

Rent affordability after hurricanes: Longitudinal evidence from US coastal states

Kelsea B. Best^{1,2} | Qian He³ | Allison Reilly⁴ | Nhi Tran⁴ | Deb Niemeier⁴

¹Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, Columbus, Ohio, USA

²Knowlton School of Architecture, City and Regional Planning, The Ohio State University, Columbus, Ohio, USA

³Department of Geography, Planning, and Sustainability, Rowan University, Glassboro, New Jersey, USA

⁴Department of Civil and Environmental Engineering, University of Maryland, College Park, Maryland, USA

Correspondence

Kelsea Best, Department of Civil, Environmental & Geodetic Engineering, The Ohio State University, Columbus, OH, USA. Email: best.309@osu.edu

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Abstract

Climate change is expected to increase the frequency and intensity of natural hazards such as hurricanes. With a severe shortage of affordable housing in the United States, renters may be uniquely vulnerable to disaster-related housing disruptions due to increased hazard exposure, physical vulnerability of structures, and socioeconomic disadvantage. In this work, we construct a panel dataset consisting of housing, socioeconomic, and hurricane disaster data from counties in 19 states across the East and Gulf Coasts of the United States from 2009 to 2018 to investigate how the frequency and intensity of a hurricane correspond to changes in median rent and housing affordability (the interaction between rent prices and income) over time. Using a two-stage least square random-effects regression model, we find that more intense prior-year hurricanes correspond to increases in median rents via declines in housing availability. The relationship between hurricanes and rent affordability is more complex, though the occurrence of a hurricane in a given year or the previous year reduces affordable rental housing, especially for counties with higher percentages of renters and people of color. Our results highlight the multiple challenges that renters are likely to face following a hurricane, and we emphasize that disaster recovery in short- and medium-term should focus on providing safe, stable, and affordable rental housing assistance.

KEY WORDS

housing affordability, hurricanes, renter vulnerability

1 | INTRODUCTION

Hurricanes cause significant and widespread disruptions to communities, including through effects on housing (Brennan et al., 2022). This effect can be particularly devastating when communities, and especially low-income households, face a lack of affordable housing (Brennan et al., 2022; Petach, 2022). According to the Pew Research Center, in 2020, 46% of US renters were cost-burdened; that is, they spent 30% or more of their income on housing, and 23% spent 50% or more (Schaeffer, 2022). Renters' cost burden is increasing over time, with rent prices between 2017 and 2022 increasing at a rate faster than inflation (Schaeffer, 2022). As the frequency and intensity of a range of natural hazards are expected to increase with climate change, coupled with increasing hous-

ing insecurity, it is critically important to understand how hazards interact with housing affordability, especially for renters.

Access to safe, stable, and affordable housing is important for individual and household well-being (Bratt, 2002), and the lack of stable housing is associated with adverse physical, mental, and economic outcomes (Desmond & Perkins, 2016; Sandel et al., 2018). Yet there is a severe shortage of affordable rental housing in the United States; Americans increasingly spend more of their income on housing (United Way NCA, 2022). A 2022 study of US housing costs by the National Low Income Housing Coalition found that only 36 affordable rental housing units exist for every 100 extremely low-income renting households (United Way NCA, 2022). Cities with the largest affordable housing shortages include

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New York, Miami, and Houston, all of which are highly susceptible to severe hurricanes.

Evidence suggests that housing costs increase following disasters as a result of decreased supply due to housing damage and increased demand, which is associated with a combination of displaced individuals and an influx of temporary construction workers (Davlasherdze & Miao, 2021; Fothergill & Peek, 2004; Lee & Van Zandt, 2019; Rumbach et al., 2016). Using quarterly housing price index data for single-family homes (a measure of single-family home prices based on previous home-sale data), Murphy and Strobl (2010) found that the occurrence of a hurricane corresponded to an increase in housing prices for several years following the event, likely due to housing shortages (Murphy & Strobl, 2010). However, the empirical evidence of the effect of hazards on housing is inconsistent. For example, Ewing et al. (2007) showed that housing price indices in six cities susceptible to tornadoes and hurricanes had an immediate but short-term decrease in housing prices following a disaster with wind-related damages. For both tornadoes and hurricanes, the initial decline in housing prices was as much as 0.5%–2%, resulting in the loss of millions of dollars in housing value (Ewing et al., 2007). A limitation to this work is that it largely focused on property values rather than on implications for renters.

There is a gap in our understanding of how disasters, such as hurricanes, interact with housing affordability, especially for renters (Lee & Van Zandt, 2019). To date, much of the existing literature on the interactions between disasters and housing has focused on insights from individual disaster events such as Hurricane Katrina. Although these storm-location-specific studies are important, they can make it more difficult to draw generalizable conclusions. Other work using a broader geographic and temporal range of data is limited because it focuses on the influence of hurricanes on home prices rather than rental costs (Ewing et al., 2007; Murphy & Strobl, 2010).

Our study aims to narrow this gap by offering the first (to the best of our knowledge) analysis of hurricanes' effects on rental prices and rent affordability across multiple disaster events and locations. We distinguish between rental prices and a measure of affordability, which considers the fraction of income that must be spent to cover rental costs. We argue that it is important to differentiate between rent costs and affordability, as hurricanes may disrupt access to affordable housing via effects on housing costs, incomes, or interactions between the two. Further, affordability is likely to offer a more meaningful measure of how residents in a disaster-affected area would experience possible housing shocks because it also captures the amount of income available to spend on other recovery and non-recovery activities, such as healthcare, education, and mitigation.

1.1 | Housing and vulnerability to disasters

The severity of the effects of a natural hazard such as a hurricane can be considered a combination of exposure to the

hazard, physical vulnerability in the built environment, and social disadvantage of those exposed (Birkmann, 2007; Cutter & Emrich, 2006; Cutter & Finch, 2008; Peacock et al., 2014). As a critical dimension of the built environment and human well-being, housing falls squarely at the intersection of these three dimensions. Exposure to a hazard is influenced by location. For example, is the housing unit in a floodplain or an area prone to frequent and severe hazards? Physical vulnerability is influenced by factors, such as building age, building codes, and construction materials. Physical vulnerability affects the extent of damage that a structure will incur as a result of a hazard. Older buildings, for example, are likely to incur higher damages in a hurricane due to weakening or degrading materials, less up-to-date structural and construction choices, less strict building codes, and so on (Amini & Memari, 2020). Social disadvantage is influenced by a household and community's socioeconomic characteristics and affects their ability to withstand the negative consequences of hazards (Cutter et al., 2003). Frequently studied dimensions of social disadvantage include race, age, income, and gender (Akman et al., 2020; Bolin & Kurtz, 2018; Cutter & Finch, 2008; Flanagan et al., 2011; Fothergill & Peek, 2004). These variables capture characteristics of groups that have been systematically and structurally marginalized, rendering them with less access to resources for disaster recovery. Communities from disadvantaged groups also tend to have lower degrees of collective efficacy and less political capital to advocate for themselves regarding infrastructure improvement or neighborhood investments (Arcaya et al., 2020; Galster, 2012; Hendricks & Van Zandt, 2021; Sampson & Raudenbush, 1999).

