in the Category 3 designation. Appendix ?? provides a breakdown of rental housing characteristics for each Saffir Simpson category based on the maximum experienced wind intensity of each rental unit.

As I show in figure 1, the majority of Florida’s central counties experienced low-intensity

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<sup>3</sup>Census blocks typically represent a city block (within urban areas) and are the smallest geographical unit with available demographic data.

winds. However, the Florida Keys and counties along the west coast, including Pinellas and Hillsborough, were exposed to winds ranging between Category 1 and Category 3 on the Saffir-Simpson scale. The Saffir-Simpson intensity scale categorizes wind speeds into one of five different intensity categories based on maximum wind speeds experienced. In Florida, Irma’s maximum wind intensity identified over land by the wind speed model is 113 miles per hour (Category 3).

My main study specification assigns rental units exposed to winds greater than 73 miles per hour (Category 1) into the treatment group, while rental units exposed to winds less than 73 miles per hour make up the control group<sup>4</sup>. The Saffir-Simpson scale suggests that exposure to Category 1 wind speeds produce some levels of damage to well-constructed homes<sup>5</sup>. The assumed damages from hurricane exposure contribute to the hypothesized effects on rental prices I investigate in this paper.

### **3.2 Florida Rental Market**

The rental data<sup>6</sup> used in this analysis consists of rental listings for the entire state of Florida between the years 2014 and 2019. The data set represents a snapshot of rental listing values at the beginning of each week within the study period. I assume that a unit remains on the market if in consecutive weeks, within the same year, it is present in the data set. To capture the assumed rental value of a unit, I designate the latest listing value within a given

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<sup>4</sup>I chose to assign wind speeds at the census block level due to the small extent of census blocks and the level of resolution in the parametric wind model.

<sup>5</sup>The National Hurricane Center (<https://www.nhc.noaa.gov/aboutsshws.php>) provides descriptions for the different Saffir-Simpson categories and the assumed damages associated with each intensity level

<sup>6</sup>I purchased the data from Altos Research Inc. A nationwide real-estate research firm and supplier of rental data. The data is web-scraped from a number of different rental advertising companies online.

year as the rental cost of the unit (Boeing and Waddell, 2017)<sup>7</sup>.

The data represents a repeated cross-section at the unit level, with units entering and exiting the market at different time intervals. The web-scraped data includes rental unit variables describing the housing type (single family residential or apartment), number of beds and baths, floor size, and geographic coordinates. I use the geographic location of each rental unit to assign unit specific, spatial variables including the parcel’s elevation and distance to the nearest coast. These spatial variables are thought to influence the rental value of a unit; however, they should not influence treatment assignment (McKenzie and Levendis, 2010).

Table 1 provides summary statistics for the pre- (2014-2017) and post- (2017-2019) Hurricane Irma time periods displaying the control group along with the different treatment group levels. Throughout all of the sub groups the average rental listing prices increases from the pre- to post- hurricane periods. Rental units affected by category 1 storm intensity display the highest average increase between the two periods. For all sub-groups there is a decrease in the average size of rental units available on the market. The control group of rental units has the largest average rental size amongst groups in both periods. While both the control and category 1 groups include rental units sitting at a similar elevation, units exposed to category 2 and 3 hurricane wind speeds are on average situated at lower elevations. The lower elevation of units exposed to high intensity winds (categories 2 and 3) contributes to additional hazard susceptibility for these units.

I provide the total count and housing type break down at the bottom of table 1. The

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<sup>7</sup>Boeing and Waddell (2017) find that 37% of their online rental listings are below the Housing and Urban Development (HUD) Fair Market Rent (FMR), which is meant to represent the 40<sup>th</sup> percentile of rental payments in a given metropolitan area.

**Table 1: Summary Statistics**

	Treatment							
	Control		Category 1		Category 2		Category 3	
	Pre-	Post-	Pre-	Post-	Pre-	Post-	Pre-	Post-
Rental Listings (\$)	1968 (1835)	2022 (2081)	1693 (1176)	1825 (1804)	1456 (797)	1461 (889)	2213 (1684)	2245 (1814)
Beds	3 (1)	2 (1)	3 (1)	2 (1)	3 (1)	2 (1)	2 (1)	2 (1)
Baths	2 (1)	2 (1)	2 (1)	2 (1)	2 (1)	2 (1)	2 (1)	2 (1)
Elevation (m)	10.39 (12.82)	9.52 (12.47)	10.74 (7.87)	9.61 (7.22)	8.96 (6.64)	8.00 (6.22)	4.20 (3.48)	3.87 (3.30)
Distance to Coast (ft)	3721.63 (4387.77)	3203.24 (4228.91)	2134.12 (2372.37)	2068.54 (2268.10)	1809.48 (1958.10)	1612.58 (1763.58)	392.88 (570.58)	417.78 (643.88)
Size (sq.ft)	1634 (885)	1434 (854)	1558 (785)	1427 (739)	1339 (621)	1205 (603)	1477 (758)	1365 (754)
<b>Housing Count</b>								
Total	592657	377564	34246	22728	41327	29442	2929	2474
Single Family	350279	141987	21436	9353	24065	9535	1252	570
Apartment	242378	235577	12810	13375	17262	19907	1677	1904

Notes: This table provides summary statistics for the main variables used in this analysis. It includes the average value for each variable separated into treatment and control groups in the pre- and post- Irma periods. The standard deviation for each variable is provided below the mean value in parentheses. The control group consists of all rental units exposed to winds lower than 73 miles per hour. The treatment group consists of all units exposed to winds greater than 73 miles per hour. Additionally, this table provides counts of rental units for each of the sub-groups. It splits the counts of rental units into the two types of rental housing studied in this analysis, single family and apartment units.

total number of units in the control group is larger than the aggregated count of all units in the three treatment sub-groups (7 times larger). Between the pre- and post- time periods all sub-groups observe a switch in the dominant type of rental housing available. In the pre-hurricane time period, single family residential units account for the most available rental units. Within each group, available apartment units outnumber single family units following Hurricane Irma. This outcome is explored in my housing tenure analysis.

