The Impact of Natural Disasters on Rental Markets: Heterogeneous Effects, Rental Subsidies, and Equity in Disaster Recovery

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Abstract

This paper provides new evidence on the impact of natural disasters on rental markets and the role of existing rental subsidies through the Housing Choice Voucher (HCV) program in the wake of such destructive events. Combining a novel data set of asking rents in New York City with spatial data on flooding incurred by Hurricane Sandy, I first estimate the rental impact of the storm in affected neighborhoods using a difference in differences design. In contrast to the literature on home prices, I find initial negative impacts on rents rebound quite quickly. I also find evidence of heterogeneity by neighborhood income: asking rents in above median income neighborhoods increased by 5%, while asking rents in lower income neighborhoods decreased by 5%, effects that appear to be driven by disparate neighborhood resources for recovery. Examining the rental impacts in the voucher market supports this theory. Voucher rents increased by over 5%, driven by voucher landlords' ability to renovate their buildings earlier than other low-income landlords. Programmatic features allowed for the incidence of these increases to fall nearly entirely on the government, providing a sort of insurance for voucher landlords and tenants. These results underscore the importance of examining the impact of disasters on rental markets for understanding the distribution of disaster recovery and its implications for equity. They also highlight a trade off inherent in existing rental subsidies: while subsidies may fill gaps left by traditional disaster assistance, they may also create implicit incentives to house vulnerable populations in high-risk areas.

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1 Introduction

As natural disasters grow in frequency and intensity under climate change, understanding how these extreme events affect housing availability and affordability is increasingly important. Most studies examining the impacts of hurricanes on the housing market focus on impacts on property values and have generally found that such storms decrease property prices in the affected areas (Bin and Landry (2013); Bin and Polasky (2004); Hallstrom and Smith (2005); Ortega and Taşpınar (2018); Yi and Choi (2020)). Given that rental data is difficult to obtain, few papers have been able to focus on rents and theoretically, the impacts of storms on rents might differ from home prices. The incidence of increased user costs of housing differs for renters than for homeowners, especially since in the rental market, renters make up the demand side and landlords the supply side. Renters do not have to bear the costs of repairs to their home, or need to consider the long-term value of the property, while owners do. Therefore, there is less reason to think that storms will reduce rental demand (and hence rents) for units in affected neighborhoods. On the supply side, landlords decide whether their properties are worth the investment to repair and maintain, raise to the next price tier, or even remove from the rental market altogether.

It has been well documented that low-income and minority neighborhoods are typically more vulnerable to the harmful impacts of natural disasters (Cutter et al. (2012); Van Zandt et al. (2012)), and that lower income neighborhoods are slower to recover with respect to amenities and home prices (Meltzer et al. (2021), Ellen and Meltzer (2024)). In the wake of historic Hurricanes Helene and Milton amidst a contested vote to provide FEMA with additional funding, examining the role of rental voucher subsidies in the aftermath of a hurricane can shed light on how gaps in traditional disaster assistance can be filled by existing transfer programs. Indeed, the Housing Choice Voucher market includes a third actor, the government, that can shoulder some of the incidence of increased user costs of housing, generating an interesting theoretical trade off. Landlords may be able (or required) to renovate their properties earlier than other low-income landlords, and programmatic features may allow them to recoup renovation costs through higher rents without the risk of losing their tenants if the government subsidizes some of the rent increases. This may enable voucher landlords and their tenants to recover from storms more quickly than other low-income landlords/tenants, although at a cost not currently considered when tallying expenditures on recovery efforts. It may also generate incentives to house vulnerable populations in areas at higher risk of climate change-related damage. To understand the ways in which government intervention is altering impacts for those it supports, examining the population of existing rental voucher subsidy recipients is critical.

This paper provides new evidence that the impact of natural disasters on rental markets does differ from the owner-occupied market, though rents similarly exhibit disparate recovery across neighborhood income. Specifically, on average, rental markets rebounded faster than the owner-occupied market in New York City after Hurricane Sandy but, sample averages mask heterogeneity: rents appear to have increased in higher income neighborhoods and decreased in lower income neighborhoods. I examine several possible explanations for this impact heterogeneity, and deduce that the most plausible explanation is differential resource/recovery capacity. Given that lower-income neighborhoods were slower to recover, I then examine how government rental voucher subsidies through the Housing Choice Voucher program affected the rental impacts for recipient low-income households compared to unassisted households in lower income neighborhoods and consider the implications of an existing subsidy program filling some of the gaps left by traditional assistance from FEMA.

Hurricane Sandy (2012) is an ideal storm to study these questions because it was not only a large and sudden event that caused substantial damage across the city, but its storm surge also affected the city locally in unpredictable ways. This meant that neighboring city blocks experienced wide variation in damage from the storm, providing plausibly quasi-exogenous variation across otherwise similar, small geographic areas.

Exploiting this variation, this paper makes three main contributions to the existing literature on housing markets and assistance in the wake of disasters. First, while most previous research on the impact of natural disasters on housing markets, due in part, to data constraints, has focused on owner-occupied housing, by combining a new and unique data set of unit-level asking rents from StreetEasy listings with city block level information on storm surge heights, I am able to assess the impacts of the storm on market rents and contrast those findings with evidence on home prices. Using an event study methodology, I find that, in the 14 months immediately after the hurricane, rents in affected areas experienced a negative impact relative to non-affected areas within the same ZIP code of 5 percent ($219). This drop likely reflects a dis-amenity effect from the blight and damage incurred, further supported by the fact that no such drop occurred in low surge areas. It is also consistent with the work of Meltzer et al. (2021), which found that retail businesses on blocks with high storm surge levels experienced an increase in closure rate that was twice as high as that for establishments in areas without any surge. The effects were also particularly pronounced in the years immediately following the storm.

However, contrary to the literature on home prices that shows persistent 11-22% price discounts for at least 6 years after Hurricane Sandy (Ellen and Meltzer (2024), Ortega and Taṣpınar (2018)), rents rebounded quite quickly. Two years after the storm (by 2014), quality-adjusted asking rents in high surge areas had recovered substantially and by four years post-storm they had returned to rent levels in non-surge areas. A rough estimate of the average price to rent ratio across high and non-surge blocks over time suggests that after the hurricane, it did become more affordable to purchase rather than rent in high surge areas relative to non-surge areas. However, both areas have price-to-rent ratios of between 15-20 for most of the period suggesting it is still "typically better to rent than buy[1]."

Second, I find strong evidence that the average impacts mask heterogeneity by neighborhood income, contributing to a substantial literature on disparate recovery across neighborhoods along racial and socioeconomic lines after natural disasters (Park and Franklin (2023); Hong et al. (2021); Wyczalkowski et al. (2019); Lee (2017); Finch et al. (2010); Donner and Rodríguez (2008); Cutter et al. (2003); Chappell et al. (2007)). Quality-adjusted rents in above median income neighborhoods increased by roughly 5% more on high surge blocks than non-surge blocks immediately after the storm (2013), while quality-adjusted rents for units in below median income neighborhoods decreased by roughly 5%. I rule out the possibility that these differences are driven by differences in insurance coverage/rates or rent stabilization. Rather, I find evidence suggesting that the heterogeneity in rental impacts is driven by the differential ability of neighborhoods to recover: while renovations in above median income neighborhoods appear to begin in 2013, a year after the storm, below median income neighborhoods do not experience an increase in renovation permits until around 2016/2017, when the city's recovery funds were distributed.

Finally, given that this gap in assistance timing seems to have primarily affected lower income neighborhoods, the third contribution of this paper is to examine the extent to which Housing Choice Voucher subsidies may have mitigated the impacts of this gap for participating households and landlords. While there is considerable literature documenting the distortions

[1]https://www.forbes.com/sites/greatspeculations/2010/11/02/rent-ratio-tells-you-whether-renting-or-buying-is-the-better-deal/?sh=4096cc6e9d08

created by explicit subsidization of disaster relief through insurance (Kousky (2010); Gregory (2017); Gallagher (2014)) and a burgeoning literature on the implicit subsidization of development and habitation of areas prone to damage from climate change (Ostriker and Russo (2022); Baylis and Boomhower (2019); Wagner (2022)), little work has examined the role of existing, non-disaster specific subsidy programs in supplementing assistance after disasters.

The Housing Choice Voucher (HCV) program provides an opportunity to test whether landlord resources present a constraint to their reinvestment in lower-income communities after a natural disaster. The program offers ways in which such barriers could be circumvented, so that in theory, we might expect to see different impacts in this market if resources and the ability to recoup costs through rents do play a role in landlord decision making. In the HCV program, the local housing authority pays the difference between the rent charged and 30 percent of a tenant's income, up to the local rent ceiling. Therefore, as long as the rents landlords charge to voucher holders remain below the allowable rent ceilings (or payment standards), rent increases will be paid for by the housing authority[2]. Rents in the voucher program change through local housing authorities' rent reasonableness assessments, conducted when new tenants lease a unit, or when a landlord requests a rent increase.

I analyze the change in rents charged to voucher holders with the same event study methodology using administrative records from the Department of Housing and Urban Development (HUD)'s Housing Choice Voucher program, and, in contrast to the broader findings, I find a steady relative increase in voucher rents in high surge areas compared to non-surge areas. Voucher rents appear to have been "sticky" downward, meaning they were resistant to downward pressure from decreases in demand, with no average decrease in the years immediately after the storm. Therefore, voucher landlords were protected from the negative rental impacts experienced by other units in low-income neighborhoods.

In addition, voucher landlords were nearly 10% more likely to file for renovation permits in 2013 than non-voucher landlords in low-income neighborhoods and rents increased for units in these buildings. Within three years of the storm (by 2015), voucher rents had increased by 3 percent ($45) in high surge areas relative to non-surge areas and by 2017 they had increased by 5.2% percent ($87) more in high surge areas than non-surge areas.

[2]When households first enter contract on a new apartment with a voucher subsidy, the program requires that the tenant pay no more than 40% of their income to rent. No such official limitation exists as the voucher holder remains in the unit.

It appears landlords were able to capitalize quality improvements into rents so quickly because the government bore a substantial amount of the incidence of increased user costs of housing, so they did not risk losing their tenants. I find that the incidence of these Sandy-induced rent increases for voucher households fell nearly entirely on the government such that voucher tenants were shielded from the rent increases by the housing authority. There was virtually no increase in the portion of rent paid by voucher holders in high surge areas compared to non-surge areas in the same ZIP code, and the payments from the housing authority mirror the increases in the contract rents. This appears to have been possible for two types of voucher tenants: a subset of those that had rents below the payment standard to begin with, and those that had enhanced vouchers[3]. In this way, the program may have acted as a type of insurance for both voucher landlords and tenants. Finally, I find evidence that these features of the voucher program may have made voucher tenants more attractive to landlords in areas that were hit hardest by the storm, as the number of existing voucher holders living on high surge blocks increased significantly compared to those on no-surge blocks after the storm.

Together, the results in this paper imply that when examining the impacts of climate change on the housing market, we should consider both the home sales and rental markets, as the impacts may differ between the two. In the case of Hurricane Sandy, while considerable research suggests the hurricane led to a persistent decrease in home sales prices, I find evidence that while hedonic rents decreased initially, they rebounded much more quickly than home sales prices. Average effects on quality-adjusted rents can mask considerable heterogeneity in disaster recovery across neighborhood income based on resources and the timing of disaster assistance. These results have important implications for the distribution of disaster recovery, including how it may lead to changes in the composition of the population and the economic development of neighborhoods, and have longer-term effects on equity.