It is this combination of exposure, physical vulnerability, and social disadvantage, as well as how these dimensions operate in concert across space and time that makes disaster effects and recovery complex. For example, historic discrimination in housing policies across the US means that racial minorities and low-income populations are more likely to live in areas that have less investment in infrastructure (higher physical vulnerability) and increased exposure to hazards (Arcaya et al., 2020; Hendricks & Van Zandt, 2021). Systemic exclusion and lack of resources mean that socially disadvantaged populations face greater exposure to hazards, have access to infrastructure that is generally older, less well maintained, and are more susceptible to damage, and households possess fewer resources with which to recover after a disaster (Fothergill et al., 1999; Fothergill & Peek, 2004; Hu et al., 2022; Lee & Van Zandt, 2019; Peacock et al., 2014). As an example, subsidized housing units in Houston, TX were disproportionately located in areas experiencing greater flooding during Hurricane Harvey, and those units had higher percentages of low-income renters and older households (Chakraborty et al., 2021). This outcome is a result of historic racism in urban planning policy in Houston (such as redlining) which forced communities of color to settle in designated hazardous areas. Chronic underinvestment in urban infrastructure in these neighborhoods, such as drainage systems, further exacerbated the effects of Harvey-related flooding (Daniels et al., 2021; Lieberknecht et al., 2021).

Peacock et al. (2014) compared housing recovery outcomes between Hurricane Andrew in Miami, FL and Hurricane Ike in Galveston, TX. Using a multivariate regression analysis of owner- and renter-occupied single-family homes (from yearly tax appraisal data) from both locations, they found that race and ethnicity were key predictors of high disaster damages and slower recovery times in Miami, and income was the most important predictor of higher damages and slower recovery times in Galveston (Peacock et al., 2014). Although the explicit reason for these findings in these locations is unclear, it is likely a combination of interacting exposure, physical vulnerability, and social disadvantage. These overlapping vulnerabilities acting in concert give rise to housing's contribution to long-term inequality in disaster recovery (Howell & Elliott, 2019; Peacock et al., 2014).

1.2 | Renter vulnerability to disasters

There are multiple ways that housing tenure, specifically renter or owner status, can interact with vulnerability to natural hazards across all stages of a disaster (Lee & Van Zandt, 2019). Rental units are more likely to be more physically vulnerable to hazards due to lower-quality construction and materials, less maintenance, and generally older buildings (Morrow, 1999). Renter status often also overlaps with other social indicators of disadvantage such as race and income, as low-income and minority groups are more likely to rent versus own their housing (Lee & Van Zandt, 2019). The historical exclusion of people of color from access to home-financing and federal homeownership programs, structural segregation, racism, and systematic discrimination in housing markets, and the exclusion of minority groups from wealth-building opportunities all have worked to increase structural inequities (Braverman et al., 2022; Galster, 2012; Solomon et al., 2019; Van Zandt, 2007). Even today, Black households are more likely to be denied a mortgage (Quillian et al., 2020).

Renters, especially low-income and minority renters, also have a greater risk of displacement after a disaster (Burby et al., 2003). One reason for this is that damage to rental housing is likely to be more extensive than damage to owner-occupied housing. Peacock et al. (2014) also found that, after Hurricane Ike, owner-occupied housing assessments were 71% higher than rental housing, indicating much higher damage was experienced by rental units. Rental housing is typically not prioritized in reconstruction efforts and multi-family housing is often slower to recover than single-family housing leading to greater displacement (Peacock et al., 2014; Zhang & Peacock, 2009). After Hurricane Ike in Galveston, four public housing developments were demolished due to damage, and many residents, who were predominantly low-income and people of color, were displaced (Hamidah & Rongerude, 2018).

Natural hazards can exacerbate affordable rental housing challenges in areas that already have a shortage, making it

more difficult to find post-disaster stable housing for renters (Bates & Green, 2009; Green et al., 2007). There is evidence that the relationship between disasters including hurricanes and eviction rates across the United States, especially for low-income renters, exacerbates challenges related to stable housing (Brennan et al., 2022). The risk of eviction, which has known negative consequences for the economic, mental, and physical health of evicted tenants, is therefore an additional and unique vulnerability to natural hazards facing renters (Adams et al., 2009; Brennan et al., 2022; Collinson & Reed, 2019; Desmond & Kimbro, 2015). Renters also often have access to fewer post-disaster aid options following a disaster than homeowners (Greer & Trainor, 2021; Wilson et al., 2021).

Hurricane Katrina and the subsequent recovery efforts highlight many of the vulnerabilities to disasters facing renters, especially those in socioeconomically disadvantaged groups. First, the greatest amount of damage from Hurricane Katrina resulted in predominantly poor and Black neighborhoods in New Orleans, indicating higher exposure risks (Moore, 2007). The effects on housing in these neighborhoods were devastating; as much as 70% of housing units were flooded when the levees were breached (Fussell, 2015). Renters in New Orleans faced particular challenges in returning after the storm (Fussell & Harris, 2014). Renters in post-Katrina New Orleans were likely displaced from housing in three ways: low-quality rental housing being more susceptible to damage, landlords electing not to repair damage, or increased demand and costs of rental housing following the disaster (Fussell, 2015).