### 3.3 Tenure Decisions - Single Family Residential Units

This section introduces my housing transaction data used to analyze rental supply changes resulting from shifts in tenure decisions after hurricane exposure. For this analysis, I use single family residential units because of the challenges in identifying transacted rental units from apartment buildings. The spatial joining algorithm I describe in section 4.2 cannot link transacted apartment units with rental units using my spatial overlap method. Apartment buildings (parcels) include a large number of units within the same geographic location that cannot be differentiated without unit specific identifiers.

The single family rental and transaction units used in this analysis only include properties from coastal counties. As demonstrated in appendix B, results are similar between the full analysis and the coastal analysis.

**Table 2:** Summary Statistics for Single Family Residential Rentals

	No Match		Match	
	Mean	SD	Mean	SD
Pre-Irma Listing (\$)	2040	1731	2028	1694
Post-Irma Listing (\$)	2103	2675	2096	2340
Beds	3	1	3	1
Baths	2	1	2	1
Size (sq.ft)	1772	857	1812	835
Elevation (m)	6.77	7.91	7.32	7.66
Distance to Coast (ft)	3128.88	3642.50	3016.03	3499.45
<b>Housing Count</b>				
Total	131 990		126 926	
Control	111 483		104 290	
Treatment	20 507		22 636	

Notes: This table presents average values for rental units that had a matching transaction parcel and those rental units that did not. Average listing values are calculated for individual rental units over the Pre- (2014 – 2017) and Post- (2018 – 2019) Irma periods to provide an average Pre- and Post- rental listing for each rental unit. This is done to account for the fact that many rental units have numerous listings within each Pre- and Post- period. The total housing count represents the number of rental units within each group of "No Match" or "Match". Control and treated counts represent the number of units within each group that are either not exposed to winds > 73 miles per hour or are exposed to these Category 1 winds.

Table 2 provides summary statistics for the joined data set with splits between non-matched and matched rental units. For each rental unit the average rental listing is calculated

throughout the given Pre- (2014-2017) or Post- (2018-2019) Irma time period. For example, I take the average of three rental listings for a unit with listing values in 2015, 2016, and 2017 to capture the Pre-Irma listing value for that unit. This is also done for the Post-Irma period. The “Pre-Irma Listing (\$)” and “Post-Irma Listing (\$)” averages presented in table 2 are therefore the average over all rental units within the given “No Match” or “Match” group.

Table 2 suggests there are no significant differences in the composition of rental units with matching transactions and those without. Listing prices are marginally higher in the “No Match” group, while “Match” units are on average 40 square feet larger. Additionally, “Match” units are located a little higher and closer to the coast than “No Match” units. The number of units in either group is nearly identical. This table supports the assumption that the composition of the two groups is similar.

## 4 Methods

My goal in this analysis is to identify Hurricane Irma’s effect on rental markets in Florida. This section describes the research design for my analysis. First, I analyze how exposure to Irma’s high intensity winds impacted the listing price of rental units. Second, I investigate how exposure to Irma impacts the supply of rental units on the market through household tenure decisions. Finally, I explore the consequences of changing rental market conditions through an analysis on rental evictions following Irma. The causal interpretation of these estimates relies on the assumed randomness in Irma’s path resulting in exogenous wind exposure for each rental unit.

## 4.1 Rental Listing Models

Do rental market disruptions from Hurricane Irma lead to increased rental prices for hurricane exposed units? Using equation 1, I explore this question with a difference in differences research design to estimate Irma’s effect on rental prices.

$$Y_{iwy} = \delta(Treatment_b * Post_{wy}) + \alpha'Post_{wy} + \beta'X_i + \gamma_{yc} + \gamma_b + \gamma_s + \epsilon_{iwy} \quad (1)$$

The dependent variable  $Y_{iwy}$ , represents the listing price of rental unit  $i$  in week  $w$  of year  $y$ . The unit of analysis is a rental unit located within census block  $b$  of county  $c$ . The variable of interest,  $\delta$ , estimates the effect of hurricane winds on the listing price of an impacted rental unit. The *Treatment* indicator takes on the value 1 if a rental unit is exposed to hurricane winds ( $> 73$  miles per hour). Additionally, to check for variation amongst treatment levels, a binned analysis is conducted. Bins are separated by groupings from the Saffir-Simpson Hurricane Scale including exposure to category 1, 2, or 3 hurricane winds<sup>8</sup>. The *Post* indicator takes on a value of 1 for rental listings observed any week after Irma (September 10, 2017). The parameter  $\alpha$  estimates the change in rental unit listing prices between the two periods for all units.

