Who Pays the Price of Climate Change in the Real Estate Market?

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Abstract

This paper presents evidence on the causal effects of climate change on rent exploitation and rental profit. We define rent exploitation as situations where landlords overcharge tenants relative to the value of the home they rent. Rental profit is defined as the rent received, minus taxes, divided by the property value. By analyzing annual county-level property values, rental costs, and taxes, alongside other control data from 2005 to 2022 across the United States, we find that natural events significantly exacerbate rent exploitation, particularly impacting regions with low-value houses. Specifically, these events lead to an increase in rent exploitation by an average 0.28 percentage points in the year they occur, followed by an additional 0.21 percentage points in the subsequent year. Conversely, the effect is not significant in regions with higher-tier houses. Consequently, tenants in low-value properties bear a disproportionate financial burden compared to those in higher-value homes. This inequity persists even when adjusting for tax, which also shows an increase in rental profit, suggesting landlords do not align rent adjustments with decreases in property values. The effects of natural events on rent dynamics can last up to two years.

Key words: real estate, house prices, rent exploitation, rental profit, climate change

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Abstract

This paper presents evidence on the causal effects of climate change on rent exploitation and rental profit. We define rent exploitation as situations where landlords overcharge tenants relative to the value of the home they rent. Rental profit is defined as the rent received, minus taxes, divided by the property value. By analyzing annual county-level property values, rental costs, and taxes, alongside other control data from 2005 to 2022 across the United States, we find that that natural events significantly exacerbate rent exploitation, particularly impacting regions with low-value houses. Specifically, these events lead to an increase in rent exploitation by an average 0.28 percentage points in the year they occur, followed by an additional 0.21 percentage points in the subsequent year. Conversely, the effect is not significant in regions with higher-tier houses. Consequently, tenants in low-value properties bear a disproportionate financial burden compared to those in higher-value homes. This inequity persists even when adjusting for tax, which also shows an increase in rental profit, suggesting landlords do not align rent adjustments with decreases in property values. The effects of natural events on rent dynamics can last up to two years.

1. Introduction

Climate change has been threatening both the U.S. and global economies and welfare by damaging infrastructure, health, ecosystems, and productivity with limited time to prevent catastrophic impacts ((Hay et al. 2015), The Office of Management and Budget (OMB), 2022). Research suggests that changes in global temperature has secondary effects on terrestrial ecosystems (Van Aalst 2006). Additionally, recent studies have estimated that flooding would reduce global real GDP by 0.19% in present value terms, with significantly higher rates in some countries: 7.60% in Vietnam, 9.37% in Thailand, and 5.37% in Bangladesh (Desmet et al. 2021).

Data indicates that the frequency of billion-dollar weather and climate disasters, such as drought, wildfires, severe storms, and tropical cyclones, in the US, has increased heavily in recent years, increasing from 3.3 events per year between 1980-89 to 22 between 2021-2023 (NOAA National Centers for Environmental Information (NCEI) 2024). The average annual cost between 2021 and 2023 is approximately $145 billion (see Fig. 1) and has been increasing. The Economist reports that in Europe, where extreme weather is not as common as in the US, the losses have amounted to $5bn per year over the past three years (The Economist 2024).

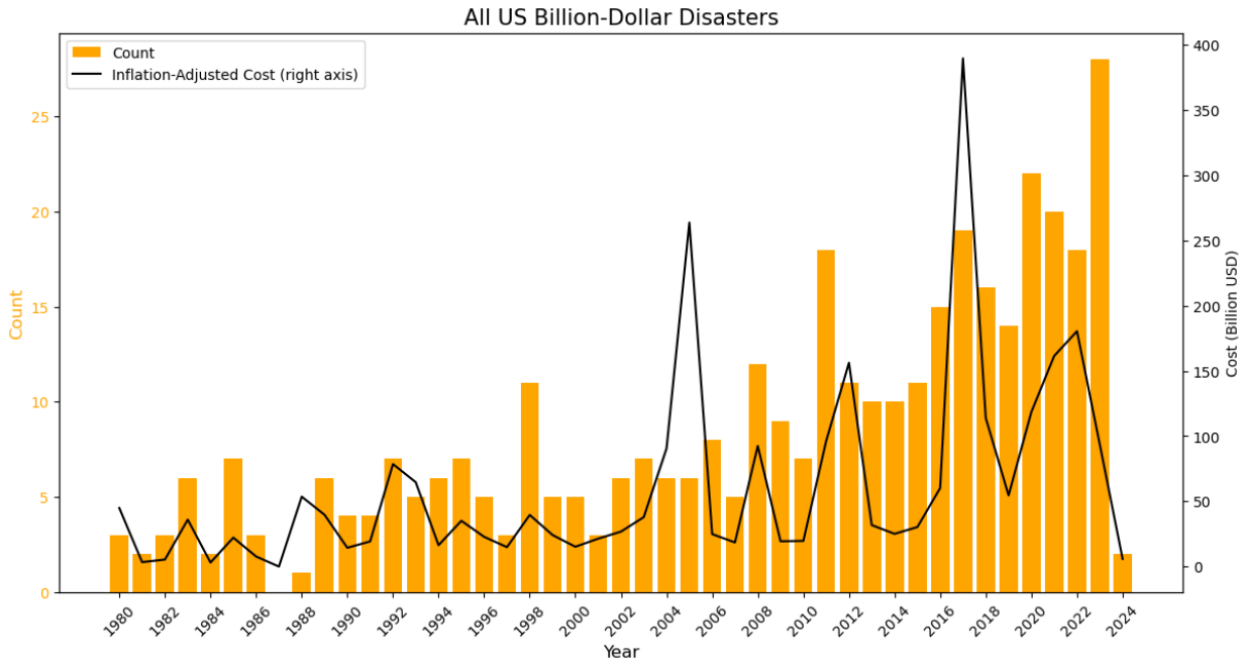


Fig. 1:US Billion-Dollar Disasters (Source: National Centers for Environmental Information (NCEI))