After Hurricane Katrina, low-income, minority, and female residents then experienced longer and more difficult recoveries, in part, due to fewer available resources (Fussell & Harris, 2014). Renters, especially subsidized housing residents, faced an increased risk of being displaced, meaning that they were less likely to be able to return to their original homes (Fussell & Harris, 2014). Beyond returning to their original homes, many people displaced by Hurricane Katrina permanently moved outside of the city or to other states entirely (Bliss, 2015). This resulted in widespread and long-term shifts in the population characteristics of New Orleans and surrounding areas, including changes to housing prices and new pathways for racial segregation and economic exclusion of displaced residents (Adams et al., 2009; Aune et al., 2020; Daapp et al., 2023; Fussell, 2015).

Households and individuals with renter status may be especially susceptible to temporary or even permanent displacement following a disaster. Generally, renters are considered more mobile than homeowners and may also be more likely to engage in post-disaster migration as an adaptation strategy to reduce risk (Otsuyama et al., 2021). However, people's ability to migrate is strongly influenced by income. For this reason, low-income renters often lack the capacity or resources to migrate from an affected area, even if they

wanted to (Chen & Lee, 2022; Sheldon & Zhan, 2022). This raises the concern that the lowest-income renters in a disaster-affected community may not be able to move to an unaffected area to seek more affordable housing. Rather, it is possible that these groups become “trapped” in locations with compounding risks associated with heightened affordable housing challenges and high vulnerability to hazards.

1.3 | Research questions

Using a longitudinal panel dataset covering 19 states between the years 2009 and 2018, we employ two-stage least square panel regression models to address the following research questions:

1. How do the occurrence and intensity of a hurricane influence median rent prices?
2. How do the occurrence and intensity of a hurricane influence rent affordability for renters?
3. How do socioeconomic and housing characteristics affect this relationship between a disaster and rent affordability?

We hypothesize that the occurrence of a hurricane (at the county level) will have a significant but lagged effect on rental prices, corresponding to increases in median rent in the first year and second year following a hurricane. We hypothesize this is due to decreases in housing supply following a disaster, either due to damage-related decreases in housing availability in severely affected counties or due to an influx of displaced people in surrounding counties. We similarly hypothesize that the occurrence of a hurricane will have a significant though lagged effect on rent affordability, making rents less affordable in the year and second year following a hurricane. Lastly, we hypothesize that these effects, both for gross rents and rent affordability, will be felt most strongly by low-income and minority communities.

2 | DATA AND METHODS

2.1 | Data

We construct a 10-year (2009–2018) panel dataset for every county in 19 states along the US East Coast and Gulf of Mexico with a range of socioeconomic, demographic, housing, and disaster variables. During this period of analysis, 13 unique hurricanes reached the level of a Presidential Disaster Declaration (PDD) within our designated study area (i.e., a disaster warranted federal intervention). Figure 1 shows counties included in the study area and how many PDD hurricanes impacted each county in the 10-year time period¹.

For each county-year observation, we assembled sociodemographic and housing data from the American Community Survey (ACS) 5-year estimates. ACS data is obtained using the `get_acs()` function in the `tidycensus` package in R (Walker et al., 2021). From the ACS, we collect median income and percent of the population that is White as socioeconomic indicators. We focus on these indicators of race and wealth because of the clear ways that they often interact with renter status, as previously described. For general county characteristics, we use total population and total housing units to calculate housing units per capita. Our housing indicators include the percentage of renters and the percentage of vacant housing units. We also generate an indicator of crowding by calculating the percentage of renter-occupied housing units with more occupants than rooms (similar to the crowding metric used in the CDC Social Vulnerability Index) (CDC/ATSDR, 2022; Flanagan et al., 2011).

Disaster data is obtained from FEMA via the OpenFEMA data portal, which provides summary information about all historic PDDs (FEMA, 2023). We use this data source to create three disaster-related variables for each county-year observation: a variable indicating the number of hurricanes in that county-year, a lagged variable indicating the number of hurricanes in the previous year, and a second lagged variable indicating the number of hurricanes 2 years prior. In addition to the hurricane frequency variables, we use maximum sustained wind speed (m/s) experienced within the county in a given year as an indicator of storm intensity to control for hurricane effects. We also include 1- and 2-year lagged maximum sustained wind speed variables. Finally, we include a binary variable indicating whether or not a flood event occurred in a county in a given year. We include 1- and 2-year lagged flood event variables. Flooding is an important additional indicator of storm severity because it can capture additional sources of damage beyond wind, including inland flooding. Storm severity indicators (wind speeds and flood events) are obtained using the `hurricaneexposure` and `hurricaneexposuredata` packages in R (Anderson, Yan et al., 2020; Anderson, Ferreri et al., 2020).

We have two primary outcome variables of interest. The first is county-level gross median rent adjusted to 2018 USD equivalent. The second is what we refer to as a “rent affordability ratio.” To calculate this ratio, we obtain annual county-level fair market rents (FMRs) data for a two-bedroom housing unit from the US Department of Housing and Urban Development (HUD) (HUD, 2023). FMRs, which are annual estimates of the 40th percentile gross rents for “standard quality units,” are used by HUD for a range of housing-related programs including the Housing Choice Voucher program. Where there are multiple FMR values for a given county (i.e., multiple metropolitan areas), we calculate the mean FMR for the county. Our rent affordability ratio is calculated at the FMR divided by the median county income

¹ The data includes all counties that were included in a hurricane PDD within the study period. Inland counties are not included in error. For example, Lubbock County in

Texas was included in the 2010 PDD for Hurricane Alex and received FEMA Public Assistance aid.