The vector  $X_i$  represents unit specific variables including both housing characteristics and spatial variables. The housing variables include the number of beds, baths, the total square footage of the unit, as well as a distinction between single family residential and apartment units. The spatial variables include the elevation and distance to the nearest coastline. The addition of housing variables control for observable unit specific effects that influence the

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<sup>8</sup>Category 3 winds are the highest experienced on-land intensities during Hurricane Irma



listing price of a given rental unit. Additionally, the inclusion of the spatial variables control for a unit’s baseline propensity to be exposed to hurricanes.

In equation 1 three sets of fixed effects, year by county (yc), census block group (b), and seasonality (s), are included to control for unobservable characteristics influencing trends in rental listings. The year by county fixed effects are used to control for unobserved rental trends within each county-year throughout the study period. Census block group fixed effects are included to control for unobserved amenities within the neighborhoods of each rental unit. Examples of these amenities include school quality, proximity to grocery stores and shops, as well as environmental amenities such as parks. Finally, seasonality fixed effects control for trends in rental prices during different quarters of the year.

I cluster standard errors at the census block group level to account for potential spillovers between rental units. Shr and Zipp (2019) suggest that clustering standard errors at the neighborhood level while including fixed effects for the same geographic level assists in accounting for spatial autocorrelation between housing transactions. I use a similar rationale for rental listings.

#### 4.1.1 Event Study

I check for impact heterogeneity over time using the event study research design. Equation 2 describes the model:

$$Y_{iwy} = \sum_{j=-44}^{27} \delta_j(Treatment_b * Post_{wy}) + \alpha' Post_{wy} + \beta' \mathbf{X}_i + \gamma_{yc} + \gamma_b + \gamma_s + \epsilon_{iwy} \quad (2)$$

In equation 2 the variable of interest,  $\delta_j$ , varies over time indexed by  $j$  and estimates the impact of exposure to Irma in each of the months post-Irma. The time resolution varies at the month level, assuming that the week of September 10, 2017 acts as the point of reference for the treatment effect.

Similar to the model assuming homogeneous timing effects, I cluster standard errors at the block group level. All other variables in model 2 are the same as in model 1

#### 4.1.2 Rental Probabilities

Impacts to the rental market are influenced by both price and the quantity of available rental units. I follow Graff Zivin et al. (2023) to model an individual rental units probability of appearing in the listings market with the following linear probability model:

$$\mathbb{1}(RentalListing)_{iby} = \sum_{j=-3}^2 \delta_j (Treatment_b * Post_y) + \alpha' Post_y + \beta' \mathbf{X}_i + \gamma_{yc} + \epsilon_{iy} \quad (3)$$

Equation 3 describes the listing outcome for individual rental unit  $i$  taking the value of 1 if a rental listing is observed in year  $y$  and 0 if no listing for unit  $i$  is available. There are two outcomes modeled with equation 3. The first outcome estimates the probability that a unit has a new rental listing, meaning that the individual unit  $i$  has not appeared in the rental listing data set prior to year  $y$ . The second outcome models the probability of a rental listing for unit  $i$  for both new and repeat listings.

All independent variables included in model 3 are consistent with model 1. The parameter of interest,  $\delta_j$ , represents the increased likelihood that a hurricane impacted unit (exposed

to winds  $> 73$  mile per hour) is listed for rent relative to a non-impacted unit. I cluster standard errors at the block group level.

## 4.2 Rentals and Transactions

Next, I ask whether exposure to hurricane winds results in changing tenure decisions for single family residential households. I construct a data set of rental listings and transaction information as described in section 3.3. In the construction of this data I make a number of assumptions that allow me to identify rental listings as either a new listing, a renewal, or a renter to owner switch. First, I assume that all rental units without a matching transaction data point are not sold during the study window (2014-2019). Therefore these units are consistently identified as rental units. Second, and consistent with the main analysis, I assume that a rental unit's first listing in the rental data set is considered a new listing for that unit. Third, I assume that units with a prior listing (from a past year in the data set) that do not reappear on the market in a given year and are not transacted are considered renewal units. I assume that the current tenant agrees to renew the lease which keeps the rental unit from being re-listed on the market. Finally, I assume that rental units transacted in a certain year, without a subsequent rental listing, are units that transition from renter to owner occupied. This assumption can be thought of as a property being taken out of the market for rental units.

In equation, 4 I describe the linear probability model used to statistically test whether exposure to high intensity hurricane winds decreases the supply of available rental housing. I follow Graff Zivin et al. (2023) in using a linear probability function to model the limited

dependent variable.

$$\mathbb{1}(RentalStatus)_{iby} = \sum_{j=-3}^2 \delta_j(Treatment_b * Post_y) + \alpha'Post_y + \beta'X_i + \gamma_{yc} + \epsilon_{iy} \quad (4)$$

In equation 4  $\mathbb{1}(RentalStatus)$  represents two different outcomes. The first outcome is used to test whether hurricane exposure increases the likelihood of a transition from renter to owner tenure by setting  $\mathbb{1}(Switch)$  equal to 1 if a property transitions and 0 otherwise. The second outcome is used to test whether hurricane exposure decreases the likelihood of a new unit entering the market where  $\mathbb{1}(NewListing)$  is set to equal 1 if a rental listing is a new rental unit and 0 otherwise. The rest of equation 4 follows the same design as model 2. Additionally, standard errors are clustered at the block group level.