The fact that the nature of the subsidy created different rental impacts in the Housing Choice Voucher sub-market should also prompt discussion about the role of existing rental voucher subsidies in the wake of natural disasters. The housing voucher program appears to have shielded both landlords and tenants from broader market fluctuations by shouldering additional costs. This additional level of "insurance" afforded to landlords might encourage participation in

[3]Enhanced vouchers allow for higher payment standards to enable tenants to stay in their units despite improvements to their buildings:
https://www.hud.gov/sites/documents/ENHANCED_VOUCHERS_ENG.PDF

a program plagued by low landlord engagement. However, it may also mean that rental voucher subsidies create an implicit incentive for housing vulnerable populations in neighborhoods at high risk of disaster-induced damage.

The rest of the paper is organized as follows: Section 2 provides background on Hurricane Sandy and the Housing Choice Voucher Program; Section 3 discusses the relevant empirical literature more fully; Section 4 provides detail on the data used and the estimation strategy; Section 5 presents empirical results; Section 6 presents robustness checks; and Section 7 concludes.

2 Background

2.1 Hurricane Sandy

Hurricane Sandy hit the east coast of the United States (US) in October of 2012 and provides an ideal setting for studying the impact of natural disasters on rental markets for two reasons. First, the hurricane caused considerable damage across a fairly large geographic area. In New York City, it inflicted roughly $19 billion in damages and damaged over 69,000 residential properties. The storm surge affected nearly 9 percent of residential units in the city (NYC.gov).

To distinguish areas that experienced higher levels of damage from lower levels of damage, I follow previous work of Ellen and Meltzer (2024) and designate areas as high surge if they experienced more than 2ft of surge and low surge if they experienced 0-2ft of surge[4]. Figure 1 shows a map of ZIP codes across the city, with blocks shaded by this storm surge designation. Naturally, most of the high surge areas are along the coast, though notably many blocks along the coastline experienced low or no surge. The surge also covered all five boroughs of New York, generating substantial variation in the populations and neighborhoods affected.

Second, the storm surge was somewhat unpredictable and varied substantially, creating exogenous variation in storm exposure across neighboring city blocks. Figure 2 provides an example of an Upper East Side neighborhood where the surge levels vary considerably across neighboring blocks, as well as across the flood zone boundary, depicted in grey. High, low, and non-surge blocks are contiguous and cross in and out of the flood zone, creating plausibly exogenous "treatment" and "comparison" groups across small geographic areas.

[4]This categorization is discussed in more depth in both Sections 4.1 and 4.2.

2.2 The Housing Choice Voucher Program

The Housing Choice Voucher program is the largest rental subsidy program in the country, providing assistance to over 5 million people in approximately 2.3 million households nationally (Center for Budget and Policy Priorities, 2021), and over 100,000 households in New York City. Voucher households are expected to pay 30% of their income toward rent, and the housing authority subsidizes the rest of the rent to the landlord as long as the rent falls below a specified local payment standard, generally a percentage of the area's Fair Market Rent. If rent exceeds the payment standard, the voucher household is responsible for the remaining difference. While not explicitly targeted toward disaster assistance in most instances, the nature of the subsidy in the housing choice voucher program may shield some of its participants from the hurricane's impacts on the rental market in two important ways.

First, sitting voucher rents may be "sticky" downward. Housing authorities typically conduct "rent reasonableness" assessments to ensure that the rents charged to voucher holders are comparable to other rents for similar units in the area. However, they only conduct these assessments when a voucher tenant is moving into a new unit or when the landlord requests a rent increase. Therefore, sitting voucher rents may have remained stable rather than responding to any acute rental shocks other renters in lower-income neighborhoods may have experienced.

Second, voucher landlords may not have been subject to the same resource constraints as other low-income landlords. If voucher landlords knew they would be able to recoup renovation costs through higher rents without risking losing their tenants, they may have been able to renovate sooner than other landlords in low-income neighborhoods. In this way, the voucher may have acted as insurance for voucher landlords in high surge areas. An employee at one of the largest housing authorities in New York City conveyed that voucher landlords may very well have passed some of their renovation costs onto tenants through rent increases, especially incrementally over a longer period of time. He noted that if a landlord improved their unit and requested a "reasonable" rent increase in accordance with that improvement, a rent reasonableness assessment by the housing authority "would not have presented a significant barrier" and the increase would likely have been granted.

In the broader market, we would not expect landlords to easily be able to pass renovation costs onto tenants through increased rents, as they might risk losing that tenant. However, voucher tenants might not have borne the incidence of these rent increases if rents were initially below the payment standard in affected neighborhoods (78% of the sample), where voucher landlords could raise rents up to that payment standard and have the housing authority cover the difference. In addition, there are some types of vouchers that allow for household-level accommodations to payment standards. In particular, "enhanced vouchers" are designed to help tenants remain in their unit when their building undergoes a conversion, such as a renovation, by sometimes allowing for higher payment standards[5].

3 Empirical Literature

This paper contributes to three key strands of literature. First, the effects of natural disasters on rental markets more broadly, which due primarily to data constraints are largely understudied. Second, this paper also contributes to literature on the uneven disaster recovery across neighborhoods and households along racial and socioeconomic dimensions. Third, it relates to a growing literature on the implicit subsidization of disaster assistance through various assistance programs, which thus far has mainly focused on those targeted at disaster recovery.

3.1 Existing Evidence of Disaster Impacts on Housing Markets

Damage from a hurricane makes affected neighborhoods less desirable, either because of the blight incurred or because of new information about the riskiness of the neighborhood. Research has shown evidence of such a negative demand shock in the owner-occupied market. Several papers document negative effects of hurricane and flooding risk on residential property prices ((Bin and Polasky, 2004); Ortega and Taşpınar (2018); Gillespie et al. (2020); Hennighausen and Suter (2020)). Many of these papers also find that new information about the relative riskiness of neighborhoods is a strong driver of the decrease in demand in the longer term. Hallstrom and Smith (2005) find that prices decreased in Florida counties that did not experience damage from Hurricane Andrew, but where the hurricane would have conveyed risk information to the homeowners. Ellen and Meltzer (2024) find evidence that after Hurricane Sandy, while housing prices decreased in areas affected by the storm across the board, prices remained depressed for a longer time period outside the flood zone than inside the flood zone. They interpret this

[5] https://www.hud.gov/sites/documents/ENHANCED_VOUCHERS_ENG.PDF

finding to mean that that prospective buyers of properties outside the flood zone received new information about the relative riskiness of the properties that was already known to buyers within the flood zone through the requirement to purchase flood insurance. Kousky (2010) shows a similar effect in Missouri, where property prices in 100-year floodplains did not change significantly after a 1993 flood of the Mississippi River, but prices in the 500-year floodplains significantly declined where home buyers would not have initially been informed about their property's flood risk. Tanaka and Zabel (2018) are able to isolate the effect of risk information from disaster impacts themselves by examining changes in house prices near US power plants after the Fukushima nuclear disaster in Japan and find significant (and temporary) declines in house prices.

It is not clear, however, how strong we should expect the negative demand effect to be for renters because of the differing incidence of increased housing user costs from homeowners. Renters experience the same dis-amenity effect of blight as homeowners, but renters do not have the same long-term stake in property. Renters care about the use-value of housing and are not concerned with the long term asset value of the unit. In addition, they are not required to purchase flood insurance and are less likely to need to pay for repairs if damages are incurred. Flood zone and surge level boundaries are likely to be less salient borders to renters for these reasons and renters have less reason to be discouraged by potential long-term outcomes of property in these areas.

That said, renters may have less initial information about flood risk than homeowners since they are not required to purchase flood insurance, and thus storms may provide a larger information shock to renters. While they are not likely to incur large repair costs to the unit, they may suffer damage to personal property. In addition, if enough displaced households join the rental market in nearby, non-damaged blocks, this could lead to rental increases in unaffected areas (relative to negative impacts in affected areas).

In addition, supply adjustments might lead to an increase in rents. The damage inflicted by the storm might initially considerably reduce the supply of rental housing, with fewer habitable properties leading to a rise in rents for the remaining stock (Vigdor (2008)). Landlords, as separate actors from tenants, may choose to renovate their properties if they have the resources, but may be unable or unwilling to do so in certain neighborhoods, or for certain units.

Ultimately, since the theory suggests the possibility of a variety of countervailing forces, the question of the impact of the hurricane on rents in affected neighborhoods is an empirical one.

3.2 Disparate Recovery after Storms

Importantly, these demand and supply adjustments might have occurred to varying degrees across different neighborhoods. Several papers have explored the impacts of disasters on home prices stratified by neighborhood income, with mixed results. Smith et al. (2006) find that higher income households are more likely to stay in their homes and invest in preventing further damage, while lower income households prefer to move to more affordable housing. Cohen et al. (2021) and Ellen et al. (2024) actually find larger initial impacts in higher income neighborhoods, but the latter find that these neighborhoods recover more quickly. They suggest their results may reflect what other work has shown: residents of higher income neighborhoods have more resources to repair damage and blight, and to insure themselves from damage from future disasters (Park and Franklin (2023); Hong et al. (2021); Wyczalkowski et al. (2019); Lee (2017); Finch et al. (2010); Donner and Rodríguez (2008); Cutter et al. (2003); Chappell et al. (2007)). As a result, lower income neighborhoods may be more likely to see property abandonment, sustained damage, and reduced property values (Ma and Smith (2019)). Lee (2020) finds that lower income neighborhoods see larger increases in poverty rates after disasters and using cell phone data, Hong et al. (2021) find socioeconomic and racial disparities in evacuation and mobility responses across neighborhoods. That said, Wyczalkowski et al. (2019) find more recovery and change over the long-run in lower income census tracts in counties hit by storms in the Houston area, which they argue may result from active speculation as property values fall.

Again, research on disparate recovery in rental markets is largely missing from this literature, and since renters tend to be a more vulnerable population than homeowners, examining the impacts on this population is critical.

3.3 Implicit Impacts of Government Subsidies

The question of the role of housing voucher subsidies in disaster mitigation contributes to a growing body of literature on the ways that the explicit and implicit government subsidies distort incentives and market outcomes in regard to the development and habitation of areas at high risk of climate change. A number of studies have focused on behavioral changes with flood insurance and rebuilding in the wake of damaging flood events (Kousky (2010), Gregory (2017), Gallagher (2014)), and several find that these policies actually encourage rebuilding and renovation in high-risk areas.

The topic has been explored in the context of wildfires too. Baylis and Boomhower (2019) and Olmstead et al. (2012) both find that government attempts at wildfire mitigation create implicit subsidies for homeowners and encourage development in fire-prone areas. The former's estimates suggest that the implicit subsidy from firefighting mitigation can reach up to 20% of the home's value.

Few papers, however, have taken into account the role of existing social safety net programs when estimating the costs of government subsidization and mitigation of climate risk. The research that does exist suggests that omitting existing program transfers from analysis on government spending on disaster relief can lead to a gross underestimate. Deryugina (2017) shows that affected counties receive extra transfers through non-disaster social insurance programs such as income maintenance payments, unemployment insurance, and public medical benefits, which average about \$780–\$1,150 per capita on top of on average \$155–\$160 per capita of official disaster aid. Therefore, if we are interested in understanding the extent to which the government subsidizes climate risk, examining the impact of disasters on existing programs is important.