The direct impact of climate change in the housing market is about the value of the houses. Property owners have been facing substantial expenses. Recent studies demonstrate that American homes at risk of flooding are overvalued, with estimates ranging from approximately $44 billion according to (Hino and Burke 2021) to $150 billion according to (Gourevitch et al. 2023)[3]. (Gourevitch et al. 2023) state that the risk is even higher for lower-income households are at a greater risk of losing more value, in case of flooding. According to the Economist, the world is facing an estimated $25 trillion impact (The Economist 2024). Moreover, (Indaco and Ortega 2024) demonstrate that high climate-risk counties in the U.S., particularly those in the South and Northeast, have experienced more growth compared to low-risk areas. They attribute this to the influx of white, working-age individuals into urban areas that have high residential capital. This suggests that despite the increasing risk, people do not refrain from moving into these high-risk areas.

Fluctuations in house prices (P) would ultimately be reflected in rent contracts (R). Data from United States Census Bureau indicates a indicates a trend toward increased renting in most of the states (32 of the 51 states) between 2010 and 2023 (United States Census Bureau 2024). Similarly, this trend is observed in 16 of the 27 European Union countries (Eurostat 2024). However, the causes of the increase are not clear.

(Desmond and Wilmers 2019) used R/P as a measure to explore tenant exploitation. By analyzing a national survey of landlords and data from Milwaukee, they find that renter exploitation is higher in poor neighborhoods, where rents are high relative to property values. They also point out

[3] Using a 5% discount rate.

to a need “to paint a comprehensive picture of the inner workings of rental markets, where the vast majority of low-income families reside.” This study seeks to address this need.

The question of exploitation is important, mainly because at the very extreme, this might lead to eviction, which is referred to as “one of the most pressing social issues in contemporary capitalism” by (Soederberg 2018a). There are various studies which ties rent exploitation to racial segregation and systemic inequalities. For example, (Crowell 2022) explores how rent exploitation, intensified by residential segregation, correlates with neighborhood characteristics and contributes to higher eviction rates and rent burdens, particularly in racially minoritized and poorer neighborhoods in Harris County, TX. (Rosenbaum and Friedman 2024) examines racial/ethnic disparities in housing insecurity, revealing through data from the Household Pulse Survey that Black renters are significantly more likely than whites to experience prolonged rent arrears and perceived likelihood of eviction. Eviction is hardly an American problem. It poses significant risks to society in Europe too, where in 2021, 30 percent of the people resided in rented homes, according to Eurostat. (Soederberg 2018b) mentions that in Germany, where the majority of the people (51 percent) rent instead of own, 335 thousand individuals were made homeless in 2014.

In this paper, we explore the extent to which climate change affects rent exploitation. We will use rent/property values (R/P), proposed by (Desmond and Wilmers 2019) as a measure for assessing rent exploitation. Additionally, we will utilize a tax adjusted version of this measure to analyze rental profits accrued by landlords. We use natural terrestrial events as a proxy to explore the effect of climate change. Our analysis shows that natural events significantly increase both rent exploitation and rental profit particularly in neighborhoods with low-value houses. The influence of natural events on rent dynamics can persist for up to two years.

The rest of the paper is organized as follows: Section 2 introduces the data, data resources, and the variables. Section 3 provides a concise overview of the propensity score matching (PSM) and difference-in-difference (DID) methodologies. Section 4 presents the results and Section 5 concludes.

2. Data

The idea of renter exploitation was introduced by (Desmond and Wilmers 2019), who define it, following the concept of exploitation as paying more for less relative to market value of a property, as the ratio of annual rents from a rental unit to the property value *(R/P)*. They also pointed out that higher exploitation does not necessarily mean that landlords are reaping extreme profits as they pay maintenance cost, insurance, taxes etc. Thus, they deduct these costs to calculate the rental profits made by landlord.

In this study we aim to measure renter exploitation across the US and measure how climate change affects tenant exploitation. For this purpose, we gather annual county-level data across the US from 2005 to 2022, covering 18 years. Following (Desmond and Wilmers 2019), we calculate rent exploitation as follows:

$$RE = \frac{R}{P}$$

where, *P* represents house prices, and *R* stands for median contract rent. We collect house prices, *P*, from Zillow.com, which reports prices monthly and uses annual median contract rent, *R*, from the US Census Bureau, which reports contract rates annually. Since we utilize annual data, we take contract rent as is and use end-of year house prices as an indicator of annual house prices.

As the only county-level rental-related cost that is publicly available is property taxes, we also define rental profit as follows:

$$RP = \frac{R - T}{P}$$

where *T* stands for tax which we obtain from the US Census Bureau.