## 5 Rental Market Results

In this section I provide evidence of Irma's affect on rental markets in two parts. First, I show that exposure to high intensity winds from Hurricane Irma increases the listing price of rentals compared to non-exposed units. Second, I present results describing Irma's affect on the supply of rental housing and analyze household tenure decisions following hurricane exposure.

**Table 3:** Difference in Difference Estimates

	Rental Prices			
	Model 1	Model 2	Model 3	Model 4
Hurricane Effect	49.31*	64.07**	64.08**	
	(24.15)	(20.74)	(20.74)	
Category 1 Hurricane				66.55**
				(25.26)
Category 2 Hurricane				62.71***
				(18.48)
Category 3 Hurricane				31.36
				(76.83)
Num.Obs.	1 103 367	1 103 367	1 103 367	1 103 367
Housing Attributes		X	X	X
Spatial Attributes			X	X
FE Housing Type		X	X	X
FE County by Year	X	X	X	X
FE Block Groups	X	X	X	X
FE Seasons	X	X	X	X
SE Clusters	Block Group	Block Group	Block Group	Block Groups

+ p < 0.1, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

Notes: This table presents OLS regression results for the difference in differences analysis of Hurricane Irma’s affect on the price of rental housing in Florida. Standard errors are provided in parentheses and are clustered at the block group level for each specification. Housing attributes are used in models 2-4 and include number of baths, beds, and total square footage of the unit. Spatial attributes are used in models 3-4 and include elevation of the rental unit (at the given longitude and latitude) and the distance to the nearest coastline. The variable (Hurricane Effect) is composed of the interaction term between the (Post) and (Exposure) variable. In models 1-3 (Exposure) is determined by units experiencing winds  $\geq 74$  miles per hour. Model 4 incorporates a similar interaction term, but splits exposure into 3 hurricane categories. Categories are split according to the Saffir Simpson Scale with winds between 74 and 95 in Category 1, winds between 96 and 110 in Category 2 and winds between 111 and 129 in Category 3.

## 5.1 Changes in Rental Prices

Table 3 reports the results of the difference in differences analysis with estimates for  $\delta$ , my estimand of interest in equation 1. Recall that  $\delta$  estimates the change in the average rental listing price for units impacted by Irma relative to what their price would have been absent hurricane exposure. The first three specifications (Model 1 - Model 3) use the simple difference in differences model with a binary indicator for treated and control groups. Model 3 is the fully identified specification, including all control variables and fixed effects for county-year, block group, and seasonality of the rental listing. Results from Model 3 provide evidence that rental units exposed to winds greater than Category 1 ( $\geq 74$  miles per hour) increase in their average listing price by \$64.08 relative to non-exposed units. The increase

in rental listing price, as estimated by model 3, represents 4% of the average pre-Irma listing price for units located in impacted neighborhoods.

The three point estimates, representing different model specifications, for Irma's effect on rental listings in table 3 are within \$15 of each other. When incorporating housing characteristics such as the size, type, count of beds and baths in a unit there is an observed \$15 jump in the estimated effect of exposure to Irma on rent. This increase in the point estimate demonstrates the effect that housing characteristics have on rental listing prices. The addition of spatial variables including home elevation and distance to the coast does not influence the target estimate after housing characteristics are accounted for. Typically, in housing hedonic analysis these spatial variables influence the transaction price of a home (McKenzie and Levendis, 2010). However, the lack of importance of these variables is likely due to the fact that renters have different household utility functions than homeowners. In particular, their living choices likely operate on a different time horizon and thus they may not care as much about a homes elevation.

Model 4 in table 3 displays the results of a binned analysis delineating exposure based on different categories of experienced intensity. For rental units exposed to Category 1 or 2 winds Irma's estimated effect on the average listing price is similar. However, for units exposed to Category 3 winds the estimate remains positive, but is less than half the estimated impact for units exposed to Categories 1 and 2. Additionally, the standard errors on the point estimate for Category 3 impacts imply a noisy estimate where the hypothesis of a null-result cannot be rejected. A lack of variation in rental prices due to low counts of Category 3 exposed units (see Table 1) is likely contributing to the noise observed in the point estimate.

Yet, the lack of increasing rental prices for greater intensity exposure between Category

1 and 2 winds suggests that housing damages may not be driving changes in rental prices. Deryugina (2017) finds that exposure to higher hurricane intensity leads to greater per capita government transfers to account for greater damages. The lack of increasing rental prices associated with increasing wind exposure suggests that damages may not be the main mechanism behind increasing rental prices. If damages to supply drive price increases, I would expect for supply decreases to be greatest in the most impacted locations and thus the available rental properties would be more expensive. The following sections further investigate the contributing mechanisms to the observed increase in rental prices for hurricane exposed rental units.