4 Empirical Strategy

I estimate the impact of Hurricane Sandy on market rents and voucher rents using a difference-in-differences design that compares city blocks that experienced higher levels of storm surge to blocks that experienced no storm surge within the same ZIP code. To do this, I gather a rich data set of spatially detailed data on the storm surge from the hurricane, market rents, Housing Choice Voucher Program data, and administrative data from New York City.

4.1 Data

4.1.1 FEMA Surge and Flood Maps

I use FEMA's surge map to capture the impact of the storm through water inundation. The FEMA Modeling Task Force (MOTF), a group that uses statistical modeling and on the ground surge sensors and field observations to regularly update flood impacts, uses high-water marks and surge sensor data to interpolate water surface elevation after the storm. They report surge levels at one or three square meters but following previous work, I collapse these interpolated micro estimates to the block level (Ellen and Meltzer (2024)).

I categorize surge heights to facilitate a comparison between areas that were clearly impacted by the storm and those that were not. In Figure B.1, I examine the relationship between surge heights and FEMA's estimate of "major damage"[6], aggregated to the block level, to find an appropriate surge-level threshold to identify blocks that were severely affected by the storm. The main goal of identifying a surge-level cut off is to capture as many blocks that experienced major damage due to the storm as possible, while excluding properties that were likely damaged due to other, potentially endogenous factors, like the quality of the structure. The red line indicates a block level average of 2ft, this paper's threshold for categorization as a "high surge" block. Using the 2ft threshold, properties that did not experience any surge but still incurred a substantial amount of damage, as well as properties that experienced low levels of surge and damage are excluded from being categorized as highly affected by the storm. While 2 feet appears to be a reasonable threshold, I do experiment with other surge thresholds, as discussed more in section 4.2.

With a 2ft threshold for "high surge" areas, "low surge" areas are designated as experiencing an amount less than 2ft of flooding, and non-surge blocks did not experience any storm surge. I also use the boundaries of the 100-year flood zones in effect at the time of Hurricane Sandy and categorize areas into high-risk areas (flood zone = 1) and low risk areas (flood zone = 0).

4.1.2 Asking Rents

To examine the impact of the hurricane on asking rents, I use unit-level asking rent data from 2010-present from StreetEasy, provided through a partnership with the Furman Center. The data includes the asking rent for the unit, the number of bed and bathrooms in the unit, whether the unit listing required a broker fee, the date of the posting, the address, and geolocation.

Historically, it has been quite difficult to obtain data on asking rents, which in part, explains why there is such limited research on the subject. Asking rents are an ideal data source for ex-

[6] I choose to use surge heights rather than FEMA's plot level estimates of damage because surge heights are a major factor that goes into FEMA's damage calculation and surge heights are more likely to be exogenous to rental changes than damage. This follows other papers on Hurricane Sandy (Ellen and Meltzer (2024) and Meltzer et al. (2021)).

amining market fluctuations because they respond quite quickly to changes in market dynamics. For these reasons, this data from StreetEasy provides a novel opportunity to examine a largely unexplored topic. However, like most rental data, it is not without its limitations.

Since StreetEasy started in 2006, by 2010 it was still relatively nascent. While at present, StreetEasy is ubiquitous in rental searches in New York City, at the time of Hurricane Sandy StreetEasy listings were concentrated in high rent neighborhoods and buildings. Figures B.2a and B.2b show the composition of the sample over time across borough and type of building, respectively. Listings are concentrated in Manhattan, especially in the early years, though Brooklyn and, to a lesser extent Queens, gain listings over the time period. Listings are predominantly in elevator buildings, condo buildings or walk-ups with 3 or more units, initially, though the share of listings in walk-ups increases dramatically from 2010-2015. By the end of the period walk-ups make up a greater share of listings than elevator buildings.

Figures 3a and 3b show the geographic distribution of listings in the sample by surge area, first in 2011, and then across the whole time period. They reflect the same initial concentration in Manhattan and subsequent spread to other boroughs, across all three surge designations. The same apartments do not appear often enough in the sample to attempt a repeat-rent model; however it is noteworthy that, while the increase in listings is clear over time, most listings are concentrated in ZIP codes that contained listings before the storm. This means that limiting the sample to ZIP codes that appear in 2010 and 2011 still captures over 90% of listings in the entire sample.

Over time, the sample across all three surge areas increases in the number and variety of listings. Plotting the average asking rents over time misleadingly indicates a decrease in rents over the time period as more lower rent units are added to the sample. Figure 4 plots the average block level change in rent from the prior year, holding constant the number of bedrooms, over time. Around the time of the hurricane, it is clear that there is more volatility on high surge blocks than low and non-surge blocks. There is almost no increase in average rents in high surge areas the year after the hurricane, but then rents increase by more than $200 in 2015 compared to an increase of around $100 in low and non-surge areas. This volatility is particularly notable given how closely the trends track each other later in the period. However, it is important to note that over much of the time period, with the most dramatic exception in 2020 when the COVID-19 pandemic first hit, rents were increasing each year across all three surge groups. As discussed in more detail under Section 4.2, the impacts found in this paper are relative to the comparison group and do not reflect absolute changes in rents.

To identify whether rents changed in neighborhoods impacted by the hurricane, I limit my sample to ZIP codes that have at least one city block that experienced some level of surge.

Panel A of Table 1 reports the number of individual listings, city blocks, and ZIP codes in the StreetEasy sample in 2011, one year prior to the hurricane, and for 2017. In 2011 there were 2,070 listings in 110 blocks that would experience high levels of surge across 56 different ZIP codes. As noted previously, in 2011 StreetEasy was a relatively new service in earlier years of the time period so the sample grows over time.

Table 2 shows baseline (2011) summary statistics for StreetEasy units by surge level. Units in high surge areas tend to look fairly similar to those in the comparison group, non-surge areas; though notably the buildings they are in are about 10 years newer, the neighborhoods are slightly whiter with slightly lower median neighborhood rents. Low surge units tend to be in substantially larger and newer buildings, with higher baseline average rents.

4.1.3 Housing Choice Voucher Program Data

I use annual administrative data on all housing choice voucher households in New York City from 2007 through 2019, which housing authorities are required to submit to HUD for program analysis and monitoring. This restricted-use data set includes a household ID and building address that has been geocoded to include a Borough Block Lot (BBL) identifier, census tract and block identifiers which I use to match to other data sets. Importantly, it includes the total rent charged for the unit, the payment standard, the total tenant payment (TTP) to the landlord, and the housing assistance payment (HAP) which is the payment made by the housing authority to the landlord to cover the balance of the rent. It also provides demographic information on the household head such as the race and ethnicity, age, number of children and income as well as the number of bedrooms in the unit. I am also able to identify if the household has an enhanced voucher.

Panel B of Table 1 shows the sample of voucher units across surge levels and Table 3 shows summary statistics for all voucher holders living in surge and non-surge areas in 2011. Unsurprisingly, voucher holder rents are much lower than StreetEasy in the same areas, and the census tracts they live in are poorer with a higher share of minority households than represented in the

StreetEasy listings.

While voucher holders, their buildings and neighborhoods look similar across surge levels, there are some modest differences. Voucher holders in surge areas are slightly more likely to be white and less likely to be Hispanic. They are older, and slightly less likely to have children. They are charged slightly higher rents, though their average neighborhood rents are lower.

4.1.4 Building permits

To observe whether rent changes are associated with new building permits, demolition permits, or renovation permits for damaged properties, I include Department of Buildings (DOB) data on jobs permits during the time period. This data is collected by the city for all job applications submitted through the Borough offices since January of 2000. Jobs are classified as "new building", "demolition" or "alteration". Alterations are further classified as "A1", for "a major alteration that will change the use, egress, or occupancy of the building", "A2" for "an application with multiple types of work that do not affect the use, egress, or occupancy of the building" and "A3" for "one type of minor work that doesn't affect the use, egress, or occupancy of the building." Of the renovation permits in the sample filed within four years of the storm (2013-2016), 65% were categorized as "A2", 33% as "A3" and only 2% were categorized as "A1".

4.1.5 PLUTO

To identify characteristics of buildings, I use the city's publicly available Primary Land Use Tax Lot Output (PLUTO) building data from 2007-2021. This data includes annual extensive land use information at the tax lot level. I match on the tax lot number (BBL) to retrieve the number of units in the buildings, the number of floors, and the age of the building.

4.1.6 Building Sales

I use data from the Department of Finance (DOF) combined with the Automated City Register Information System (ACRIS) to obtain information on property records and deeds from 2004 -2019. Among the information included in this data is the address, the date of sale, and the price. I use this data to estimate the impact on the hurricane on home prices, observe the number of sales over time in affected areas, and identify whether there is heterogeneity in the rental impacts by landlord turn over (whether an arms-length sale occurred).

4.2 Estimation

I estimate the impact of Hurricane Sandy on rents in the affected neighborhoods using a difference in differences methodology that compares city blocks that experienced high and low levels of surge to city blocks within the same ZIP code that experienced no surge before and after the hurricane. I begin with the following standard difference in differences equation

$$\begin{aligned} y_{ht} = \sigma_{z(h)} * \tau_t + \sigma_{z(h)} * surge_{b(h)} + \sum_{s \in S} \beta_s Post_t \times 1(s(b(h)) = s) \\ + \gamma_1 floodzone_h + \theta X_{ht} + + \varepsilon_{ht} \end{aligned} \tag{1}$$

Where y is the log of asking rent in \$2021, for housing unit h, in time t. Within the summation, $Post$, an indicator for years post 2012, is interacted with a set of dummy variables indicating the surge level, s(b(h)) of the block, b, on which the housing unit is located, so the set s is defined as $S = high, low$. High surge blocks experienced storm surge levels of more than 2ft of water, and low surge blocks experienced surge levels of less than 2ft. As discussed in Section 4.1, I experiment with other thresholds and find qualitatively similar results, shown in Appendix Table B.1.

Importantly the equation contains ZIP code by year ($\sigma_{z(h)} * \tau_t$) and ZIP code by surge level fixed effects ($\sigma_{z(h)} * surge_{b(h)}$) to remove variation from time trends in the ZIP code and baseline differences between surge levels in the ZIP code. I choose to cluster my analysis within ZIP codes because while census tracts are often considered to be the best proxy for neighborhoods, the limitations on rental data coverage discussed in Section 4.1 mean the sample includes very little variation in surge within tracts[7]. As a robustness check, I do re-estimate the main results with census tract fixed effects rather than ZIP codes and results look very similar. See Figure B.15.

This empirical strategy allows for the interpretation of the coefficients of interest, β_s, to be the changes in rents in high and low surge areas, relative to non-surge areas within the same ZIP code, before and after the hurricane.

I include a vector of housing unit characteristics, (X_{ht}), which include the number of bedrooms and bathrooms, and whether the unit required a broker fee. I also include building level

[7] Only 25% of census tracts include listings on blocks with more than one type of surge, compared to 95% of ZIP codes.

controls including the number of units in the building, units squared, the age, age squared and the number of floors, along with whether the unit is located in a building with subsidized or controlled rents, where regulations might have prohibited rental increases.

In addition, I include an indicator for whether the unit is located in the the flood zone. Standard errors are clustered at the ZIP code by block level.

To estimate the impact on rents in the voucher program, I use the same estimation strategy with a couple modifications: the voucher sample is from 2007-2019, rather than 2010-2021, and the number of bathrooms in the unit and broker fee indicator are not available in the voucher data, so they are not included as controls.