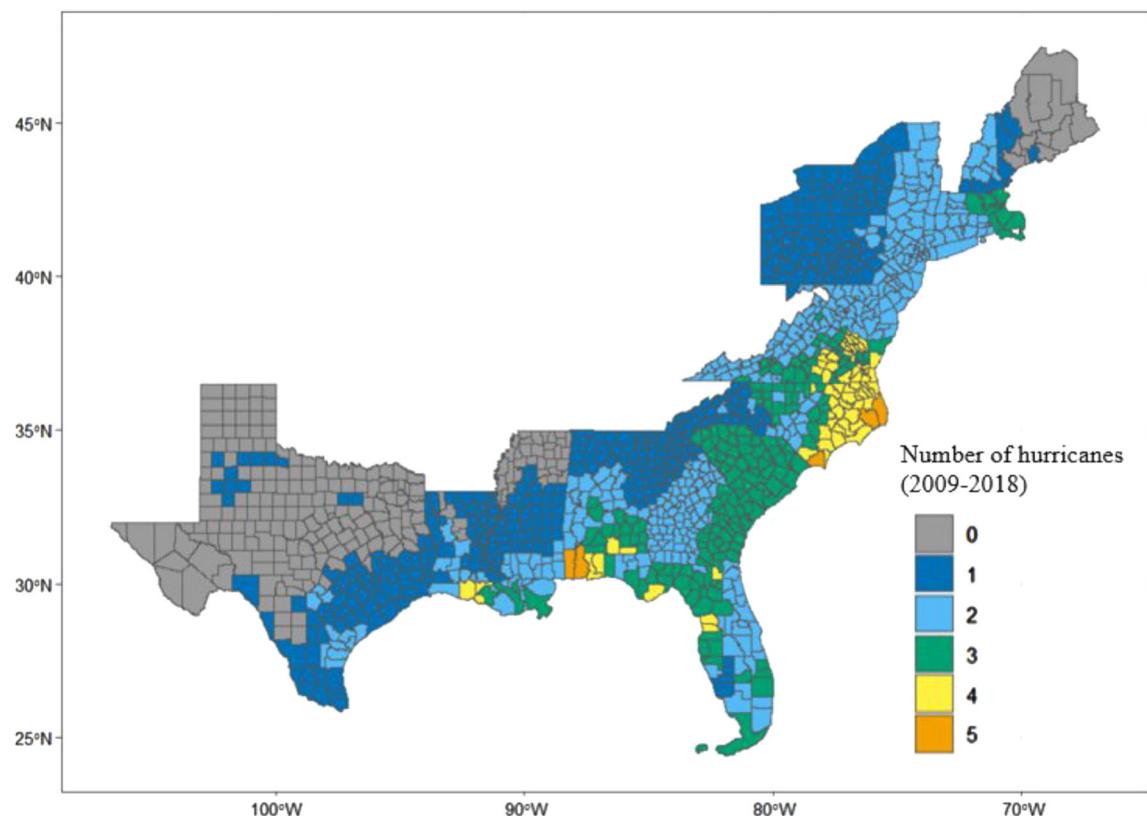


FIGURE 1 Counties in the study area with shading indicating the total number of hurricanes impacting that county (based on Presidential Disaster Declaration [PDDs] between 2009 and 2018).

as shown in the following equation:

$$\text{AffordabilityRatio} = \frac{FMR}{\text{MedianIncome}} \quad (1)$$

This ratio captures the proportion of income that is needed to pay rent in the county-year. A higher value of our rent affordability ratio means that a higher proportion of income is required for rent, indicating *less* affordable rents, whereas a lower ratio indicates greater affordability.

2.2 | Panel model specification

For the panel model, we group FIPS county IDs over the 10-year period. By pooling time-series and cross-sectional data together, this dataset allows us to explore the relationship between housing cost, rental affordability, and the occurrence of hurricane events, while controlling for individual-specific county effects (such as the socioeconomic status and other housing profiles), which would otherwise be under-observed or unobservable without appropriate modeling specification. In this case, the individual characteristics of each county, from code adoption to local housing policies, could differentially affect how rent affordability is affected by disaster events.

To identify the potential effects of hurricanes on median rents and the affordability ratio, we construct a set of two-stage least square panel regression models with instrumental variables (hurricane frequency, 1-year lagged hurricane frequency, 2-year lagged hurricane frequency, maximum wind speed, 1-year lagged wind speed, 2-year lagged wind speed, flood event indicator, 1-year lagged flood event indicator, and 2-year lagged flood event indicator), using the housing units per capita as an instrumental estimator with random-effects. That is, we assume (reasonably) that housing units per capita is an endogenous variable to rent and affordability, with the hurricane events and their characteristics (frequency and wind speed) as the exogenous variables to rent and affordability. In other words, this model construction allows us to test our hypothesis that hurricanes and hurricane intensity can influence rent prices and affordability via their impacts on available housing units.

Instrumental variables allow us to address the problem of omitted variable bias: in this case, the effect of hurricanes on rental housing price and rent affordability. Two-stage least squares specification also allows us to solve the classic errors-in-variable problem in our panel dataset. With the two-stage random-effects model, the simple panel-data estimators for exogenous variables can be better specified with the two-stage least-squares generalizations.

We use the Stata code *xtivreg* with the “ec2sls” implementation (Baltagi & Chang, 1994; Baltagi & Liu, 2009). There are two common implementations for two-stage least square panel regression methods, “G2SLS” from Balestra and Varadharajan-Krishnakumar (1987) and EC2SLS from Baltagi (Balestra & Varadharajan-Krishnakumar, 1987; Baltagi & Chang, 1994). Research shows that the standard errors of EC2SLS are smaller than those of G2SLS (Baltagi & Liu, 2009). In this case, the random-effect specification allows us to efficiently examine the time-variant characteristics within each county while also capturing the effects of disasters on rent affordability across the decade-long analysis period. After checking the multicollinearity between the tested variables, we specify the model based on our disaster, housing, and socioeconomic indicators to examine the relationship between hurricane events and rent affordability. We use both the adjusted median rent and the rent affordability ratio as our outcome variables of interest. The model specifications are shown in the following equations:

Rent Model—Stage 1:

$$\begin{aligned} \text{HousingUnitsPerCapita}_{it} = & \beta_0 + \beta_1 \text{HurricaneFrequency}_{it} \\ & + \beta_2 \text{HurricaneFrequency1YearLag}_{it} \\ & + \beta_3 \text{HurricaneFrequency2YearLag}_{it} \\ & + \beta_4 \text{MaxWindSpeed}_{it} + \beta_5 \text{MaxWindSpeed1YearLag}_{it} \\ & + \beta_6 \text{MaxWindSpeed2YearLag}_{it} + \beta_7 \text{FloodEvent}_{it} \\ & + \beta_8 \text{FloodEvent1YearLag}_{it} + \beta_9 \text{FloodEvent2YearLag}_{it} \\ & + \beta_{10} \text{MedianIncome}_{it} + \beta_{11} \text{PercentageWhite}_{it} \\ & + \beta_{12} \text{PercentageRenters}_{it} + \beta_{13} \text{PercentageVacant}_{it} \\ & + \beta_{14} \text{PercentageCrowdedUnits}_{it}. \end{aligned}$$