The natural disaster data is obtained from The National Oceanic and Atmospheric Administration (NOAA). We created the dummy variable NE, which equals to 1 the total damage in county *i* at time *t* exceeds the median total damage, 0 otherwise.[4]

Although natural events seem to be an exogenous treatment which do not choose counties depending on its characteristics, as it is shown by (Gider et al. 2024) the characteristics of counties exposed to natural event are different than that of counties not exposed to natural events. Especially, distance to water (CO), elevation (EL) and income level of counties exposed to natural events (INC) are significantly different than that of counties not exposed to natural events. Addition to these some other demographic and economics characteristics including education level (EDU), housing supply (HU) and the share of conventional loans (CONV) are also added to the model as control variables. Naturally, all of these control variables are expected to have significant impact on rental profit and /or exploitation. Table 1 provides a summary of the definitions of all the variables that are utilized in the analysis of this paper, along with the data sources and units of measurement for each variable.

[4] As there are many counties with zero damage the median value of NE is very low, i.e. $20,000, we cross-checked our results with another dummy variable, where the median is calculated across all countries with positive damage (i.e. equals 1 if the damage in county i exceeds the median total damage of all counties where the total damage is greater than zero). This did not change the main results and conclusions.

Variable	Description	Source	Unit
RE	Rent exploitation	Zillow.com, US Census Bureau	percentage
RP	Rental profit	Zillow.com, US Census Bureau	percentage
NE	Natural event dummy: Equals 1 if the total damage in county i exceeds the median total damage, 0 otherwise	NOAA	unitless
CO	Coastal dummy	Google Map	unitless
EL	Distance above sea level	Google Map	m
INC	Average income of mortgage applicants	HMDA	$
HU	Housing inventory	US Census Bureau	unitless
EDU	Share of residents having higher than bachelor's degree	US Census Bureau	percentage
CONV	Share of conventional loans	HMDA	percentage
POP	Population of county	US Census Bureau	person

Table 1: Definition of variables

The descriptive statistics for all variables in the data set is presented in Table 2. The very first row of Table 2 shows the rental exploitation variable (*RE*) which ranges from 0.678 to 16.793, in the second we have the rental profit variable (*RP*) which ranges from 0.353 percent to 14.46 percent. This indicates that in some countries there has been a month where the annualized rent minus tax constituted 14% of the house value. The variables *NE,* and *CD* are dummy variables, which take values 0 or 1. *CONV* is a proxy variable for the economy of county, and it shows the share of conventional loans in mortgage market. The variables *INC*, *POP*, *HU* are used in natural logarithms to account for scaling.

Variables	Observations	Mean	SD	Min	Max
RE	12,920	4.594	1.334	0.678	16.793
RP	12,920	3.462	1.213	.353	14.462
NE	50,994	.496	.5	0	1
CO	50,994	.083	.275	0	1
CONV	46,317	.588	.243	0	1
EL	48,546	348.29	429.005	-12	3097
log (INC)	30,866	4.233	.355	2.079	8.135
log (HU)	13,773	11.325	.871	9.95	15.108
log (POP)	13,773	12.176	.891	10.983	16.135
EDU	11,371	.288	.105	.073	.782

Table 2: Descriptive statistics of the whole sample

To analyze whether the relationship between rent exploitation/rental profit and climate change varies by house value, we present the descriptive statistics of the variables across different quantiles in Table 3. The bottom quantile consists of counties where the value of houses is at the bottom 20%. The middle quantile covers the counties from 20% to 80%, while the top quantile includes the counties of top 20 % in terms of house value. We also test the mean difference of variables regarding their quantiles. We reject the hypothesis that the means of the variables are equal ($H_0: \mu_{j,bottom} = \mu_{j,middle} = \mu_{j,top}$, where $\mu_{j,k}$ represents the mean of variable j in the quantile k). Fig. 2 also shows the rent exploitation in different neighborhoods before and after a natural event. Two points are particularly noteworthy: First, the highest rent exploitation occurs in neighborhoods with the lowest 20% of house values. Second, these same neighborhoods experience the most significant increase in rent exploitation following a natural event. However, these statistical observations need to be further examined for other covariates and causality. And this is what we are going to perform in the next section.

Variables	Bottom 20%		Middle 60% (20%-80%)		Top 20%		p-value of the Wald Test, Equality of group means
	Obs.	Mean	Obs.	Mean	Obs.	Mean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RE	409	7.52	7,766	5.04	4,745	3.61	0.00
RP	409	6.07	7,766	3.86	4,745	2.58	0.00
NE	8,149	0.49	24,414	0.51	8,131	0.42	0.00
CO	8,149	0.01	24,414	0.06	8,131	0.30	0.00
EL	7,873	250.80	23,362	321.17	7,445	437.51	0.00
log (INC)	4,087	4.10	13,727	4.23	4,717	4.58	0.00
log (HU)	409	10.81	7,766	11.17	4,745	11.73	0.00
log (POP)	409	11.59	7,766	12.01	4,745	12.62	0.00
CONV	6,716	0.55	21,915	0.58	7,469	0.68	0.00
EDU	349	0.19	6,550	0.25	4,109	0.37	0.00

Table 3: Descriptive Statistics and Mean Difference Test of Variables regarding Quantiles of House Value

Note: This table shows the descriptive statistics of the variables with respect to house prices. The columns (1) and (2) provide descriptive statistics for counties where house prices fall within the lowest 20%. The columns (3) and (4) present the descriptives statistics for counties where house prices are between the 20^{th} and 80^{th} percentiles. The columns (5) and (6) show the counties where house prices are in the top 20 %. The very last column tests the mean differences across these quantiles for the variables RE, RP, NE, CD, EL, log(INC), log(HU), log(POP), CONV, EDU. This test evaluates the null hypothesis that the means of each variable do not differ by quantile ($H_0: \mu_{j,bottom} = \mu_{j,middle} = \mu_{j,top}$, where $\mu_{j,k}$ represents the mean of variable j in the quantile k).