The preferred specification for this paper is an event study framework that takes the following form

$$\begin{aligned} y_{ht} = \sigma_{z(h)} * \tau_t + \sigma_{z(h)} * surge_{b(h)} + \sum_{\tau=2010}^{2021} \sum_{s \in S} \beta_{\tau,s} 1\left(t - 2012 = \tau, s\left(b(h)\right) = s\right) \\ + \lambda X_{ht} + \gamma_1 floodzone_h + \varepsilon_{ht} \end{aligned} \tag{2}$$

Here, the indicator variable in the summation interacts event years τ, from 2010-2021, rather than the simple $Post_t$ variable, with the dummy variables indicating the unit's block's surge level, s(b(h)). Since the event study allows for a better understanding of the dynamics of rental changes over time, it is the preferred specification.

One caveat of this empirical strategy is that it ignores general equilibrium effects: both equations 1 and 2 estimate the local effects of the hurricane on rents. It is possible that Hurricane Sandy affected rents in the city more broadly. For instance, a reduction in the rental supply in the affected areas could have led to an increase in rental demand in other areas of the city and rents may have increased city-wide. This estimation strategy will not be able to capture those broader effects.

In addition, I am not able to completely rule out the possibility that some of the mechanisms discussed here could spillover into non-surge blocks. It is possible that displaced homeowners join the rental market on non-surge blocks, which could increase demand and increase rents in these areas. I attempt to address this through robustness checks in Section 6, but in general, with this empirical strategy, I am only able to isolate the difference in rental changes between surge and non-surge areas, and the results do not necessarily imply that rents remained unchanged in non-surge areas or that they were completely unaffected by broader consequences of the storm.

When turning to the incidence of the rent changes, I estimate equation 2 with two additional changes. First, since tenant payments are dependent on the household's income, I include income as a control when estimating the impact on the tenant's portion of the rent. Second, when households first enter contract on a new apartment with their voucher subsidy, the program requires that the tenant pay no more than 40% of their income to rent (the 40% rule) but no such official limitation exists as the voucher holder remains in the unit. If there were differential rates of voucher households moving over time between surge and non-surge areas, and thus differential rates of households subject to the "40% rule", estimates equation 2 of the change in tenant payment might be biased toward the group with fewer restricted households. For this reason, I include an indicator for whether the household was new to the building in that year. This indicator covers those households that are new to the program as well as those that simply moved to a new unit with their voucher.

Finally, to estimate differences in the impacts along a variety of measures of heterogeneity including neighborhood income, renovation permits, and insurance premiums[8] I estimate an event study with a triple difference which takes the following form

$$y_{ht} = \sigma_{z(h)} * \tau_t + \sigma_{z(h)} * surge_{b(h)} + \sum_{\tau=2007}^{2019} \sum_{s \in S} \sum_{r \in R} \beta_{\tau,s,r} 1(t - 2012 = \tau, s\,(b(h)) = s, r(b) = r)$$
$$+\lambda X_{ht} + \gamma_1 floodzone_h + \varepsilon_{ht} \tag{3}$$

where the double summatory from equation 2 is now interacted with an indicator for the measure of heterogeneity. The coefficients $\beta_{\tau,s,r}$ then depict the differential changes across surge level and time for rents in buildings along these measures of heterogeneity.

[8]Other measures of heterogeneity include: building height, and whether the building houses a voucher

5 Results

5.1 The Impact of Hurricane Sandy on Asking Rents

I begin by first estimating a simple version of equation 1 without controlling for any building or unit characteristics, except for the number of bedrooms. Column 1 of Table 4 shows that raw rent expenditures on high surge blocks increased by 5.3% more than on non-surge blocks. Yet, this difference disappears as I begin to add building and unit quality controls. In Column 2, I add controls for building age and building age squared, and the point estimate decreases considerably and becomes insignificant. In Column 3, I add the rest of the controls. The results change very little and continue to reflect no significant change in quality-adjusted rents. Rather, it appears that the change in raw neighborhood rents is driven by the age of the building. Throughout all three specifications, there appears to be no impact on rents in low surge areas [9].

Figures 5a, 5b, and 5c confirm the high surge block results from columns 1-3 in Table 4 in the event study framework of equation 2. However, they also reveal that the simple difference in difference estimation does mask some heterogeneity over time. Initially, in the period immediately after the storm (late 2012 and 2013) rents were negatively impacted in high surge areas relative to non-surge areas by roughly 5% ($219), likely reflecting a dis-amenity effect due to blight. This finding is consistent with previous work on the impact of Hurricane Sandy on commercial establishments (Meltzer et al. (2021)), which found an 11 percentage point increase in the annual closure rate for retail businesses after the hurricane, with the strongest effects in the years immediately following the storm. It is also consistent with Figure 6 which shows a binscatter plot of the growth rate in the number of block level rental listings in StreetEasy. The pronounced growth in listings in 2013 in high surge areas suggests that more rental units were available at the time, likely due to vacancies, bringing down rents.

However, across all specifications, by 2014 rents in high surge areas began to rebound. Four years after the hurricane (by 2016), quality adjusted rents (Figure 5c), had rebounded back to non-surge block levels. Toward the end of the period they appear to be increasing relative to non-surge blocks. This finding is in contrast to the 11-22% house price discounts that persist for at least 6 years after the hurricane (Ellen and Meltzer (2024), Ortega and Taṣpınar (2018)),

[9] Results are remarkably similar using continuous measures of surge, as well as different thresholds for high surge. See Table B.1.

despite the fact that over half the households that requested FEMA assistance, indicating their dwelling was damaged, were renters (Furman Center for Real Estate and Urban Policy (2013)). These differing results provide evidence of substantially different responses to natural disasters across owner-occupied and rental markets.

Much of this house price literature finds larger negative effects outside the flood zone, which they interpret as evidence of a strong information effect causing a decrease in demand. Unfortunately, the data from StreetEasy has a limited sample of listings in non-surge areas within the flood zone, especially in the pre-period, so I am not able to conduct the same stratified analysis for rents. Results for properties outside the flood zone, presented and discussed more fully in Appendix A (Figure B.22), do indicate slightly larger negative impacts on rents than for the full sample, but rents still rebound by 2016-2017. This provides suggestive evidence that while information may play a small role for renters, it is capitalized into home prices to a much greater degree than rents, particularly in the longer term. However, caution is encouraged in interpreting these results since the analogous comparison for properties within the flood zone cannot be estimated.

5.2 Price to Rent Ratio

To further investigate the difference in impacts across rents and home prices, I estimate a version of equation 2 to identify the impact on sale prices on the same blocks for which I have rental information. Roughly half (51%) of all sales in ZIP codes that experienced any surge from 2010-2021 occurred on blocks on which I also have rental listings in that year[10]. Very similar to what has been found in previous literature, I find persistent 10-20% price discounts on high surge blocks after the hurricane. Figure 7 shows the impact estimates for prices next to the same impact estimates for rents from Figure 5c, on the same scale to highlight the contrast.

The difference between the impacts across tenure in the housing market suggest there may have been a change in the relative affordability of purchasing compared to renting across high and non-surge blocks. To try to examine this, I create a measure of the price/unit to rent ratio at the block level by dividing the median annual price/unit by the median annual rent. Since prices appear to have fallen more and remained more depressed than rents, we would expect a

[10]The geographic overlap increases to roughly 72% if I do not restrict both data sets to having transactions on the same block within the same year

larger drop in the numerator than the denominator and, therefore, a larger decrease in the ratio on high surge blocks compared to non-surge blocks, implying purchasing has become relatively more affordable in high surge areas than non-surge areas. Though I am not powered to estimate a regression on the price/unit to rent ratio, Figure 8 shows the average ratio across high and non-surge blocks over time. While the ratio is increasing over time across both groups, it is clear there is a divergence in the trend on high surge blocks around 2014-2015 when rents appear to have rebounded on these blocks while prices did not. This reflects suggestive evidence that it may have become more affordable to buy than rent in high surge areas relative to non-surge areas after the hurricane. However, the ratio remains between 15-20 for most of the period in both groups, so while the change in trend is clear, it may not indicate a difference qualitatively in the favorability of buying vs renting.

5.3 Heterogeneity in Rental Impacts by Neighborhood Income

To examine whether the impacts on quality-adjusted rents differ by neighborhood income, I estimate a version of equation 3 where the measure of heterogeneity in the triple interaction is whether the unit is in a census tract where the tract median income is above the city median income in that year. This measure accounts for the endogeneity in tract income levels after the storm by allowing the distribution to adjust each year and holding constant the threshold (median) in the distribution. Figures 9a and B.5b show that quality-adjusted rents increased for above median income neighborhoods and decreased for lower income neighborhoods[11].

I explore several possible explanations for this heterogeneity including neighborhood resources and ability to rebuild, non-random changes in insurance premiums, and rent-stabilization restrictions on rents that may have contributed to these impacts.

5.3.1 Neighborhood Resources

These heterogeneous results are consistent with Ellen and Meltzer (2024)'s finding that higher income neighborhood home prices rebounded quicker than lower income neighborhoods, suggesting the drop in demand for these neighborhoods was not as severe. Indeed, Figures B.3a and B.3c show that there is a clear spike in rental listings in high surge areas in higher income neighborhoods but it does not appear to be accompanied by any increase in time spent on the

[11]Coefficients for the difference in difference estimates from equation 1 can be found in Table B.3

market (Figure B.3d). These trends together suggest that while there may have been more initial turnover in higher income neighborhoods, it was not accompanied by a decrease in demand. In lower income neighborhoods, there does not appear to have been an increase in listings; though, there was a slight increase in time on the market in 2013-2014 in high surge areas (Figure B.3b).

Some work has suggested that an explanation for differential recovery across neighborhood income is the financial resources of the property owners. Smith et al. (2006) find evidence that higher income property owners are more likely to reinvest in their properties to prevent the damage reoccurring in another disaster, rather than selling/vacating the property compared to lower-income owners.

I find some evidence suggesting landlord resources played a large role in the heterogeneity in rental impacts. Figures 10a and 10b show that in higher income neighborhoods, there was an immediate increase in renovation permits, while in lower income neighborhoods, the increases do not appear until around 2016 and 2017, when as Figure 11 shows, substantial amounts of the city's "Build it Back" recovery funds were disbursed[12]. Despite this evidence of differential recovery, I do not find that the rental increases were singularly concentrated in buildings that renovated (Figures B.18a and B.18b)). Rather, these results suggest the possibility of a different channel. If recovery began nearly immediately in higher income areas, they may have avoided the initial drop in demand due to blight. Amenities may have recovered faster in these neighborhoods, consistent with research from LeSage et al. (2011) on the aftermath of Hurricane Katrina. The quicker recovery may also have led to an increase in demand from renters in neighboring areas that view the rental stock as more storm-resistant or the neighborhood as rebounding.

5.3.2 Insurance Premiums

A possible alternative explanation for why rents increased in higher income neighborhoods and decreased in lower income neighborhoods is a differential change in insurance premiums across the neighborhoods. The Biggert-Waters Flood Insurance Reform Act of 2012 (BW-12) made changes to the National Flood Insurance Program (NFIP) and went into effect right before Sandy hit. BW-12 would have increased NFIP premiums for buildings built before 1983 within the flood zone and it is possible that the owners of these buildings would have tried to pass these increased costs onto renters. If more BW-12-affected buildings are located in high surge, or high-

[12]https://www.nyc.gov/content/sandytracker/pages/build-it-back

income areas, it's possible the changes in insurance premiums could be driving the rental results. To test for this, I estimate a version of equation 3 where the additional measure of heterogeneity is whether the building would have qualified for the increased premiums under BW-12. Figures B.4a and B.4b show that, if anything, asking rents decreased for BW-12 buildings which may reflect that BW-12 buildings were older and may have been more susceptible to damage from the storm.