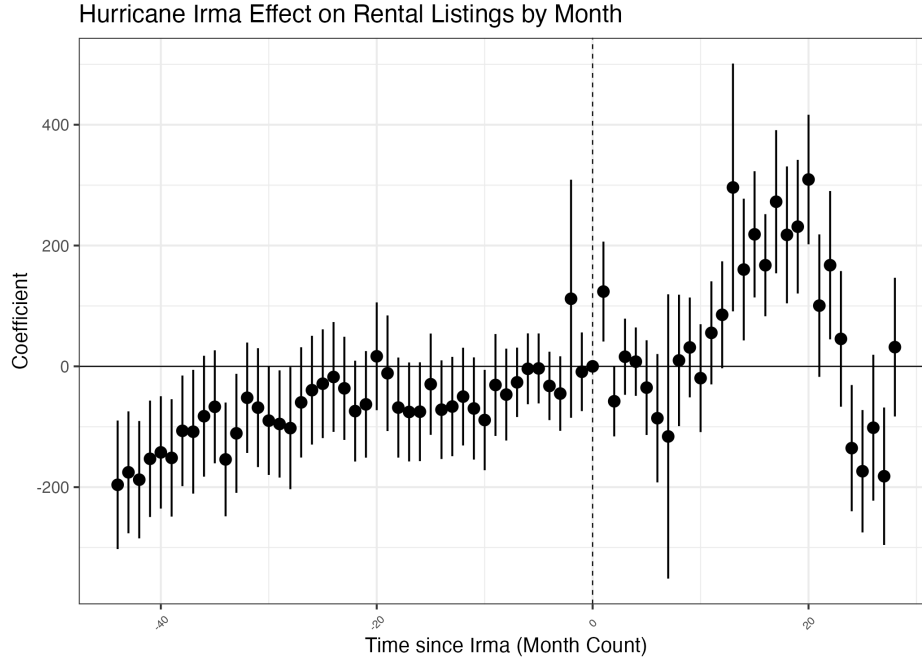
### 5.1.1 Event Study

Figure 2 provides monthly point estimates with 95% confidence intervals for the event study defined by model 2 in section 4. From figure 2, Irma's effect in the first two months<sup>9</sup> is an immediate jump in average rental price followed by an opposing decrease. The following 8 months suggest a flat price effect. Starting in September 2018, a statistically significant increases in listing price is observed. In 9 out of the 10 following months (September 2018 - May 2019) Irma's affect on average rental listings remains higher than the counterfactual listing. There is a subsequent drop in the average rental listing price between September 2019 and November 2019.

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<sup>9</sup>I use the week of Irma's occurrence September 10, 2017 as the base year

**Figure 2: Hurricane Irma Winds Effect on Rental Prices - Event Study**



Notes: This figure presents results of the event study for Hurricane Irma’s effect on rental unit listings at month intervals. Point estimates are presented with error bars at the 95% confidence interval. Standard errors are clustered at the census block group level. The x-axis provides the number of months since Irma occurred. The y-axis provides values for the estimated effect of hurricane exposure ( $\geq 74$ ) on rental listings in any given month relative to non-exposed rental units.

## 5.2 Listing Probabilities

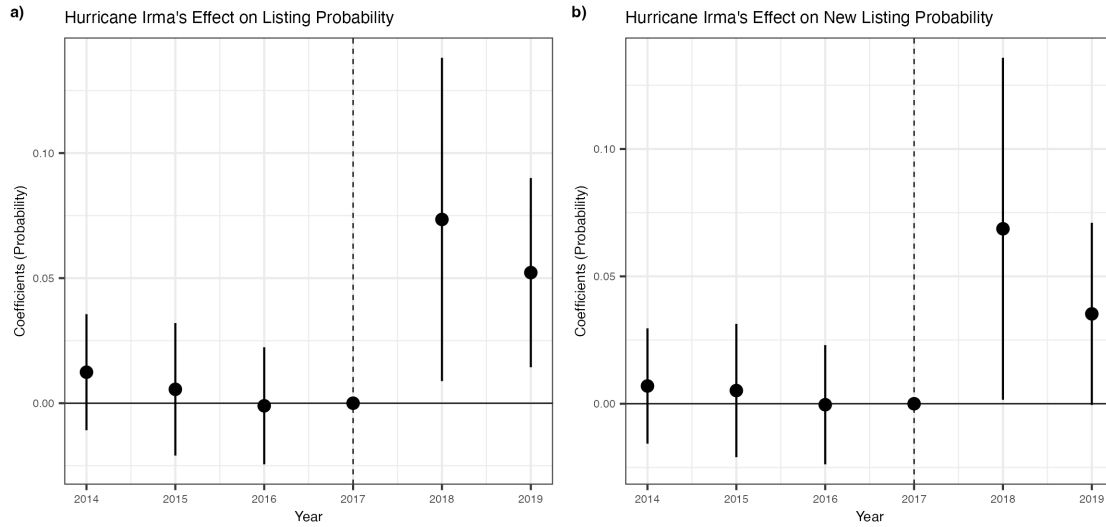
Figure 3 presents the event study results for model 3 which estimates the change in likelihood that a hurricane impacted unit will appear in the rental listing market. Panel a) describes how units impacted by winds  $> 73$  miles per hour are more likely to appear in the rental listing data set following the hurricane event than units not impacted by Hurricane Irma’s high intensity winds. These results suggest that housing units in impacted areas are more likely to be available for rent than non-impacted units; however, these results do not directly suggest a change in the quantity of available rental units.

Figure A.1 provides evidence of a reduction in the average number of available rental units for both impacted and non-impacted regions following Hurricane Irma. The decreased



count of available units aligns with the increased rental prices signaling a supply shift in the rental market equilibrium.