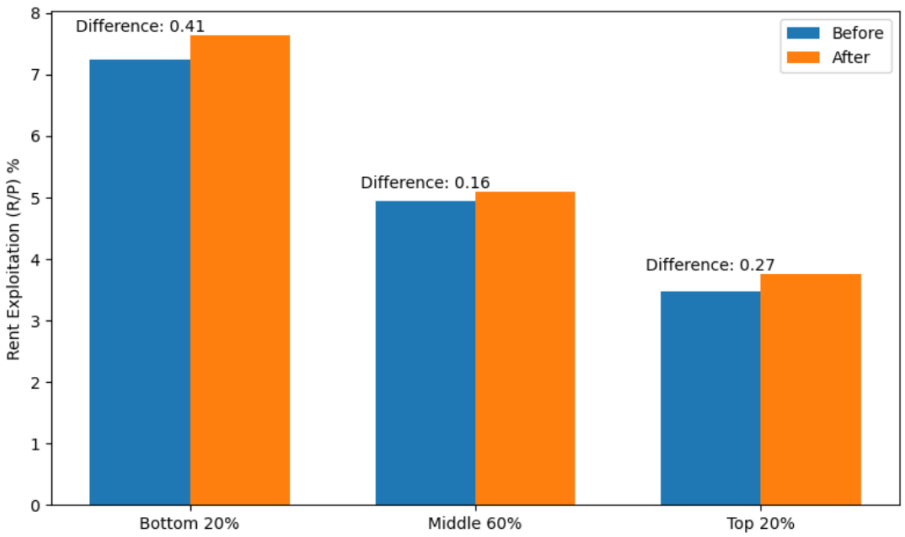


Fig. 2: Rent Exploitation in Different Neighborhoods before and after a Natural Event

3. METHODOLOGY

3.1. Difference in Difference (DID) with Propensity Score Matching (PSM)

In this study, we will analyze two separate outcomes: rent exploitation (*RE*), and rental profit (*RP*) under two conditions: exposure to a natural event (active treatment) and non-exposure (control treatment). $RE_{i.t}^{j}$ will represent the potential outcomes for county *i* in year *t*, under condition *j*, where *j=0* indicates the control/nonexposed condition and *j=1* indicates the treatment/exposed condition. Specifically, we will measure, the outcome $RE_{i,t}$ for each county *i* in each year t, resulting $RE_{i.t}^{1}$, following exposure to a natural event, or $RE_{i.t}^{0}$, in the absence of exposure (same holds for *RP*, too).

Each county receives only one treatment, either the control or the active treatment, resulting in the observation of a single outcome –$RE_{i.t}^{1}$, or $RE_{i.t}^{0}$, – following either exposure to a natural event or its absence. The challenge arises in measuring the real treatment effect, which is defined as the treatment effect on treated (ATT), which is calculated as $RE_{i.t}^{1} - RE_{i.t}^{0}$. However, as we observe either $RE_{i.t}^{1}$ or $RE_{i.t}^{0}$, not both, for each county and each year this makes direct observation of the real treatment effect infeasible. Nonetheless, the average treatment effect (ATE), which reflects the average impact of moving an entire population from untreated to treated, can be calculated by

$E[RE^1] - E[RE^0]$. This calculation produces an unbiased estimate of $E[RE^1_{i.t} - RE^0_{i.t}]$ only if selection of counties exposed to natural events is randomized (Austin 2011).

In Randomly Controlled Trial (RCT) framework, it is typically assumed that the counties exposed to the treatment will not differ systematically from the general population on average. However, the treatment counties are not randomly distributed across the country. For example, a county in Florida may be more prone to natural events compared to a county in Texas. Thus, an unbiased estimate of the ATE cannot be directly obtained by comparing outcomes between the two treatment groups. In this context, estimating the impact of natural events on rent exploitation/rental profit might be better addressed through ATT. At this point, DID with Propensity Score Matching offers a methodology to estimate ATT, regarding the impact of natural events on the desired outcome (Austin 2011), which are rent exploitation and rental profit.

Propensity Score Matching (PSM) is a statistical method used in the analysis of observational data, designed to estimate the effects of a treatment, policy, or intervention. This technique, introduced by (Rosenbaum and Rubin 1983) aims to address the issue of selection bias by adjusting for covariates that may predict the likelihood of receiving the treatment. The adjustment is needed because, without it, an analysis might wrongfully attribute observed differences in outcomes between treated and untreated groups to factors influencing treatment allocation, rather than the treatment itself.

PSM works by calculating a propensity score – e(X), which is the probability of treatment assignment given observed covariates X. Using this score e(X), PSM matches units in the treated group (*NE*=1) with similar units in the untreated group (*NE*=0), where j specifies different conditions of exposure defined in Table 1 .