However, I find no evidence that these buildings are driving the heterogeneity in rental impacts across above and below median income neighborhoods. Figure B.5 shows the impacts by neighborhood income removing BW-12 buildings from the sample and find virtually the same rental impacts as Figures 9a and B.5b.

5.3.3 Rent Stabilization

A concurrent explanation for the differential rent impacts across above and below median income neighborhoods is the share of units that are rent stabilized. In New York City, almost half of all apartment units are rent stabilized, a form of tenant protection that limits the annual amount a landlord can increase rents. Over 30% of units in the sample in lower-income neighborhoods are in buildings with more than 75% rent stabilized units, compared to only 20% of units in higher income neighborhoods. One theory is that landlords with large shares of rent stabilized units may have had less of an incentive to renovate and improve damaged properties if they knew they were not able to capitalize those costs into higher rents. Figure B.6 does show some slight differences in rental impacts across different building-level thresholds of rent stabilization: less than 25% of units, 25-75% of units, and more than 75% of units. Buildings with lower levels of rent stabilization appear to have slightly more positive rental impacts compared to buildings with higher levels of rent stabilization, but all coefficients remain insignificant.

To examine how the inclusion of buildings with higher shares of rent stabilized units may be generating differential results across neighborhood income, I rerun the heterogeneity analysis across above and below median income neighborhoods solely for buildings with less than 25% of their units rent-regulated[13]. In Figure B.7, I find that these buildings actually experience larger negative impacts in below median income neighborhoods than the more heavily rent stabilized stock. This result is somewhat logical: landlords of rent stabilized units may have a

[13]Due to sample size/power limitations.

strong incentive to not lower rents because doing so will put those units on a lower rent path where they are limited to how much they can raise rents when the market rebounds. I also find, on average, that the owners of these buildings still did not file for renovation permits until 2016/2017 (Figure B.8a), suggesting that rent stabilization was not the primary factor preventing renovations in these areas.

If, as the results thus far suggest, landlord resources do restrict their ability to invest in repairing their properties, we should expect to see different impacts within the HCV market, where programmatic features may allow them to circumvent these barriers.

5.4 The Impact on Voucher Rents

For comparability to the StreetEasy sample, Table 5 reports key coefficients from the difference in difference estimation for the four specifications of equation 1 presented using the StreetEasy data for the full repeated cross section of voucher units. Column 1 omits all controls except for the number of bedrooms, column 2 adds the age of the building, column 3 adds the rest of the controls. Unlike in the StreetEasy results, the impact on voucher rents is remarkably robust to the addition of controls. While the coefficients are insignificant, they indicate a relative increase in rents of roughly 3% in high surge areas compared to non-surge areas.

Estimation of equation 2 provides a clearer picture of the results. As Figure 12a shows, there is a clear increasing trend in rents in high surge areas compared to non-surge areas, and by 2016, voucher rents in high surge areas were roughly 5% higher relative to voucher rents in non-surge areas[14]. Most notably, though not statistically significant, Figures 12c and 12d clearly show that voucher rents increased in both lower income and higher income neighborhoods, in contrast to the broader market which saw negative impacts in lower income neighborhoods[15].

5.5 The stickiness of sitting voucher rents

The dynamic figures also highlight an additional difference in the rental response of the voucher sample compared to StreetEasy asking rents: sitting voucher rents do not decline following the hurricane. Rather, voucher contract rents were "sticky" downward, and increase

[14]While the estimates in low surge areas are slightly larger and more significant in Table 5, the figures show that the trend is relatively similar and if anything, noisier.

[15]Key coefficients for the simple difference in differences estimation of Equation 3 can be found in Table B.3

gradually in the areas that experienced damage due to the storm. This is perhaps unsurprising when considering the mechanism through which rents are assessed in the voucher program. Rent reasonableness assessments are conducted when a voucher holder moves into a new unit or when a landlord requests an increase. If neither happen, we should expect to see this stickiness in voucher rents for sitting units that do not have a new tenant, and that rents for new tenants in the years immediately following the hurricane experience the negative impact found in the broader market, particularly in lower income neighborhoods. Figures 13a and 13b confirm this hypothesis. Figure 13a displays the impact of the hurricane on rents for a repeated cross section of sitting voucher units, omitting any observations where a tenant newly moves into a unit. Figure 13b shows the impact on the repeated cross section of units in the year they have a new tenant. It is clear that sitting voucher rents did not experience a drop after the hurricane and instead remained relatively constant, while "new" voucher rents did adjust to the broader market in 2012, 2013 and 2014. This appears to be one way in which the voucher program creates stability for tenants and landlords amidst market shocks.

5.6 Exploring the mechanisms for voucher rent increases

Though standard errors are large, the results thus far not only suggest that sitting voucher rents did not experience the same negative impacts as other units in lower income neighborhoods, but they also appear to have increased. Since the heterogeneous effects across neighborhood income in the broader sample appear to be driven by differential recovery, one testable theory is that voucher landlords were able to, or required to, renovate their buildings earlier than other low-income landlords. As the market-rate results showed, on average landlords in lower-income neighborhoods did not invest in renovations until the Build it Back funds were largely being dispersed in 2016 and 2017. Yet, voucher landlords need their units to pass inspections to continue to house voucher holders, so the public housing authorities may have required these landlords renovate their properties earlier. They may have readily acknowledged the improvements made by the landlords, allowing them to recoup their investments quite quickly through rental increases. While non-voucher landlords run the risk of losing their tenants through rent increases, voucher tenants might not bear the marginal cost of these rent increases if rents were below the payment standard initially, or if housing authorities made payment standard accommodations to keep tenants in their units.

5.6.1 Renovations

To examine this theory, I begin by showing, in Figures 14a and 14b that voucher landlords were significantly more likely to file for renovations in lower income neighborhoods in the year after the hurricane (2013), than other low-income landlords. While buildings that do not house any voucher holders in Figure 14a look quite similar to the previous results (Figure 10b) that showed landlords in lower income neighborhoods waiting to file for renovation permits until 2016 and 2017, Figure 14b shows that voucher buildings were around 8% more likely to file for renovations in 2013.

The renovations initiated in 2013 appear to have led to an increase in rents in the voucher sample. Figure 15a shows the impact of the hurricane on rents for voucher buildings that did not file for renovations in 2013, and Figure 15b shows the β coefficients from an estimation of equation 3, which depict the differential impact of the storm on rents in high surge areas for buildings that filed for a renovation permit in 2013. The rental increases in high surge areas for units occupied by voucher tenants appear to be driven by units where landlords filed for a renovation permit in the year after the hurricane. These increases are consistent across all three alteration types (Figure B.21) and are robust to extending the permit filing period out to 2016, though they are strongest for those that filed immediately after the hurricane[16].

If voucher rents increased, it is then critical to understand whether the pass-through of renovation costs into rents fell on the voucher holders themselves. Ordinarily, we would expect that if lower income landlords capitalize renovation costs into rents, they would be at risk of losing tenants that cannot afford the higher rent increases. However, with the government involved as a third actor that bears some of the marginal cost of rental increases, voucher landlords may not be bound to the same market constraints.

5.6.2 Voucher Rent Incidence

To estimate the incidence of the rent increases for voucher tenants, I estimate the impact of the storm on the portion of rent that is paid by the tenant and the portion of rent that is paid

[16]In high surge areas, the vast majority of these permits were filed for properties that were damaged to some degree by the storm, according to FEMA's damage assessment (Table B.2), but it is difficult to tell from the data whether the renovation led to a quality improvement or was simply repairing the existing damage. Roughly 36% of these permits were "A3", whose minor update could be as small as moving the location of the generator.

by the housing authority using equation 2.

In high surge areas, Figures 16a and 16b show that the rent increases are not reflected in rental burden on the voucher tenants. Figure 16a shows, if anything, a very slight increase in in TTP payments over time in high surge areas relative to non-surge areas. By contrast, the changes in the HAP payments in Figure 16b are large and statistically significant, mirroring the pattern for voucher contract rents. Consistent with the fact that voucher tenants are not paying larger amounts toward rent though rents are increasing, housing assistance payments for voucher holders living in high surge areas increased by over 6.6% by 2014 and over 10% by 2017.

There are multiple ways the program could have shouldered the majority of the rent increases. First, if voucher rents were originally below the payment standards, raised rents may have simply closed the gap between the rent and the payment standard. In 2011, 78% of voucher households in the sample had rents below the payment standard. Of the 25% (11,817) of households that lived in buildings that filed for renovation permits in 2013, 60% (7,059) had rents below the payment standard prior to the storm. Second, in some cases, household level accommodations are made through special types of vouchers. Enhanced vouchers are tailored to individual families with the intention of enabling households to remain in their unit while the property is undergoing a "conversion action." The enhanced voucher allows the Public Housing Authority (PHA) to pay a higher rent than the payment standard would allow for a traditional housing choice voucher (U.S. Department of Housing and Urban Development (2024)). Of the 11,817 households that lived in buildings that filed for renovation permits in 2013, 34% (4,057) had "enhanced vouchers" prior to the storm. A simple plot of the average annual log payment standard for those that had enhanced vouchers prior to the storm and those that did not shows a clear divergence in trends. Beginning in 2012 payment standards increase for households with enhanced vouchers and decrease for those without (Figure B.9).

While the analysis is not powered to examine the individual impacts for households in renovated buildings whose rents were below the payment standard or had enhanced vouchers, removing both types of households from the sample removes the initial average rent increases observed (Figure B.10), suggesting they were driving the rent increases in Figure 15b[17].

[17]Note that removing either group individually does not eliminate the effect entirely, suggesting both types of households played a role.

5.7 Voucher Population in Affected Areas

The fact that voucher landlords were able to pass renovation costs into rents without risking losing their tenants suggests that voucher holders might make more attractive tenants in areas at risk of climate change-induced destruction than other lower income tenants. If this were the case, we would expect to see an increase in the voucher population in high surge areas compared to non-surge areas over time after the storm. Removing any households that joined the program after the hurricane[18], Figure 17 shows the impact of the storm on the average number of voucher holders/city block on high surge blocks over time. There is a marked and sustained increase of about 20-40 voucher holders per block in high surge areas compared to non-surge blocks beginning in 2013. Therefore, it appears that landlords are choosing to house more voucher holders in areas that were damaged by the storm, suggesting an understanding of their ability to use the program as a type of "insurance" in the aftermath of these storms.

6 Robustness Checks

I run several robustness tests. The key identifying assumption of the analysis presented in this paper is that absent the hurricane, rents on blocks that experienced surge would have trended in the same way as rents on blocks that did not experience surge. Since I am limited in my ability to establish pre-trends in the market rent data, I attempt to validate this assumption using a few strategies.

6.1 Pre-trends in related measures

First, while I cannot establish robust evidence of no pre-trend in rents across surge and non-surge areas in the StreetEasy data, I can show evidence of no pre-trend in other, related measures. As Figures B.11a, B.11b and B.11c show, there are no differential pre-trends in construction across high and no-surge areas via the share of lots that received new building, demolition or renovation permits prior to the storm. In addition, I am able to replicate the high and low surge results from Ellen and Meltzer (2024)in Figures B.12a and B.12b using the same high, low and no-surge designation, as well this paper's ZIP code level fixed effects and various

[18]To avoid confounding with vouchers that were given as part of disaster aid

controls used in their paper. These figures show no differential pre-trends in sale prices across the surge designations. If there were no pre-trends in various measures of construction, or home prices across surge and non-surge areas, the assumption that this extends to rents as well seems credible.