**Figure 3: Probability of Rental Listing**



Note: This figure provides two event study results for the increased probability of impacted rental units (experiencing winds > 73 miles per hour) appearing in the rental market. Panel a) looks at all rental units in the market and compares the probability of an impacted unit appearing in the market relative to non-impacted units. Panel b) looks at a units first experience on the rental market and compares the probability that an impacted unit is a new listing relative to new listings for non-impacted units.

Panel b) in figure 3 displays event study estimates on the probability that impacted rental units will appear on the listing market as new listings. Results from this analysis suggest that impacted rental units do not have a significantly higher probability of being new listings than non-impacted units. This implies that impacted housing units are not entering the rental market at higher rate than non-impacted units, even with the observed increase in rental prices of hurricane impacted units.

One potential reason that impacted units are likely to re-enter the rental market than non-impacted units could be attributed to shifts in the demand for rental. Non-impacted rentals may be less likely to re-enter the rental market because of lease renewals. However, land lords of impacted rental units may be less likely to pursue rental renewals because of

the opportunity to capitalize on increasing rents. Section 5.4 further investigates possible changes in the market composition following a hurricane event, that can lead to changes in rental prices and the decreased likelihood of rental renewals.

### 5.3 Tenure Decisions and Rental Supply

In this section, I explore the supply effects of hurricane exposure on a particular rental submarket by estimating changes to the tenure decision of impacted single family households. Table 4 provides average annual statistics for total listings, new listings, renewals, and tenure switches (defined as a switch from renter to owner occupied) within the Pre- and Post- Irma periods. Within each period units are separated into a control or treatment group based on a unit’s exposure to winds over 73 miles per hour.

**Table 4:** Supply Statistics for Single Family Residential Rentals

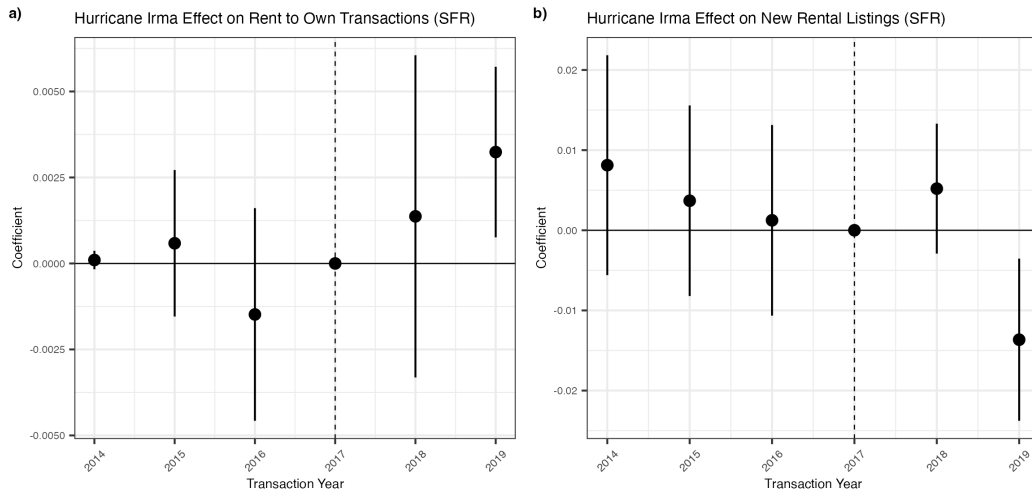
	Pre-Irma		Post-Irma	
	Control	Treatment	Control	Treatment
Average Listings	50943	10056	23452	4944
Average New Listings	46365	9155	15536	3356
Average Renewals	58950	11090	160162	29643
Average Switches	3350	916	5950	1550

Notes: This table provides summary statistics for single family residential properties. The values represent average yearly housing tenure statistics within non-impacted and impacted census block groups for the pre and post Hurricane Irma periods. The pre-event periods include years 2014 to 2017, while the post-event periods include years 2018-2019. Listings represent the total number of unit listings for both repeat and new listings. New listings represent rental units that appear for the first time within the rental data set. Renewals are rental units that are on the market in one year, but do not appear in the rental or transaction data set in subsequent years. Switches represent rental units that are identified in the transaction data set and do not reappear in the rental data set following the transaction.

The average number of listings in a given year drops by more than half between the Pre- and Post-Irma time periods for both control and treatment groups, while the drop in average count of new listings is even greater between the two periods (> one-third). This reduction in available single family units is further supported by increasing counts of renewals and

tenure switches between the Pre- and Post- Irma periods. Results from the data suggest that a bulk of the drop in available single family rental properties is due to the renewal of rental units, with only a marginal amount of single family properties leaving the rental market due to a switch in tenure status.

**Figure 4: Hurricane Irma Winds Effect on Tenure Decision - Event Study**



These graphs presents event study estimates on characteristics of rental housing supply for impacted single family residential rental units in Florida. Figure a) describes the effect of Hurricane Irma on the likelihood a single family home changes tenure status from renter to owner. Figure b) describes the likelihood that an effected single family unit is a new listing on the market. This analysis use the integrated rental and transaction data set solely composed of single family rental units identified in both data sets.

Figure 4 presents the results of the event study from model 4. Panel a shows the likelihood of an impacted rental unit switching from renter occupied to owner occupied following exposure to hurricane winds. In the second year post Irma (2019) there is a statistically significant increase in the likelihood of a rental unit transaction, switching tenure status of the unit from renter to owner. Additionally, panel b provides evidence that single family rental units exposed to high intensity hurricane winds are less likely to be new listings relative to units not exposed to hurricane winds from Irma.