The use of DID with PSM can be explained by the following equation, which aims to estimate the ATT in the following steps. First, the observed difference in average rent exploitation (*RE*) between counties exposed to natural events and those that are not can be expresses as $E\left[RE^1_{i.t} \middle| NE_{i,t} = 1\right] - E\left[RE^0_{i.t} \middle| NE_{i,t} = 0\right]$. Here, $RE^j_{i.t}$ represents the potential outcomes for county *i* in year *t*, under condition *j*, where *j=0* indicates the control/nonexposed condition and *j=1* indicates the treatment/exposed condition.

Adding and subtracting $E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]$, which is shown in bold below, to this expression yields the following:

$$\begin{aligned}E\left[RE_{i.t}^{1}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]&\\ =E\left[RE_{i.t}^{1}\middle|NE_{i,t}=1\right]&\\ +\underbrace{\boldsymbol{E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]}}_{=0}-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]&\end{aligned}$$

where $E\left[RE_{i.t}^{1}\middle|NE_{i,t}=1\right]$ refers to the expected *RE*, if a natural event impacts the county, while $E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]$ refers to the expected *RE* if the county is not affected by a natural event. Reorganizing right hand side yields equation 1:

$$E\left[RE_{i.t}^{1}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]=$$

$$\underbrace{E\left[RE_{i.t}^{1}-RE_{i.t}^{0}\middle|NE_{i,t}=1\right]}_{ATT}+\underbrace{E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]}_{selection\ bias}\qquad(1)$$

The term $NE_{i,t}$ indicates whether the county *i* at time *t* is exposed (1) or not exposed (0) to a natural event, serving as the basis for grouping in the propensity score model.

However, the actual focus of the study, the Average Treatment Effect on the Treated (ATT), is $E\left[RE_{i.t}^{1}-RE_{i.t}^{0}\middle|NE_{i,t}=1\right]$, which is the first term in the right-hand side of equation (1). This measures the difference in rent exploitation when a natural event impacts the county compared to if the natural event had not occurred. The second and the third term together, $E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]$, represent the difference in rent exploitation, *RE*, across the control and treatment counties before a natural event. This difference can be called the selection bias. As $E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]\neq E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]$, the only way to eliminate this bias is to use difference in difference approach. If we subtract pre-treatment RE differences, $E\left[RE_{i.t-1}^{1}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t-1}^{0}\middle|NE_{i,t}=0\right]$, from right hand side and left-hand side of the equation (1) , we will get

$$E\left[RE_{i.t}^{1}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]-E\left[RE_{i.t-1}^{1}\middle|NE_{i,t}=1\right]+E\left[RE_{i.t-1}^{0}\middle|NE_{i,t}=0\right]=\underbrace{E\left[RE_{i.t}^{1}-RE_{i.t}^{0}\middle|NE_{i,t}=1\right]}_{ATT}+\left(\underbrace{E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t-1}^{1}\middle|NE_{i,t}=1\right]}_{trend\ in\ exposed\ counties}\right)-\left(\underbrace{E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]-E\left[RE_{i.t-1}^{0}\middle|NE_{i,t}=0\right]}_{trend\ in\ nonexposed\ counties}\right) \quad (2b)$$

We can assume that in the absence of natural events, the trends in house prices for exposed and unexposed counties would have been similar—a condition known as the "parallel trends assumption." If parallel trend assumption holds , it can be expected that $\left(E\left[RE_{i.t}^{0}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t-1}^{1}\middle|NE_{i,t}=1\right]\right)$ is equal to $\left(E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]-E\left[RE_{i.t-1}^{0}\middle|NE_{i,t}=0\right]\right)$. However, this assumption might not hold due to inherent differences in the characteristics of each county, such as economic factors, geographical location, or demographic compositions. To address this and following (Blundell and Costa Dias 2000), we calculate propensity scores for each county based on characteristics that could influence both the likelihood of experiencing a natural event and house price trends. This calculation helps ensure that the parallel trend assumption holds. Consequently, the difference-in-differences (on the left-hand side of the equation) will yield the Average Treatment Effect on the Treated (ATT) of the natural event, as outlined in Equation (2):

$$\left(E\left[RE_{i.t}^{1}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t}^{0}\middle|NE_{i,t}=0\right]\right)-\left(E\left[RE_{i.t-1}^{1}\middle|NE_{i,t}=1\right]-E\left[RE_{i.t-1}^{0}\middle|NE_{i,t}=0\right]\right)=E\left[RE_{i.t}^{1}-RE_{i.t}^{0}\middle|NE_{i,t}=1\right] \quad (2)$$

The premise of the PSM approach is to identify for exposed county, a similar county that has not been exposed to natural event, from which we can approximate the non-observed counterfactual event. This matching technique enables us to assemble a sample of exposed and non-exposed counties that share similar characteristics prior to exposure.

These characteristics will include income levels (INC), proximity to coastlines (CO), and elevation (EL) among others. We employ a probit model for this calculation:

$$P(NE_{i,t}=1)=F(INC_{i,t},CO_{i,t},EL_{i,t}) \quad (3)$$

By matching counties on these propensity scores, we aim to align counties that are similar in all respects except for their exposure to natural events, thereby assuming more reliably that the

parallel trends condition holds for matched counties. This methodological framework aims to provide a robust analysis of the causal effects of natural events on house prices, taking into account complex interdependencies and potential biases inherent in observational data. This structured approach ensures that our findings are not only statistically valid but also relevant for policy-making and economic forecasting related to natural disasters and the real estate market.