Rent Model—Stage 2:

$$\begin{aligned} \text{MedianRent}_{it} = & \beta_0 + \beta_1 \text{MedianIncome}_{it} \\ & + \beta_2 \text{HousingUnitsPerCapita}(\text{Estimated from Stage 1})_{it} \\ & + \beta_3 \text{PercentageWhite}_{it} + \beta_4 \text{PercentageRenters}_{it} \quad (2) \\ & + \beta_5 \text{PercentageVacant}_{it} \\ & + \beta_6 \text{PercentageCrowdedUnits}_{it} + u_{it}. \end{aligned}$$

Affordability Model—Stage 1:

$$\begin{aligned} \text{HousingUnitsPerCapita}_{it} = & \beta_0 + \beta_1 \text{HurricaneFrequency}_{it} \\ & + \beta_2 \text{HurricaneFrequency1YearLag}_{it} \\ & + \beta_3 \text{HurricaneFrequency2YearLag}_{it} \\ & + \beta_4 \text{MaxWindSpeed}_{it} + \beta_5 \text{MaxWindSpeed1YearLag}_{it} \\ & + \beta_6 \text{MaxWindSpeed2YearLag}_{it} + \beta_7 \text{FloodEvent}_{it} \\ & + \beta_8 \text{FloodEvent1YearLag}_{it} + \beta_9 \text{FloodEvent2YearLag}_{it} \\ & + \beta_{10} \text{PercentageWhite}_{it} + \beta_{11} \text{PercentageRenters}_{it} \\ & + \beta_{12} \text{PercentageVacant}_{it} + \beta_{13} \text{PercentageCrowdedUnits}_{it}. \end{aligned}$$

Affordability Model—Stage 2:

$$\begin{aligned} \text{RentAffordabilityRatio}_{it} = & \beta_0 + \beta_1 \text{HousingUnitsPerCapita}(\text{Estimated from Stage 1})_{it} \\ & + \beta_2 \text{PercentageWhite}_{it} \\ & + \beta_3 \text{PercentageRenters}_{it} + \beta_4 \text{PercentageVacant}_{it} \\ & + \beta_5 \text{PercentageCrowdedUnits}_{it} + u_{it}, \quad (3) \end{aligned}$$

where i is each individual county and t is the year examined from 2009 to 2018.

3 | RESULTS

3.1 | Hurricanes and rent prices

Stage 1 of our two-stage least square random-effects model demonstrates the ways in which hurricane frequency (as well as 1-year lagged and 2-year lagged hurricane frequency) and hurricane intensity (captured by maximum sustained wind speeds, 1-year lagged maximum sustained wind speeds, and 2-year lagged maximum sustained wind speeds, flood event indicator, 1-year lagged flood event indicator, and 2-year lagged flood event indicator) can interact with housing units per capita (Table 1). These Stage 1 results correspond to the model of median rent. The Stage 1 results for the model of rent affordability are included in Table A1 and are consistent with these Stage 1 results. We see that 1-year lagged maximum sustained wind speed is significantly and negatively correlated with housing units per capita. The flood event indicator in a given year is also significantly and negatively correlated with housing units per capita. Conversely, the frequency of hurricanes and the 1-year lagged frequency of hurricanes are significantly and positively correlated with housing units per capita (at a threshold of $p < 0.1$).

Stage 2 model results for the adjusted median rent indicate that declines in housing availability (as measured by housing units per capita) correspond to an increase in median rent (Table 2). This is consistent with our hypothesis that, where hurricanes result in damage to housing or an influx of displaced people and there is a decrease in available rental housing, rent prices are expected to increase. The results further suggest that counties with higher median income, higher percentage of renters, and more vacant units also correspond to higher gross median rents. For example, based on our results, a 1000 USD increase in median income corresponds to an approximate 1.21% increase in median rent. In terms of the sociodemographic characteristics, we find that the percentage of White population is not a significant predictor of median rent. The percentage of renters living in crowded conditions is also not significant.

3.2 | Hurricanes and rent affordability

Our results of the two-stage least square random-effects model for the rent affordability ratio show that increases in housing units per capita correspond to increases in the affordability ratio, suggesting less affordable rental housing. This is inconsistent with our hypothesis that decreases in housing availability will correspond to less affordable housing. In terms of socioeconomic characteristics, our results also show that the percentage of renters is positively related to less affordable rent. A higher percentage

TABLE 1 Stage 1 output from two-stage least square random-effects model (on housing units per capita) for median rent model.

Housing unit per capita	Coefficient	Std. Err.	p > z	[95% Confidence interval]
Max wind speed_d	-8.39E-06	0.0000536	0.876	[-0.0001135, 0.0000967]
Max wind speed 1-year lag_d	-0.0001275	0.0000696	0.067	[-0.000264, 8.95E-06]
Max wind speed 2-year lag_d	-0.00007	0.000094	0.457	[-0.0002543, 0.0001143]
Hurricane count_d	0.003027	0.0008927	***	[0.0012775, 0.0047766]
Hurricane 1-year lag_d	0.003277	0.0010989	***	[0.0011231, 0.0054309]
Hurricane 2-year lag_d	0.0018478	0.001574	0.24	[-0.0012372, 0.0049327]
Flood event_d	-0.0020433	0.0009841	**	[-0.0039721, -0.0001144]
Flood event 1-year lag_d	-0.0012347	0.001134	0.276	[-0.0034574, 0.0009879]
Flood event 2-year lag_d	-0.0004925	0.0012977	0.704	[-0.0030359, 0.0020509]
Max wind speed_m	-0.0012748	0.0002836	***	[-0.0018307, -0.0007189]
Max wind speed 1-year lag_m	-0.0001678	0.0004401	0.703	[-0.0010304, 0.0006947]
Max wind speed 2-year lag_m	0.0008727	0.000427	**	[0.0000357, 0.0017097]
Hurricane count_m	0.010456	0.0057869	**	[-0.0008862, 0.0217982]
Hurricane 1-year lag_m	0.0079381	0.0075614	0.294	[-0.0068819, 0.0227582]
Hurricane 2-year lag_m	-0.0030418	0.0066024	0.645	[-0.0159822, 0.0098986]
Flood event_m	0.0262343	0.0070704	***	[0.0123767, 0.040092]
Flood event 1-year lag_m	-0.0417907	0.0109404	***	[-0.0632335, -0.0203478]
Flood event 2-year lag_m	0.0286312	0.0087485	***	[0.0114844, 0.045778]
Income_d	-0.0002862	0.0000564	***	[-0.0003966, -0.0001757]
Percent White_d	0.1140285	0.0095027	***	[0.0954036, 0.1326535]
Percent renters_d	0.0507042	0.0101745	***	[0.0307625, 0.0706459]
Percent vacant units_d	0.3141329	0.0092065	***	[0.2960885, 0.3321773]
Crowding_d	-0.0451683	0.0087467	***	[-0.0623116, -0.0280251]
Income_m	0.000081	0.0000149	***	[0.0000519, 0.0001102]
Percent White_m	0.0179726	0.0010642	***	[0.0158868, 0.0200584]
Percent renters_m	0.0303677	0.0026529	***	[0.0251682, 0.0355672]
Percent vacant units_m	0.1848491	0.0021912	***	[0.1805545, 0.1891438]
Crowding_m	-0.0659348	0.0070424	***	[-0.0797376, -0.052132]
Constant	-0.531976	0.0468353	***	[-0.6237715, -0.4401806]