6.2 Other Rent Data Sets

Rental data is difficult to obtain, which makes the StreetEasy listings a particularly novel data set. However, since the data does not begin until 2010, I attempt to validate the results using available but highly imperfect sources of rent information. Once such source is Notices of Present Value (NOPV), issued by the The Department of Finance (DOF). The DOF issues NOPVs annually to inform homeowners of market and assessed values of their property. These statements estimate the gross rental income as reported by the property owner. Li (2022) was able to scrape this data from the publicly available PDFs, from which I use the data from 2005. The Furman Center was able to gain access to more recent years of data, from which I use 2016. However, I am missing critical years in between so I am only able to conduct a longer term difference in differences estimation, rather than a full event study specification.

The data has a few other important caveats: it only covers buildings with 6 or more units, and the approximation of rental income includes commercial rents. However, on average, only 2.5% of units in rental buildings are commercial (Li (2022)). I calculate the average monthly rent per unit for each building and as Table B.4 shows, the NOPV estimated rents are much more similar to the ACS median rents in Table 2. However, the characteristics of buildings across the NOPV and StreetEasy samples are comparable.

I estimate equation 1 on the log average monthly rent per unit, controlling for the age of the building, the number of floors and whether the building is in the flood zone. Initially, as Column 1 Table B.5 shows, I find a similar near zero, insignificant effect on quality-adjusted rents. In Column 2, when I stratify the sample by neighborhood income level, results remain insignificant but move in the same direction as the estimates in the StreetEasy data: I find a positive association for higher income neighborhoods and a negative association for lower income neighborhoods.

6.3 Randomly Generated Treatment and Comparison Groups

Another concern might be that the effects I find are spurious and not due to the hurricane. If this were true, then I would expect to see similar differences in rental impacts between treatment and comparison groups where the distinction between them is orthogonal to the hurricane. To test this, I randomly split the comparison group and run the same analysis comparing the two groups in each instance. I simulate this process 100 times and plot the point estimates of all 100 estimations in Figures B.13a and B.13b. As the figures show, I find no evidence of any differences between these randomly generated groups, providing support for the assumption that any differences we see between surge and non-surge areas is due to the differential impact of the hurricane on these blocks.

6.4 Spillovers

It is worth reiterating that the identification strategy in this paper identifies *relative* impacts across high and non-surge blocks, but does not address the possibility of spillovers. Indeed, since the units of analysis are such small geographies, it is possible that many of the mechanisms contributing toward asking rent impacts addressed in this paper may have also affected non-surge blocks. If anything, we would expect the existence of such spillovers to attenuate any differential impacts on rents between high and non-surge blocks. To explore this, I compile a secondary comparison group comprised of ZIP codes along the coast, and therefore presumably comparable to other coastal areas, that did not experience any flooding. Figure B.14 shows that the impacts in the StreetEasy sample are quite similar to the main results, suggesting limited spillover effects on original comparison blocks.

Another way to address the possibility of spillovers is to run the analysis clustered at different levels of geography. Census tracts are a common level of geography used to approximate neighborhoods in the urban economics literature. However, census tracts are particularly small in New York, and many did not experience much variation win flooding, which is why the main analysis is clustered at the ZIP code level. Still, replication of the results using census tract fixed effects does yield similar results (Figure B.15).

7 Discussion

In this paper, I find evidence that hedonic rents in high surge areas of New York City experienced a negative impact in the years immediately after Hurricane Sandy relative to those that experienced no surge but contrary to home prices, rebounded quite quickly and returned to levels comparable to non-surge areas 3 years after the storm. Stratifying the results by neighborhood income reveals heterogeneity in quality-adjusted rental impacts: rents for higher income neighborhoods increased, while rents for lower income neighborhoods decreased. These results appear to reflect that landlords in higher income neighborhoods had more resources to begin renovations and restoring the neighborhood earlier than lower income neighborhoods.

Importantly, I find that rents in the Housing Choice Voucher market behaved differently than the rents for other low-income units. The program appears to have protected both landlords and tenants from market fluctuations. Sitting voucher rents were "sticky" downward, so that voucher landlords did not have to reduce their rents in response to market conditions. In fact, voucher rents increased, prompted by renovations to their units. The government subsidized these renovations, so that rental increases did not fall on the tenants themselves.

A few important implications emerge from this work. First, it is worth stressing that the relative impacts in rents of Hurricane Sandy clearly differ from those found for house prices in the wake of hurricanes. Since one-third of the population rents and roughly 40% of the occupied rental stock is located in areas at moderate risk of damage from natural disasters (The Joint Center for Housing Studies (2022)), ensuring that housing market research accounts for the differences between the owner-occupied and rental markets is critical for policy making. Additionally, differential recovery across tenure and by neighborhood income has broader implications for equity and the demographics of these neighborhoods over time.

In a similar vein, as rental housing costs continue to rise, there have been national discussions of increasing the scale of the voucher program. In light of these results, it is important to consider the implications of such an expansion in areas at high risk of damage due to natural disasters. On the one hand, vouchers appear to enable landlords to improve the quality of their units and shield low-income tenants from bearing the rent increases on those units. The Housing Choice Voucher program is plagued by low landlord participation, and if this sort of "insurance" acts as an incentive for participation, the increased costs to the government may have additional positive consequences. On the other hand, this level of "insurance" may be explicitly subsidizing and therefore unintentionally encouraging the housing of vulnerable, low-income households in areas at high risk of climate change-induced damage. This creates important questions for policymakers as to the role of existing voucher rental subsidies and their potential unintended consequences in light of the increasingly frequent and destructive events caused by climate change.

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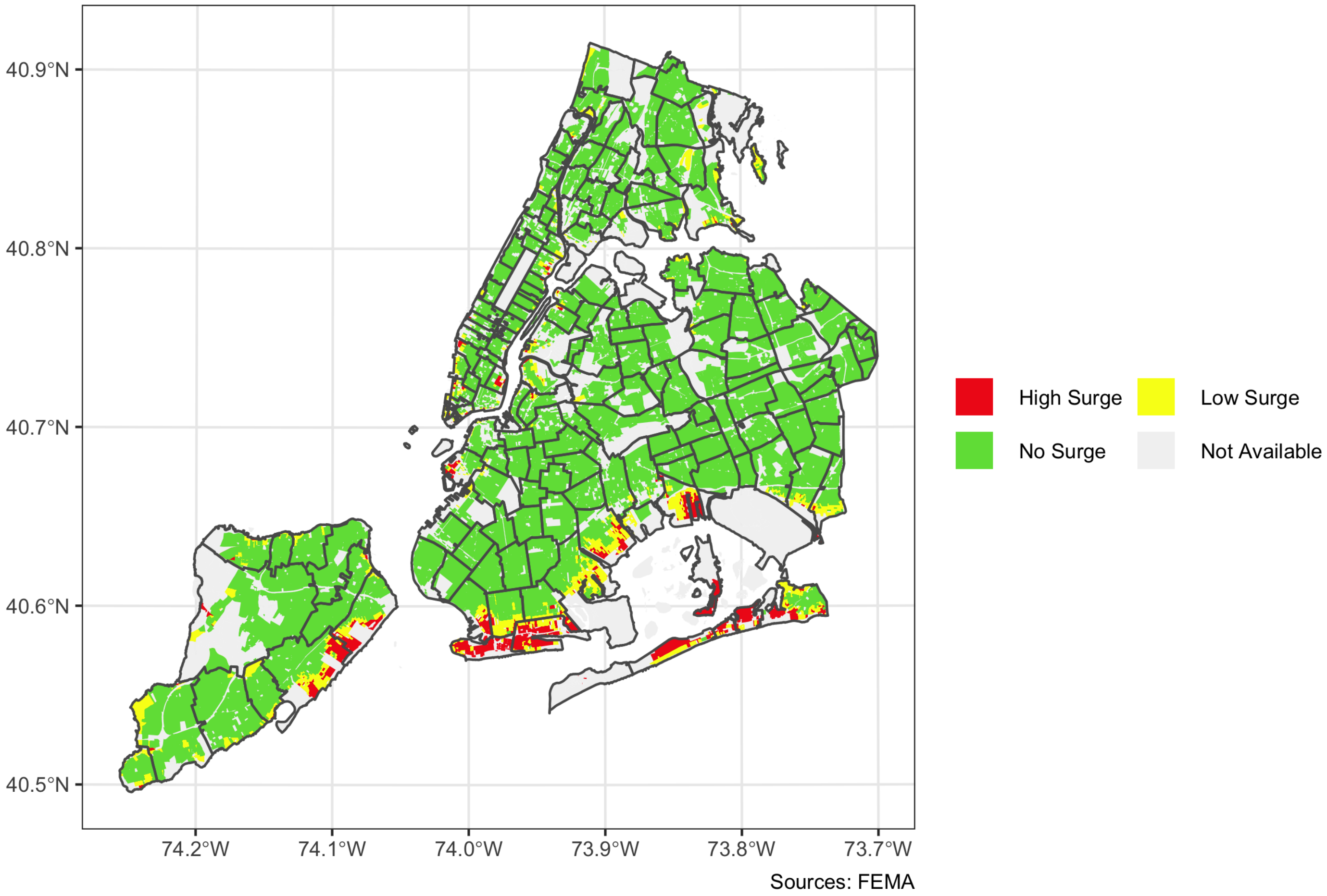
8 Figures

Figure 1: New York City ZIP codes by Storm Surge Level



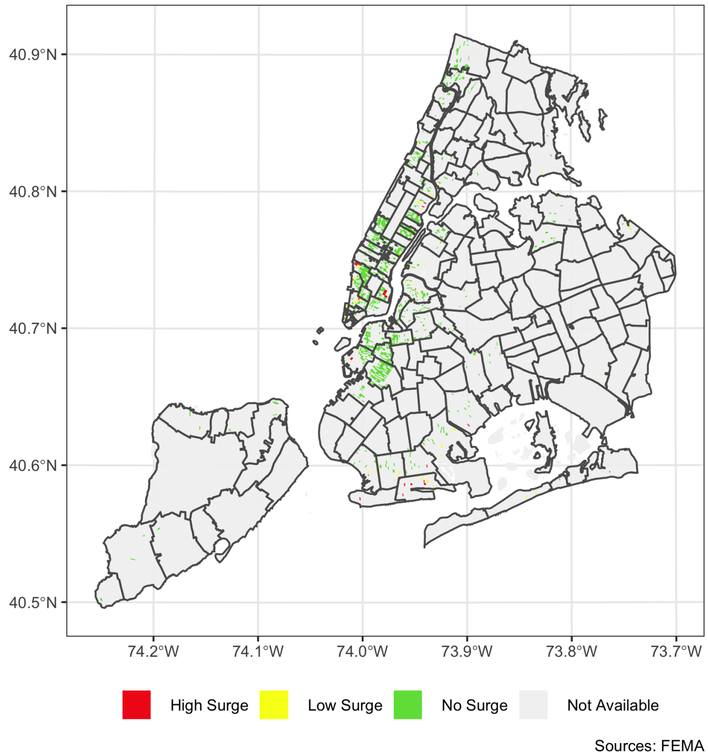
Notes: Figure 1 is a map of ZIP codes in New York City, with city blocks shaded by the level of storm surge they experienced in Hurricane Sandy (high surge = more than 2ft, low surge = less than 2ft, no surge = 0 ft).