Once the propensity scores are calculated, we can select the county that is closest in terms of its propensity score to serve as a matched counterpart. Moreover, we check the balancing condition, ensuring that each independent variable does not differ significantly between counties exposed to natural events and those that are not (Bandick et al. 2014).

3.2. Fixed Effect Panel Data Model with Driscall Kraay Standard Errors

The econometric model used in the fixed effect panel data analysis can be defined as follows:

$$RE_{i,t} = \beta_0 + \beta_1 NE_{i,t} + \beta_2 NE_{i,t-1} + \beta_3 NE_{i,t-2} + \beta_4 HU_{i,t} + \beta_5 POP_{i,t} + \beta_6 CONV_{i,t} + \beta_7 EDU_{i,t} + \beta_8 INC_{i,t} + \varepsilon_{i,t} \quad (4)$$

where $RE_{i,t}$ indicates rent exploitation in county *i* at year *t*. $NE_{i,t}$ is the dummy variable that shows whether the total damage in a county is higher than the median or not. EDU shows the education level, HU shows the housing supply and CONV stands for the share of conventional loans in a county. All variables are as defined in Table 1.

A similar regression analysis is conducted with RP:

$$RP_{i,t} = \beta_0 + \beta_1 NE_{i,t} + \beta_2 NE_{i,t-1} + \beta_3 NE_{i,t-2} + \beta_4 HU_{i,t} + \beta_5 POP_{i,t} + \beta_6 CONV_{i,t} + \beta_7 EDU_{i,t} + \beta_8 INC_{i,t} + \varepsilon_{i,t} \quad (5)$$

One of the possible threats for the reliability of panel data analysis is the possible cross-sectional dependency. In this panel data analysis, neighborhood effects among the counties could generate mutual dependency between the cross-sectional units (Driscoll and Kraay 1998). Neglecting the possibility of a link between regression disturbances across time and between cross-sections can lead to an inaccurate statistical conclusion (Cameron and Trivedi. Pravin K. 2005; Hoechle 2007).

(Driscoll and Kraay 1998) provide a nonparametric covariance matrix estimator that generates heteroskedasticity- and autocorrelation-consistent standard errors that are robust to general kinds of spatial and temporal dependency. Therefore, in this study, the fixed effect model is estimated

with Driscoll and Kraay standard errors, which are heteroskedasticity- and autocorrelation-consistent and robust to cross-sectional dependency.

3.3. Generalized Propensity Score Matching

As (Fong et al., 2018) mention, that the dichotomization of continuous treatment variables may lead to loss of information, limiting the insights from the subsequent data analysis. Thus, in the second, we will follow (Brown et al., 2021) and (Imai and van Dyk, 2004) to use the continuous treatment variable, total damage, TD, instead of the dummy NE.

Running the following regression

$$TD_i = \beta C_i + \varepsilon \qquad (2)$$

where $\varepsilon \sim N(0, \sigma^2)$ and C is a matrix composed of the input variables. Ensuring the normality of the residuals from this regression, using the Shapiro-Wilk test, we will proceed to the calculation of the generalized propensity score (GPS).

The propensity score of each state will be calculated as follows:

$$\widehat{\Theta}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left(-\frac{1}{2\hat{\sigma}^2}\left(TD_i - \widehat{TD_\iota}\right)^2\right), \qquad (3)$$

where TD_i is the true value of the continuous treatment for state i, $\widehat{TD_\iota}$is the state-specific predicted treatment from equation (2), and $\hat{\sigma}^2$ is the estimated variance of the regression model.

(Hirano and Imbens, 2004) proposed implementation of the estimated GPS, $\widehat{\Theta}_i$, through direct covariate adjustment. Covariate adjustment using the GPS involves regressing the outcome on both the continuous treatment and the GPS, using a flexible function of the treatment and GPS (ie, quadratic approximation).

4. Results

4.1. DID with PSM Results

The central idea of DID with PSM method is to match each treated participant to nontreated participants on matching variables which are variables that covary with the treatment. Then the ATT of the treated participants is compared with the ATT of the matched nontreated participants. The resultant difference is an estimate of the sample average treatment effect (Guo & Fraser, 2015). In DID with PSM, instead of sample average of outcome variable, the ATT effect of treatment group is compared to control group. The difference between ATTs is called DID estimate which would be our main measure of interest.

In this study covariate variables proxying for amenities are chosen. These variables include coastal dummy (CO), elevation (EL), and income level of counties (INC). The treated and control group observations are compared depending on their propensity scores. The results of difference in difference with propensity score matching method are as follows:

Panel A **Probit Regression for Propensity Score Matching** **Treatment Effect: Natural Event**		
	(1)	(2)
CO	-.304*** (.076)	-.112 (.08)
EL	-.0003*** (0.0001)	-.0002** (0.0001)
log(INC)	-.32*** (.096)	.334** (.136)
log(P)		-.583*** (.085)
N	2,282	2,282
LR Chi^2	41.97	90.11
p-value	0.00	0.00
Panel B **Balancing Test Between Treatment and Control Group** **p-Value of Mean Difference t-test**		
CO	0.76	0.66
EL	0.82	0.99
log (INC)	0.54	0.62
log (P)		0.93
PANEL C **Average Treatment Effect on Treated (ATT)** **Outcome: Rent Exploitation**		
Treated	4.968	4.921
Control	4.746	4.995
Difference	0.222	-.074
t-stat	6.30***	-2.07**
Number of Treated on Support	5,162	5,162
Number of Untreated on Support	2,730	2,730
PANEL D **Average Treatment Effect on Treated (ATT)** **Outcome: Rental Profit**		
Treated	3.81	3.78
Control	3.65	3.79
Difference	0.15	-.01
t-stat	2.72***	-0.31
Number of Treated on Support	1,319	1,319
Number of Untreated on Support	950	950