Note: The EC2SLS estimator constructs pairs of instruments where “_m” indicates the panel mean value of the variable and “_d” indicates the deviation-from-panel mean of the variable. Number of observations = 12,020; Wald $\chi^2(28) = 12,722$. Prob $> \chi^2 = 0.000$.

*** $p < 0.01$, ** $0.01 < p < 0.05$, * $0.05 < p < 0.1$.

TABLE 2 Output from Stage 2 of two-stage least square random-effects model for median gross rent.

Ln_Median rent (2018 USD-adjusted)	Coefficient	Std. Err.	p > t	[95% Confidence interval]
Median income	0.0121057	0.0001624	***	[0.0117874, 0.012424]
Housing units per capita	-0.1659043	0.0776268	**	[-0.31805, -0.0137586]
Percent White	0.0236874	0.0209844	0.259	[-0.0174412, 0.064816]
Percent renters	0.6850272	0.0346094	***	[0.617194, 0.7528604]
Percent vacant units	0.2283285	0.0549185	***	[0.1206903, 0.3359667]
Crowding factor	0.0458692	0.0337281	0.174	[-0.0202367, 0.111975]
Constants	5.920051	0.0284976	***	[5.864197, 5.975905]

Note: $\sigma_u = 0.124$; $\sigma_e = 0.0742$; $\sigma = 0.737$ (fraction of variance due to ui). R^2 within = 0.196, between = 0.771, overall = 0.723. Number of observations = 12,020; number of groups = 1203. Prob $> F = 0.000$; Wald $\chi^2(6) = 6390.45$.

*** $p < 0.01$, ** $0.01 < p < 0.05$, * $0.05 < p < 0.1$.

TABLE 3 Output from Stage 2 of two-stage least square random-effects model for housing affordability ratio.

Affordability ratio	Coefficient	Std. Err.	p > t	[95% Confidence interval]
Housing units per Capita	0.1611132	0.0187141	***	[0.1244342, 0.1977922]
Percent White	-0.092965	0.0050758	***	[-0.1029134, -0.0830166]
Percent renters	0.1292459	0.0090716	***	[0.1114659, 0.1470259]
Percent vacant units	-0.027476	0.014581	**	[-0.0560544, 0.0011023]
Crowding factor	-0.0337387	0.0089716	***	[-0.0513227, -0.0161548]
Constants	0.1681126	0.0064965	***	[0.1553798, 0.1808454]

Note: $\sigma_u = 0.0303$; $\sigma_e = 0.0222$; $\sigma = 0.650$ (fraction of variance due to u_i). R^2 within = 0.021, between = 0.311, overall = 0.259. Number of observations = 11,979; number of groups = 1202. Prob > F = 0.000.

*** $p < 0.01$, ** $0.01 < p < 0.05$, * $0.05 < p < 0.1$.

of White population is significantly related to more affordable rent. When considering housing characteristics, we see that the percentage of vacant units is significantly associated with more affordable rental housing (Table 3). We also find that counties with a higher degree of housing crowding index are negatively associated with the affordability ratio, meaning that households with crowded living situations are more likely to spend a lower portion of their income on rent.

4 | DISCUSSION

In this work, we begin by asking: how does the occurrence and intensity of a hurricane influence median rent prices and rent affordability? We also explore how the relationship between hurricanes and rents might vary by housing and socioeconomic characteristics of a community.

In answering our first question, the findings from the two aforementioned models are consistent in supporting the broad hypothesis that the occurrence and intensity of hurricane events can contribute to increases in rental prices, exacerbating challenges related to affordable housing, but in different ways. We had hypothesized that both hurricane frequency and intensity would correspond to increases in median rents and decreases in rent affordability via reductions in housing supply, but the results were actually more complicated. Figure 2 provides a visual representation of our results, highlighting that hurricane frequency and intensity interact with both median rents and rent affordability differently.

Stage 1 of our two-stage model shows that more intense hurricanes, measured by maximum sustained wind speeds and flood events, correspond to a decrease in housing availability (Table 1) and, in turn, an increase in median rents immediately and with a 1-year lag (Table 2). This suggests that storm intensity is very important when considering effects on gross rents because of resulting direct or indirect decreases in housing supply. This is intuitively reasonable in that increased storm intensity contributes to greater housing damage, which reduces the supply of rental housing and leads to increased rental prices. This is also consistent with results from previous research that found that more severe flooding contributed to a decrease in available pub-

lic housing units and increased rents across the United States (Davlasheridze & Miao, 2021). Our results also show that the effects of hurricane damage on rental prices have a 1-year lag; at 2 years, the results are no longer significant. This suggests that it may take at least a year for the rental housing market to equilibrate to the occurrence of a hurricane, or at least for the housing response to be evident in our data. It is also possible that it takes approximately a year for homeowners to repair damaged properties before renting them again. As noted, the previous work has suggested that rental housing is slower to recover after a disaster than owner-occupied housing (Peacock et al., 2014). The significance of the lag points to the need for disaster recovery to consider both immediate and short-to-medium-term recovery needs.

Interestingly, in the model for the rent affordability ratio, we find a reverse relationship between housing availability and affordability. Our results show that an increase in the number of housing units per capita corresponds to an increase in the affordability ratio, which signals less affordable rental housing (Table 3). As mentioned, this runs counter to our initial hypothesis that decreases in housing availability would correspond to less affordable housing. However, when we consider Stage 1 model results along with these findings, we see that because of the positive correlation between hurricane frequency and the 1-year lagged frequency variables with housing availability, a hurricane would have the hypothesized effect of leading to less affordable rental housing, though the mechanism by which this occurs is less clear. This also suggests that the effects of a hurricane are potentially more immediate, as the hurricane variable in a given year as well as the 1-year-lagged hurricane frequency variable are significant and positive (Table 3).