The evidence provided by figure 4 aligns with findings from A.1 describing a reduction

in the quantity of available rental units after Irma. Additionally, the increased likelihood of a tenure switch amongst single family residential landlords may imply that landlords are seeking to take advantage of the increasing transaction costs of housing found by Graff Zivin et al. (2023).

## 5.4 Other Mechanisms

Increasing rental prices and reductions in the quantity of rental housing suggest a supply side shift in the rental market equilibrium. Yet, Pais and Elliott (2008) suggest that temporary changes in demographics due to a need for workers in hurricane clean-up and reconstruction may contribute to short-term demand shifts in the rental market. Aid and insurance payouts flow into damaged areas starting 6 to 12 months after the event. Then reconstruction on damaged housing occurs. The increased demand for short-term housing from the influx of repair contractors can affect the short-term equilibrium of the rental market. The observed rental price increases in figure 2 correlate with the schedule for reconstruction, suggesting that this short-term spike in demand may contribute to the increased rental prices in hurricane impacted areas.

Additionally, increased rental prices may result from the rebuilding process where homeowners waiting for reconstruction drive up temporary housing demand. In the direct aftermath of a major hurricane, households are displaced. The subsequent return timeline for these hurricane displaced households aligns with the observed shifts in market rent prices described in this study (Sacerdote, 2012; Sutley et al., 2019).

## 6 Conclusion

In this paper, I investigate the effect of Hurricane Irma on rental markets in Florida by estimating the change in rental prices for hurricane impacted units. I find that units exposed to hurricane level winds ( $\geq 74$  miles per hour) experience average rental price increases equal to \$64.08 relative to units in neighborhoods that are exposed to lower intensity winds. Additionally, I provide evidence of heterogeneity in the treatment effect over time, with the greatest price increases occurring between 12 – 20 months after exposure to the hurricane winds. Finally, I investigate possible supply side mechanisms contributing to the increased rental prices by estimating the likelihood of tenure switches from renter to owner households in the post Irma housing market.

While the average estimated effect of hurricane exposure provides a point estimate of \$64.08, accounting for time-varying heterogeneity suggests greater effects on a month by month basis. Average point estimates for rental price increases range between \$150 to \$300 when observing impacts at a monthly time-scale. The timing of these rental price increases coincide with the return of hurricane displaced households and the payouts from insurance or other aid distributing entities (Sacerdote, 2012). While hurricane impacted households wait for the rebuilding or renovations of their damaged homes, they are forced to look for alternative short-term housing. Since homeowners are typically wealthier than renters, these households are likely able to out-bid “typical” renters in the market for rental housing. Additionally, contractors relocating to damage impacted areas likely increase the demand for short-term rental housing, further driving up the rental listing prices.

Finally, I provide evidence of decreasing rental supply due to shifts in the tenure decisions

of hurricane impacted landlords. I find a drop in the average number of available single family residential rentals for impacted neighborhoods relative to non-impacted neighborhoods. I show that landlords of single family residential units impacted by Irma have a higher propensity to transact their rental units. These results align with outcomes from Graff Zivin et al. (2023) where hurricane impacted households observe an increase in price transactions, suggesting that landlords choosing to sell their rental units are looking to capitalize on the increasing transaction prices in the housing market.

My results provide a number of different policy implications and avenues for further study. First, there is a need to better identify the demand for short-term rental housing following a hurricane. From a policy perspective the impacts of short-term increases in demand may be offset by creating more temporary housing solutions. While the short-term increase in demand may taper off years after the hurricane, the long term effects likely lead to lower income households relocating (Deryugina et al., 2018). Displacement of low-income renters can lead to permanent demographic shifts that are similarly observed within the homeownership market (Fussell and Harris, 2014; Deryugina et al., 2018; Graff Zivin et al., 2023). For policy makers looking to reduce displacement, providing temporary rental support, such as temporary rental subsidies, to low income households may address some of the affordability challenges these households face.

I conclude with several limitation of this paper. The first is the inability to observe closing prices on rental units. While Boeing and Waddell (2017) provides evidence that rental listings closely represent monthly payments for rental properties, the disarray following a major hurricane may disrupt the demonstrated relationship between listing prices and monthly payments. Another limitation is the inability to confirm whether increases in short-term

rental demand are contributing to the increased rental prices. Rental listing data does not provide the necessary information to determine whether the renter households are transient to the renter market.