Table 4: Difference in Difference with Propensity Score Matching

Note: Panel A gives the estimations for the probit regression in equation (3). In Panel B, balancing test scores which show whether the treatment and control group is similar enough to be comparable is given. In Panel C, the ATT of natural event on rental exploitation, in Panel D the ATT of natural event on rental profit is presented. In Column (1) and (2) the treatment group is the counties to which natural events caused a total damage which is greater than the sample median. Standard errors are clustered at the county level and in parentheses. $*$ p<.1, **p<.05, ***p<.01

Panel A of Table 4 presents the Probit regression results given in (3) . Columns (1) and (2) use the dummy variable NE to proxy for natural event exposure, which equals 1 if the total damage from a natural event exceeds the median total damage in the sample, and 0 otherwise. In Column (1), CO (coastal dummy), EL(elevation), and INC (applicant income) are included as covariates to proxy for amenities related to live close to water. Balancing tests are crucial in PSM to ensure that the covariates are balanced between the treated and control groups after matching. Panel B results show that the treatment and control groups are not statistically significantly different in terms of covariates, with the p-value of the balancing test in Column (1) exceeding the 10% significance level, meaning that groups are comparable on observed covariates.

Panel C and D present our main results. In Panel C, rent exploitation variable is used as outcome variable. In Column (1) the ATT in treatment counties is 4.97 percentage, compared to 4.75 percentage in control counties, indicating that ATT is higher in counties that are exposed to natural events. The difference, using difference-in-difference method, is shown to be 0.22 and statistically significant. This implies that climate changes significantly increase rent exploitation. On the other hand, as in Column (2), when one of the channels of climate change to increase rent exploitation, house prices, is controlled, the significantly increasing impact of climate change on rent exploitation becomes negative (-.074), statistically significant at 5%. By adding house price among covariates, one potential channel through which natural events affect rent exploitation is controlled. (Gider et al. 2024) show that the impact of natural events on house prices is heterogeneous. It is concluded that the value-destroying impact of natural events on house prices is significant only for low-value houses. The disappearing significant relationship between *RE* and climate change after controlling house price suggests that the main channel of climate change to increase rent exploitation is its heterogenous impact on house prices.[5]

In Column (1) of Panel D, the ATT of rental profit in treatment counties is 3.81 percent, compared to 3.65 percent in control counties, indicating a positive DID estimate which implies a positive causal impact of natural event on rental profit. The DID estimate is shown to be 0.15 and statistically significant at even `% level. This implies that DID with PSM results suggest a positive causality between natural event and rental profit. In Column (2), the house price factor is included

[5] We run the same regressions with another dummy variable, where the median is calculated across all countries with positive damage (i.e. equals 1 if the damage in county i exceeds the median total damage of all counties where the total damage is greater than zero). This did not change the main results and conclusions.

as a covariate, proxied by the natural logarithm of the house prices. Similar to Column (1), the balancing test in Column (2) of Panel B shows no significant difference between treatment and control groups in terms of covariates. With the balancing condition of Propensity Score Matching met, the ATT results of the difference-in-difference approach with PSM can be interpreted. The results indicate that after including house prices in the covariates, the ATT impact of natural disasters on rental exploitation not only fails to increase, but actually reverses (-0.074), significant at the 5% level. This heterogenous impact can also be one of the channels for rental profit. While rents are less likely to reduce due to contracts, house price can decrease right after natural event hits the counties. This suggests that while the numerator of rental profit is not likely to reduce, the denominator of rental profit can decrease. The decrease in denominator is likely to increase rental profit. If the impact of natural event on house price is controlled by adding house price index to the equation, it is reasonable to see that the significant impact of natural event on rental profit disappears.

Overall, the results from Column (1) suggest that natural events significantly increase rent exploitation and rental profit. In other words, when a natural event hits a county, both rent exploitation (R/P) and rental profits ((R-T)/P) increase. However, the loss of significance of ATT after controlling house prices in Column (2) suggests that the significant impact of natural events on rent exploitation is due to climate change's heterogeneous impact on house prices. Thus, there is a considerable heterogeneity across housing markets. Once house prices are accounted for, the significant causality becomes insignificant.

4.2. Panel Data Analysis of The Relationship Rent Exploitation and Climate Change for Different Quantiles

In the previous section, we present results showing that climate change increases rent exploitation and rental profit mostly through changing house prices. In this section, the source of this significant relationship is explored. It can be expected that middle- and low-income people have less bargaining power against their landlord in case climate change hits their neighborhood. To test this hypothesis, the counties are divided into 3 categories based on house value. Then, we test climate change and rent exploitation relationship for all of these different county groups. We control several factors including education (EDU), conventional loan share (CONV), income level (INC),

housing unit (HU) and population (POP). We also incorporate two lags of natural event dummy into the analysis, recognizing that the impact of natural events on rent exploitation may extend beyond a single year. The results from our fixed effect panel data regression are given in Table 5.