This is especially interesting in light of the findings from our first model of gross rent prices. We see both an increase in rent prices associated with fewer housing units, and a decrease in our housing affordability measure (more affordable housing). Because our affordability ratio is a composite measure of rent and income, this suggests that income may be increasing more rapidly than rent following a disaster, leading to the appearance of “more affordable” housing. There is some evidence in the literature, though limited, of “post-disaster gentrification” after a hurricane (Aune et al., 2020; Best et al., 2023; Best & Jouzi, 2022). For example,

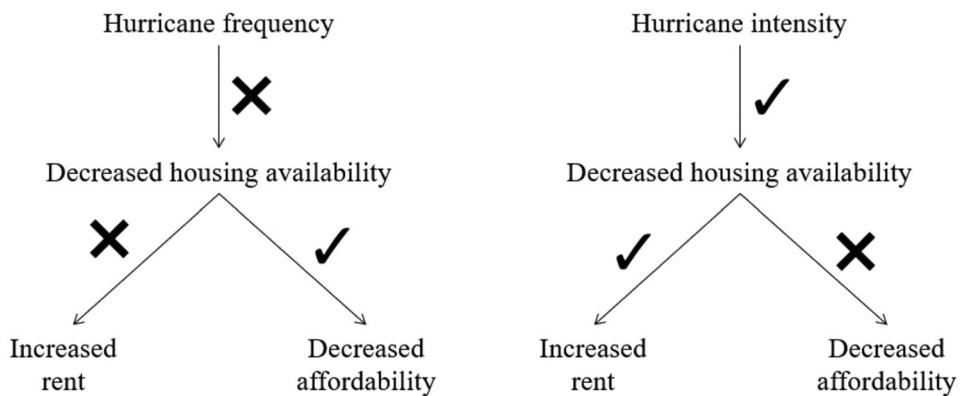


FIGURE 2 Visual summary of results highlighting how hurricane frequency and intensity operate differently to influence median rents and affordability. A check means that the hypothesized relationship between variables was supported by results, and “X” indicates that the hypothesized relationship was not supported by results of this analysis.

one study found that unequal disaster recovery efforts and an influx of resilience investments following Hurricane Sandy in New York City contributed to the political exclusion and displacement of the city’s most vulnerable and low-income residents (DuPuis & Greenberg, 2019). A study of New Orleans investigating neighborhood socioeconomic characteristics pre- and post-Katrina found that higher-elevation census tracts with greater proportions of Black, low-income, less educated, unemployed, and renting residents pre-Katrina became significantly whiter and wealthier post-Katrina (Aune et al., 2020). Our results may be capturing a similar post-disaster shift in community characteristics toward wealthier residents.

As mentioned previously, low-income renters are more likely to be displaced following a disaster (Burby et al., 2003; Hamideh & Rongerude, 2018). Once these lower income renters are displaced, they also experience greater challenges returning to their communities due to limited resources to move back and deprioritized reconstruction efforts (Fussell, 2015). The prolonged displacement of lower income renters from a county could result in an increase in the median income, thus giving the illusion of more affordable housing in the data. However, because our data only considers a 2-year lag effect of hurricanes, it is also possible that our analysis is capturing only shorter-term shifts in community characteristics resulting, for example, from the immediate and temporary post-storm displacement of low-income populations. More work is needed to explore this theory and more thoroughly investigate the relationship among housing, affordability, and displacement of vulnerable residents, especially across longer temporal scales. Our results suggest that the ways in which hurricanes could interact with rental affordability (rather than simple rental prices) are likely more complex than just effects on housing supply.

Finally, in answering how the relationship between hurricanes and rents might vary by housing and socioeconomic characteristics of a community, we also find mixed results. For our first model, we find that median county income is a

significant predictor for the median rent, with higher median incomes corresponding to higher median rents (Table 2). This suggests that areas with more affluent residents also have higher rent prices, all other factors constant. Due to collinearity concerns, we did not include the income variable in our model of the affordability ratio as the ratio was calculated using income as the denominator. We also found that the percentage of White population was significantly and negatively associated with rent affordability (Table 2). The negative sign on the percentage of White population could indicate that counties with a higher proportion of White residents would experience a moderated effect on changes in rent affordability after a hurricane. This is consistent with our hypothesis that the most vulnerable and historically marginalized communities (such as those with higher percentages of people of color) are at greater risk to face post-disaster housing challenges.

In terms of housing characteristics, we find that counties with a greater percentage of renters correspond to higher values of the rent affordability ratio, signaling greater income expenditure on rents (Table 3). This is concerning, as it suggests that rental housing is significantly less affordable in those areas with the greatest demand. Most counterintuitively, we see that the percentage of vacant properties is correlated with greater rent increases and less affordability. This is surprising, as we would anticipate that more vacant housing would correspond to more affordable rents. Although future research is needed to understand this result, one possible explanation is that, with more vacant housing, high income homeowners whose homes are damaged may not be displaced outside of an affected community after a disaster but rather stay and fill existing vacant housing. This could reduce access to this housing supply for low-income renters while also potentially driving up rental costs. Additionally, we find that the crowding indicator, which captures the percentage of renter-occupied housing units with more occupants than rooms, is negatively associated with the affordability ratio. This means that households living in crowded conditions are likely to spend less of their income

on rent. This finding suggests that living in more crowded housing could be a strategy for renters, especially those with lower economic status, to respond to a lack of affordable housing and to reduce their financial burden associated with rent. As a consequence of economic constraints, some renter households may be pushed to live in a less desirable environment with limited space in order to respond to post-disaster disruptions to housing. According to literature and clinical evidence, overcrowding can have various negative impacts on people's health and well-being, especially for children and those with weaker immune systems (Acevedo-Garcia, 2000; Robert Wood Johnson Foundation, 2011; United Health Foundation, 2022; Weitzman et al., 2013). After a hurricane, renters could therefore experience additional negative consequences to health in addition to economic challenges and housing insecurity.