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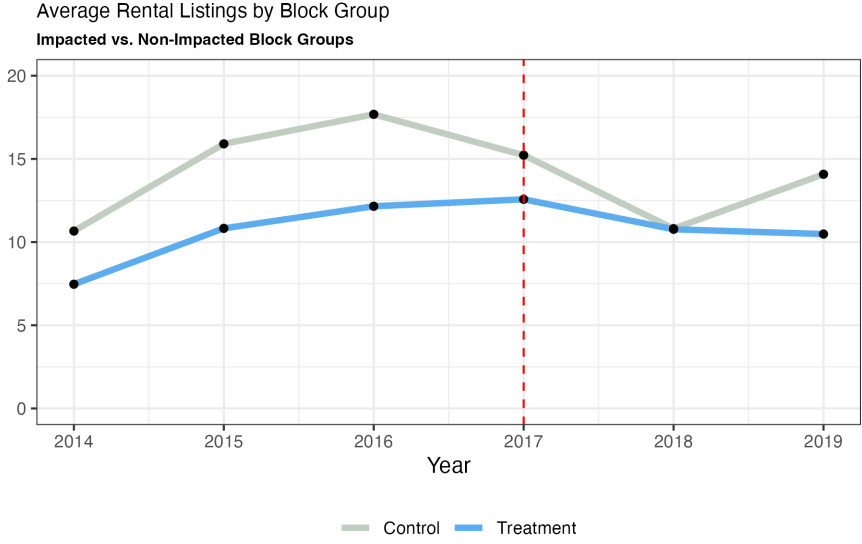


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# A Rental Unit Listings

Figure A.1: Average Listings by Block Group



Note: This figure presents the trend in average rental listings by census block group throughout the study period from 2014-2020. The control group represents block groups exposed to winds less than 73 miles per hour. The treatment group is composed of all census block groups exposed to hurricane winds greater than 73 mile per hour. The dashed vertical line at 2017 represents the year that Hurricane Irma impacted the west coast of Florida.

## B Coastal Analysis

Table B.1 provides estimates for equation 1 using a subset of rental units located only in coastal counties. This analysis is carried out as a robustness check to the main analysis and to demonstrate the continuity of the main estimates in table 3. Model 1 in table B.1 corresponds with Model 3 in table 3. Irma’s affect on rental listings is around \$7 greater for the coastal data set than the full rental data set. Meanwhile, Model 2 in table B.1 corresponds with Model 4 in table 3 and provides estimates that are up to \$16 greater for the highest level of hurricane exposure.

**Table B.1:** Coastal Analysis - OLS Results

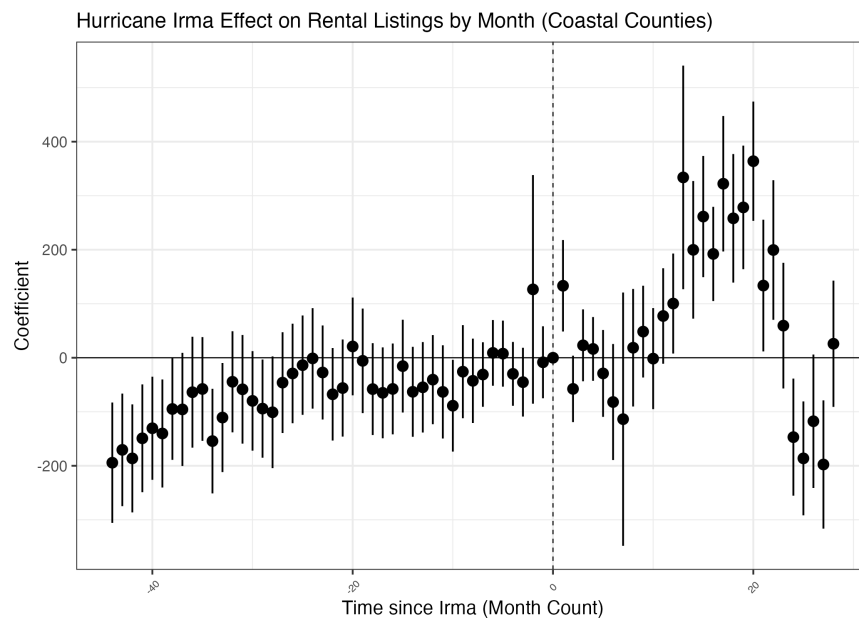
	Rental Prices	
	Model 1	Model 2
Hurricane Effect	71.950*** (21.691)	
Category 1 Hurricane		70.366** (26.234)
Category 2 Hurricane		73.996*** (19.826)
Category 3 Hurricane		48.173 (76.369)
Num.Obs.	907 105	907 105
Housing Attributes	X	X
Spatial Attributes	X	X
FE Housing Type	X	X
FE County by Year	X	X
FE Block Groups	X	X
FE Seasons	X	X
SE Clusters	Block Group	Block Groups

+ p < 0.1, \* p < 0.05, \*\* p < 0.01, \*\*\* p < 0.001

Notes: This table presents OLS regression results for the difference in difference analysis of Hurricane Irma’s affect on the price of rental housing for coastal counties in Florida. Standard errors are provided in parentheses and are clustered at the block group level for each model specification. Model 1 includes estimates for the full specified equation 1 while Model 2 provides estimates for the binned analysis. Both models include the full set of housing and spatial characteristics available as well as fixed effects for housing type, block group, season of listing, and county by year fixed effects.

Figure B.1 presents the monthly event study for the effect of Irma on rental unit listings. Event study results are similar between the main analysis and the coastal county subset.

**Figure B.1:** Hurricane Irma's Wind Effect on Rental Prices - Coastal Counties



Notes: This figures presents results of the event study for Hurricane Irma's effect on rental unit listings at month intervals for coastal rental units. Point estimates are presented with error bars at the 95% confidence interval. Standard errors are clustered at the block group level. The x-axis provides the number of months since Irma occurred. The y-axis provides values for the estimated effect of hurricane exposure ( $\geq 74$  miles per hour) on coastal rental listings in any given month relative to non-exposed rental units.