Dependent Variable	**Rent Exploitation**			**Rental Profit**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Bottom	**Middle**	**Top**	**Bottom**	**Middle**	**Top**
NE_t	**0.28*****	-0.033	-0.024	**0.21*****	-0.029	-0.0058
	(0.063)	(0.034)	(0.033)	(0.043)	(0.026)	(0.023)
NE_{t-1}	-0.050	-0.0033	0.011	-0.099	-0.0028	0.0048
	(0.10)	(0.032)	(0.023)	(0.097)	(0.025)	(0.016)
NE_{t-2}	**0.21****	-0.0052	0.018	**0.16****	-0.0060	0.0052
	(0.083)	(0.025)	(0.020)	(0.070)	(0.018)	(0.013)
log (HU)	-6.32**	3.65***	3.88***	-4.49**	2.32***	2.34***
	(2.54)	(0.81)	(0.58)	(1.82)	(0.66)	(0.50)
log (POP)	-5.96***	-1.62	-3.22**	-6.36***	-0.63	-1.61
	(2.15)	(2.24)	(1.43)	(2.13)	(1.76)	(1.19)
CONV	-1.06***	-0.46	-0.57*	-0.65**	-0.33	-0.36*
	(0.30)	(0.31)	(0.34)	(0.26)	(0.25)	(0.21)
EDU	2.00	3.25	1.63	1.27	2.04	0.71
	(5.63)	(2.35)	(1.24)	(4.25)	(1.67)	(0.68)
log(INC)	0.39	0.087	-0.25***	0.16	0.072	-0.22***
	(0.32)	(0.087)	(0.076)	(0.23)	(0.059)	(0.061)
intercept	144.8***	-16.8	-0.13	128.9***	-14.8	-3.29
	(27.4)	(23.0)	(13.4)	(18.4)	(18.7)	(10.5)
N	253	4628	2760	253	4628	2760
R^2	0.1177	0.051	0.0657	0.1123	0.051	0.0641
F	85.3	99.6	1671.1	134.2	11.8	381.2

Table 5: Fixed Effect Panel Data Analysis of Rent Exploitation/ Rental Profit and Climate Change Relationship for Different Quantiles of House Value

Note: Columns 1, 2 and 3 present the estimation results from equation (4), while columns 4, 5, and 6 display results from equation (5). Bottom quantile covers the sample of lowest 20% in terms of house value, Middle quantile covers the sample between 20% and 80% in terms of house value and top quantile covers the sample of top 20% in terms of house value. The variables housing supply, log(HU), population , log (POP), share of conventional loans (CONV), education level, EDU, and income levels, log (INC) are used as control variables. Driscall Kraay Standard errors are clustered at the county level and shown in parentheses. $*$ p<.1, **p<.05, ***p<.01

The regression results in columns (1), (2) and (3) suggest that natural events significantly increase rental exploitation for the sample comprising the bottom 20% of houses by value, as demonstrated by the significant coefficient of NE. Specifically, natural events increase rental exploitation by an average 0.28 percentage points in the year they occur, and by an additional 0.21 percentage points in the second year. Conversely, column (2) and (3) show that this significant impact vanishes once

the same regression is run for the houses of middle and top value tiers. We do not see any significant natural event dummy in Column (2) and (3).

In Column (4) of Table 5, the regression results suggest that natural events significantly increase rental profit for the sample consisting of bottom 20% of houses by value, as evidenced by the significant coefficient of NE. Specifically, natural events increase rental profit by an average 0.21 percentage points in the year they occur, and by an additional 0.16 percentage points in the second year. In Column (5) and (6) the same regression is run for different samples. In Column (5) the sample consists of houses in the middle 60%. The result shows that the significantly increasing effect of natural events on rent exploitation diminishes when the regression is run for higher-value houses. Similarly, in Column (6) the same regression is run this time for the top 20% houses in terms of value. The results again do not suggest any significant relationship between natural events and rental profit for higher value houses.

In total, columns (1) and (4) show that natural events increase both rent exploitation and rental profit, columns (2) and (3) together with (5) and (6) show that this effect is mostly seen for low-value houses. All in all, the results in Table 5 suggest that natural events mostly increase both rent exploitation and rental profits in low value houses.

4.3. Generalized Propensity Score Matching Results

5. Conclusion

In this paper, we explore the effects of climate change on rent exploitation and rental profit. Rent exploitation is defined as the ratio rent to property values, while rental profit is defined as the ratio of rent cost minus tax to property values. We use natural events as a proxy to climate change. Using annual county-level property values, rental cost, tax as well as other control variables across the US from 2005 to 2022, we reveal the followings:

Natural events cause an increase in rent exploitation, an effect that is predominantly observed in low-value houses. Therefore, tenants in these low-value properties bear a greater financial burden from natural events compared to those residing in higher-tier houses. This effect persists even if we adjust the rental exploitation by the tax, yielding rental profit. We also show that these

events also cause an increase in rental profit. This suggest that landlords do not adjust rents to reflect the decrease in property values. The impact of these events can persist for up to two years.

These results support the findings by (Desmond and Wilmers 2019), who show that tenant exploitation is higher in poor neighborhoods in Milwaukee and conclude that “people at the top try to keep people at the bottom unequal, for their own advantage.”

We should acknowledge the limitations of this study. Our rental profit analysis is restricted to encompassing only tax data, excluding other property-related costs such as maintenance and insurance. Additionally, we were unable to account for the cost of doing business in disadvantaged communities, such as turnover and vacancies. Consequently, the scope of our rental profit data limits our ability to provide reliable estimates of landlord profit margins.

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