5 | CONCLUSIONS AND IMPLICATIONS

Access to safe, stable, and affordable housing is a basic human right (Thiele, 2002). Capital-driven housing markets, historic and current discrimination, and socioeconomic disparities in the United States have, however, contributed to an affordable housing crisis. As global climate change increases the intensity and frequency of certain disasters and extreme weather events, securing safe, affordable housing has become even more challenging, especially for the most vulnerable renters. Despite the urgency and importance of this problem, relatively little is known about the relationship between natural hazards such as hurricanes and housing affordability for renters.

This work contributes to the literature by looking across a larger spatial and temporal span than previous work on hurricanes and housing and by focusing on multiple measures of housing affordability for renters, an especially vulnerable population. Based on a two-stage least square random-effects model analysis using a 10-year panel dataset for counties across 19 states in the US East Coast and the Gulf of Mexico, we find that hurricanes could increase the proportion of income spent on rents (decreasing affordability) and increase median rent. More specifically, we find that storm intensity can interact with rent prices via housing availability, with more intense storms corresponding to higher rents in the year following a hurricane. The mechanisms driving rent affordability are not as clearly driven by storm intensity and damage to housing units. Compounding the impacts of the hurricanes, we find that counties with a greater need for rental housing (higher percentage of rental status) as well as higher proportions of people of color are associated with greater affordability challenges.

Ultimately, results from this work introduce complexity to previous literature (Fothergill & Peek, 2004; Lee & Van Zandt, 2019; Rumbach et al., 2016). We had hypothesized that both the occurrence and intensity of a hurricane would be important for median rents and rent affordability, but this was not the case according to our analysis. We found that

1-year lagged storm intensity did correspond to increases in median rents through decreases in housing units per capita, but the expected relationship did not hold for rent affordability. Conversely, the occurrence and frequency of a hurricane in a given year and in the previous year corresponded to less affordable housing but not increases in rents. Future work should continue to explore this important issue, especially considering the relationship between disaster impacts, housing availability and affordability, possible resident displacement, and long-term recovery outcomes. Although our findings reveal the compounded vulnerability faced by people of renter status, such as the inverse relationship between crowding living conditions and affordability, future studies should explore whether renters are more likely to live under crowded conditions as a coping mechanism to respond to post-disaster housing stress.

This work highlights some of the complexities and compounding vulnerabilities that renters may face following a disaster event. Continuing to understand the relationship between disasters and housing affordability for both directly impacted communities and potential receiving communities is critical for policies and disaster recovery efforts that contribute to building and maintaining resilient and equitable housing. Findings from this work emphasize that deliberate attention must be given to renters, especially low-income and minority renters in recovery efforts immediately following a disaster event and in subsequent years. For example, future local, state, and federal policies should provide explicit protections and support to renters (such as eviction moratoria, limiting late fees, and access to emergency rental assistance) after disasters. Additionally, efforts that prioritize affordable and stable housing supply with up-to-date market rent price monitoring could provide critical reference for policymakers to understand and respond to renters' struggles, especially during post-disaster periods. Without such deliberate consideration of rent and renters, disaster recovery risks exacerbating the affordable housing crisis for some of the most vulnerable populations.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest.

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APPENDIX A

TABLE A 1 Stage 1 output from two-stage least square random-effects model (on housing units per capita) for rent affordability model.

Housing unit per capita	Coefficient	Std. Err.	p > z	[95% Confidence interval]
max_sust_wind_d	-8.32E-06	0.0000607	0.891	[-0.0001273, 0.0001107]
1_year_lag_wind_d	-0.0001686	0.0000788	**	[-0.0003231, -0.0000141]
2_year_lag_wind_d	-0.0001152	0.0001065	0.279	[-0.0003238, 0.0000935]
hurricane_count_d	0.0025191	0.0010072	**	[0.0005451, 0.0044931]
hurricane_last_year_d	0.0031816	0.001243	***	[0.0007454, 0.0056177]
hurricane_2_years_d	0.0022046	0.0017823	0.216	[-0.0012887, 0.0056978]
flood_d	-0.0019584	0.0011144	*	[-0.0041426, 0.0002257]
1_year_lag_food_d	-0.0009232	0.0012839	0.472	[-0.0034396, 0.0015932]
2_year_lag_flood_d	-0.0004238	0.0014703	0.773	[-0.0033055, 0.0024578]
max_sust_wind_m	-0.0016657	0.0003182	***	[-0.0022893, -0.0010422]
1_year_lag_wind_m	0.0000794	0.0004951	0.873	[-0.0008911, 0.0010499]
2_year_lag_wind_m	0.0011464	0.0004828	**	[0.0002001, 0.0020927]
hurricane_count_m	0.012861	0.006546	**	[0.0000311, 0.0256909]
hurricane_last_year_m	0.0006075	0.0085349	0.943	[-0.0161206, 0.0173355]
hurricane_2_years_m	0.0013786	0.0074781	0.854	[-0.0132781, 0.0160353]
flood_m	0.0267331	0.0079863	***	[0.0110804, 0.0423859]
1_year_lag_food_m	-0.042672	0.0123571	***	[-0.0668914, -0.0184525]
2_year_lag_flood_m	0.0367961	0.009896	***	[0.0174003, 0.0561919]
perc_White_d	-0.01449	0.0074678	0.052	[-0.0291266, 0.0001466]
perc_rente_hh_d	-0.0631601	0.0102827	***	[-0.083314, -0.0430063]
perc_vacant_d	0.2493719	0.0096812	***	[0.2303972, 0.2683466]
crowding_frac_d	-0.0633473	0.0098537	***	[-0.0826602, -0.0440344]
perc_White_m	0.0219378	0.0011824	***	[0.0196205, 0.0242552]
perc_rente_hh_m	0.0273127	0.0029439	***	[0.0215427, 0.0330827]
perc_vacant_m	0.2157889	0.0022567	***	[0.2113659, 0.2202119]
crowding_frac_m	-0.0859415	0.0079682	***	[-0.1015589, -0.0703242]
_cons	0.1348362	0.0247575	***	[0.0863124, 0.18336]

Note: The EC2SLS estimator constructs pairs of instruments where “_m” indicates the panel mean value of the variable and “_d” indicates the deviation-from-panel mean of the variable. Number of observations = 12,020; Wald Chi(28) = 12,722. Prob > Chi² = 0.000.

***p < 0.01, **0.01 < p < 0.05, *0.05 < p < 0.1