Figure 2: High, Low and Non-surge Blocks across the Flood Zone

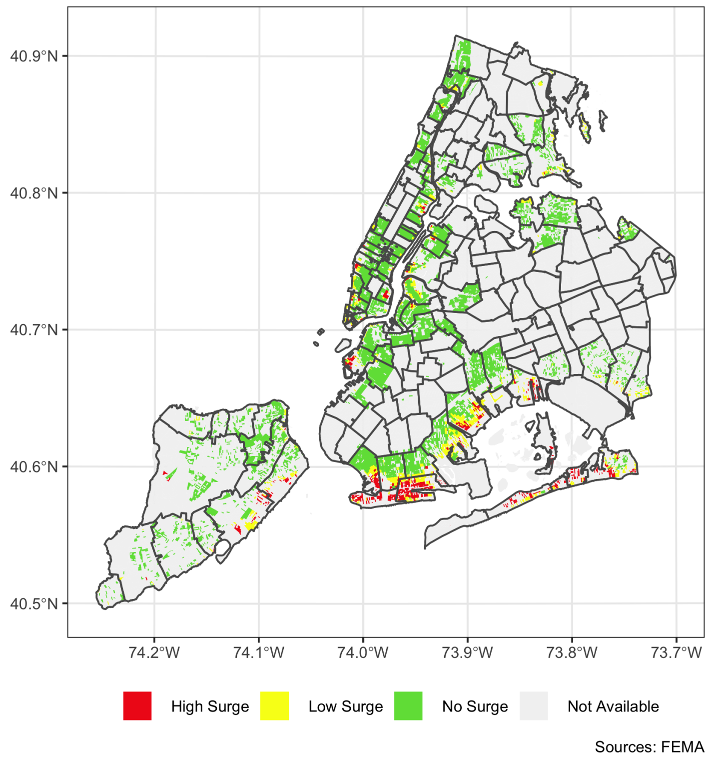
Notes: Figure 2 is a map of a section of New York City encompassing Upper Manhattan, the Bronx and Queens, with city blocks shaded by the level of storm surge they experienced in Hurricane Sandy (high surge = more than 2ft, low surge = less than 2ft, no surge = 0 ft). The 100-year flood zone boundary is in gray.

Figure 3: Dispersion of StreetEasy Sample over Time

(a) StreetEasy Sample in 2011



(b) StreetEasy Sample Across Full Time Period



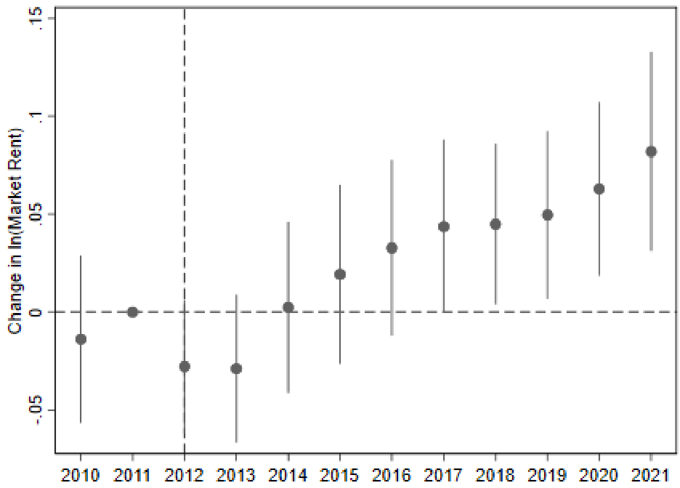
Notes: Figure 3 shows the geographic dispersion of the StreetEasy analysis sample over time. In Panel b, ZIP codes that did not experience any surge are omitted from the sample.

Figure 4: Annual Change in Average Rents Over Time

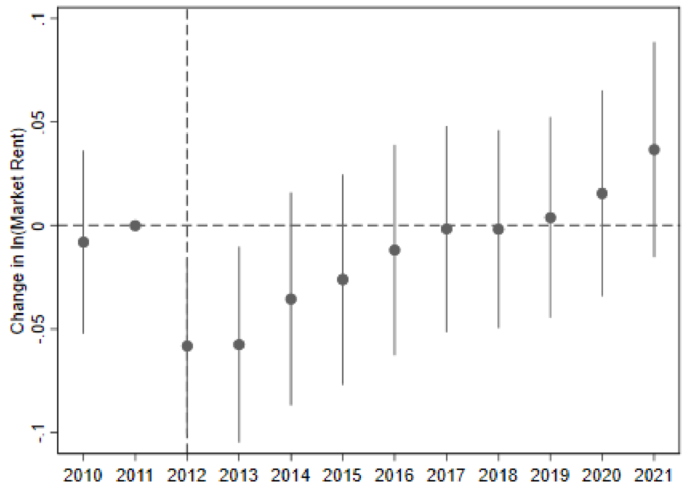
Notes: Figure 4 shows a binned scatter plot of the annual change in average block level rents by surge level.

Figure 5: Impact of Hurricane Sandy on Asking Rents in High Surge Areas

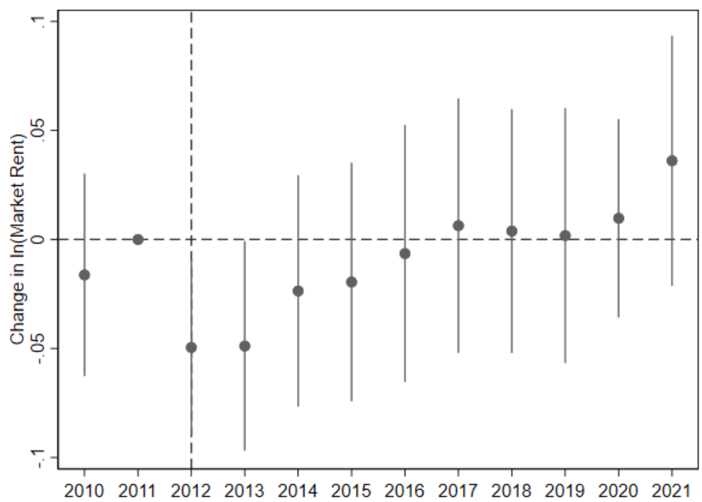
(a) No Controls (Table 4, Col. 1)



(b) Add Building Age (Table 4, Col. 2)

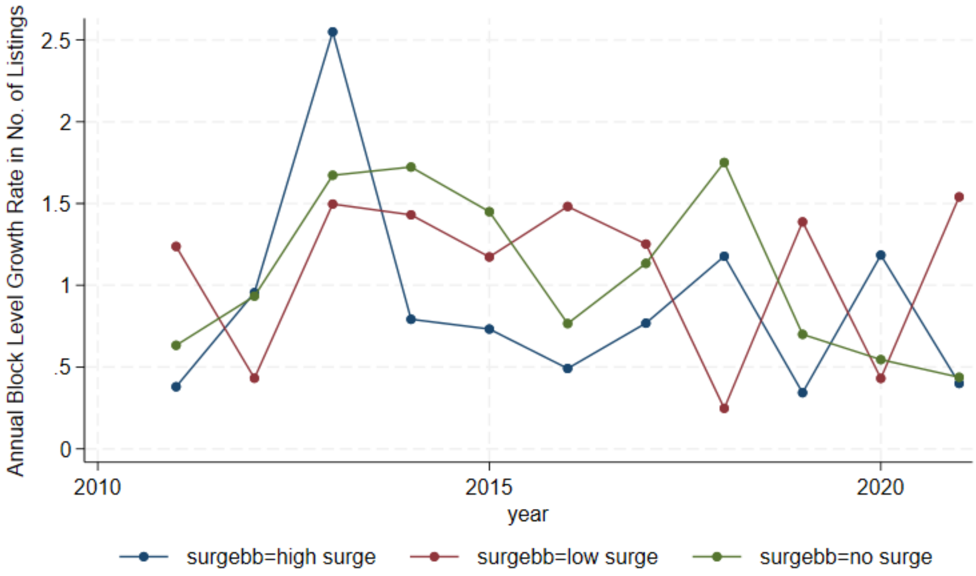


(c) All Controls (Table 4, Col. 3)



Notes: Figure 5 shows estimates of equation 2, the event study version of the DID estimates presented in Table 4 with just controls for number of bedrooms (Panel A), adding controls for the age of the building (Panel B) and adding controls for the age, number of units in the building, units squared, and the number of floors, along with whether the unit is located in a building with subsidized or controlled rents, the number of bathrooms, and whether the unit required a broker free. All regressions include ZIP code-by-year and surge level-by-ZIP code fixed effects. Standard errors are clustered at the ZIP code-by-block level.

Figure 6: Annual Block-Level Growth Rates in Number of Listings by Surge Level

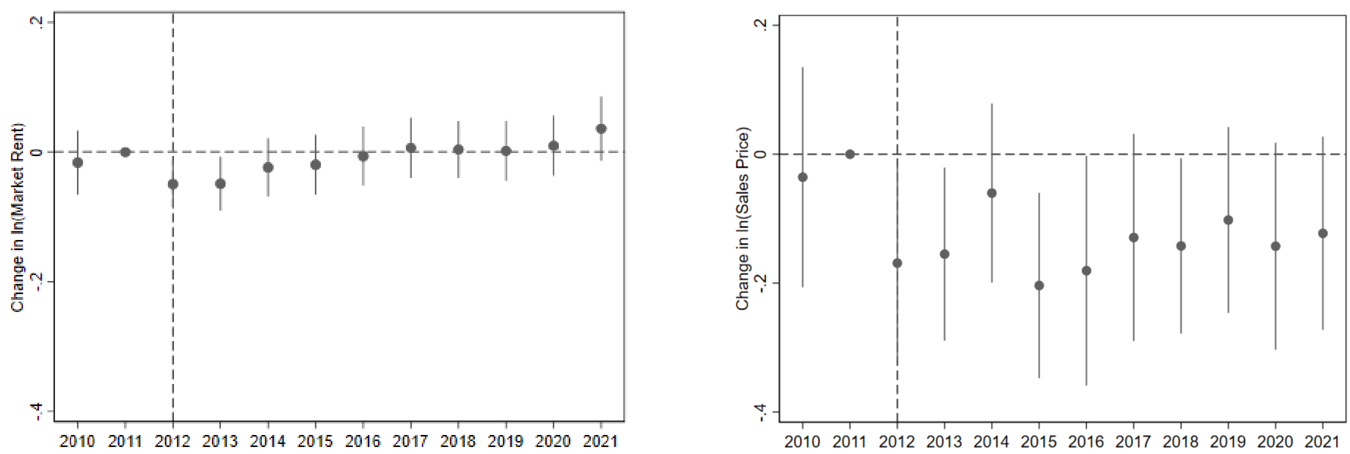


Notes: Figure 6 shows a binscatter plot of block-level annual growth rates in the number of listings, disaggregated by surge level.

Figure 7: Impact of Hurricane Sandy on Rents and Home Prices

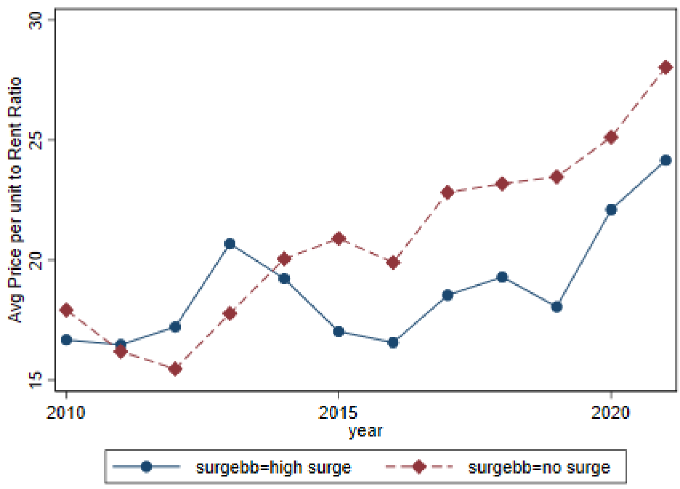
(a) Rents

(b) Home Prices



Notes: Figure 7 shows estimation of equation 2 for the outcomes log asking rents (Panel A) and log home prices (Panel B) with the same y-axis scale for comparison.

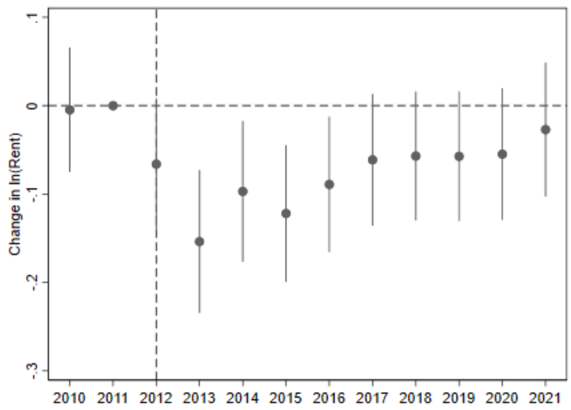
Figure 8: Average Price/Unit to Rent Ratio Over Time



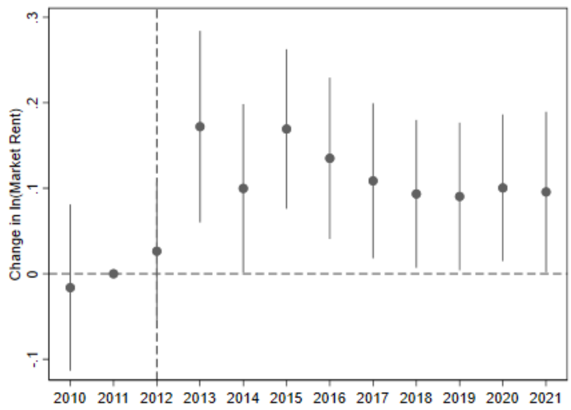
Notes: Figure 8 shows a binscatter plot of the average price/unit to rent ratio over time for high and non-surge blocks.

Figure 9: Quality-adjusted Rent Impacts by Neighborhood Income

(a) At or Below Median Income



(b) Above Median Income

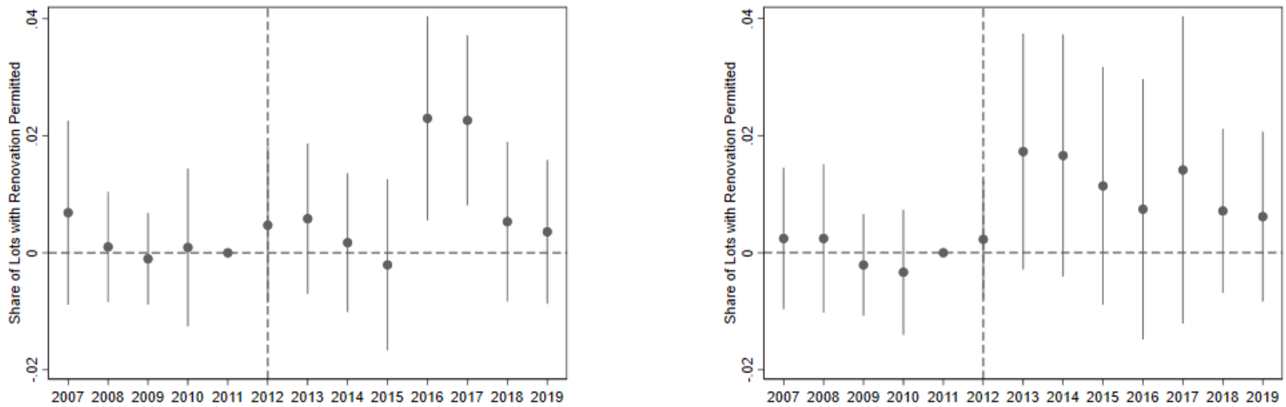


Notes: Figure 9 shows estimation of equation 3 where the measure of heterogeneity in the triple interaction is an indicator for whether the unit is located in a census tract with above city median income. Panel A shows the impact for neighborhoods at or below median income, and Panel B shows the differential effect for above median income neighborhoods.

Figure 10: Impacts on the Share of Lots with Renovation Permits by Neighborhood Income

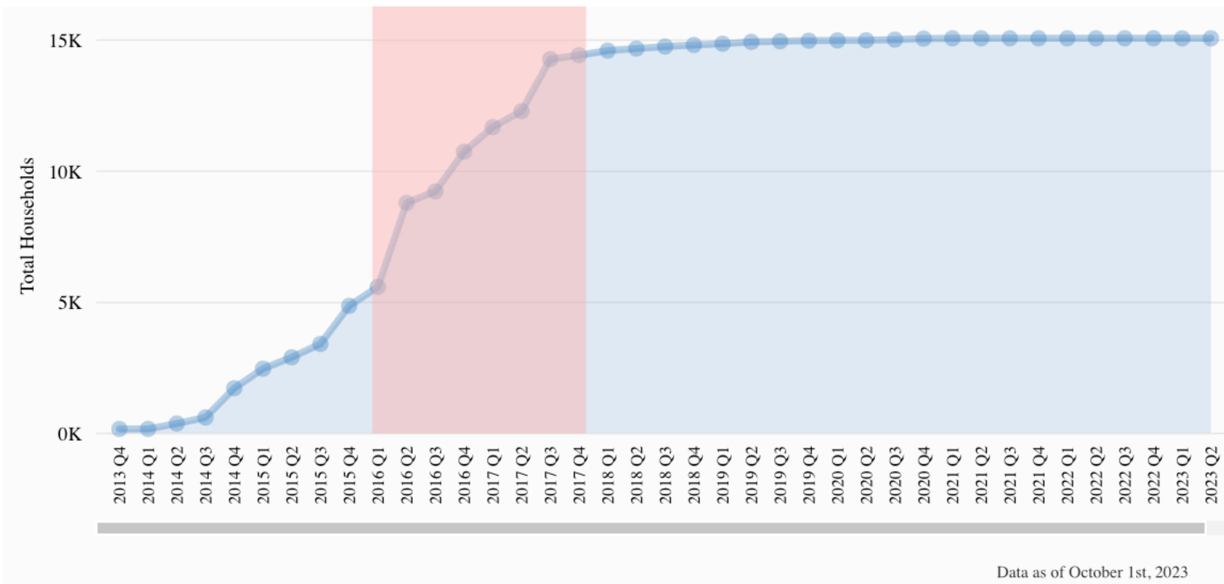
(a) At or Below Median Income

(b) Above Median Income



Notes: Figure 10 shows estimation of equation 3 where the measure of heterogeneity in the triple interaction is an indicator for whether the unit is located in a census tract with above city median income and the outcome is the block-level share of lots with renovation permits. Panel A shows the impact for neighborhoods at or below median income, and Panel B shows the differential effect for above median income neighborhoods.

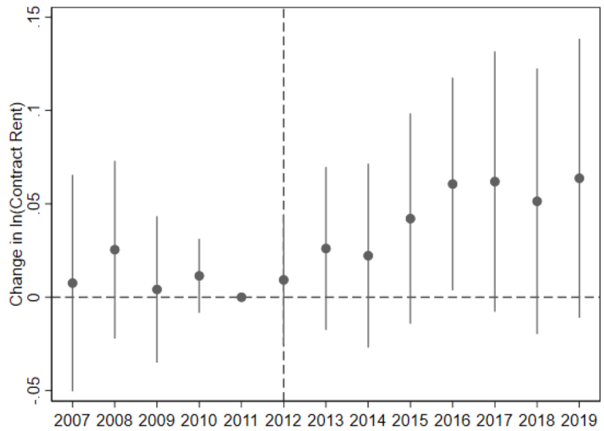
Figure 11: Build it Back Recovery Funds Distribution for Manhattan and Brooklyn



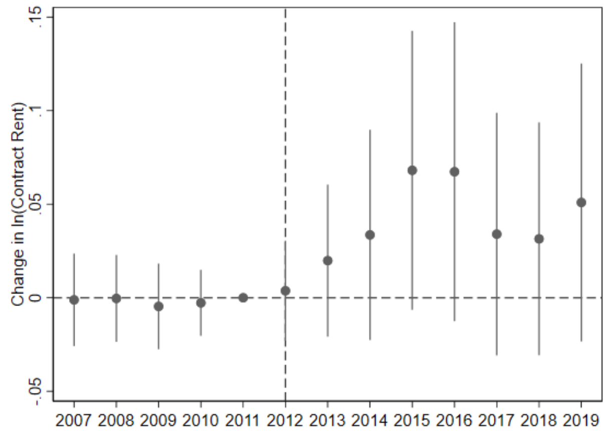
Notes: Figure 11 comes from https://www.nyc.gov/content/sandytracker/pages/build-it-back. The red section indicates the time period with an increase in renovation permits in below median income neighborhoods.

Figure 12: Impact of Hurricane Sandy on Voucher Rents

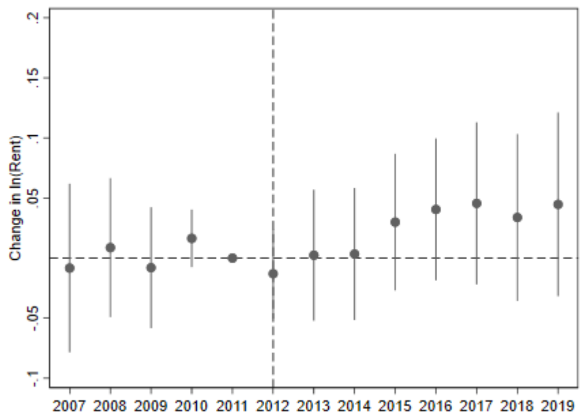
(a) High Surge Areas



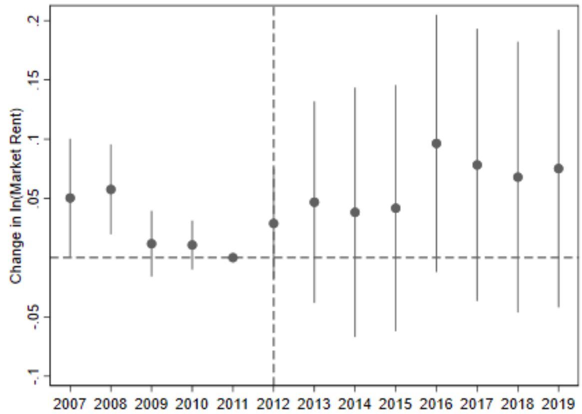
(b) Low Surge Areas



(c) High Surge, At/Below Median Income Neighborhoods



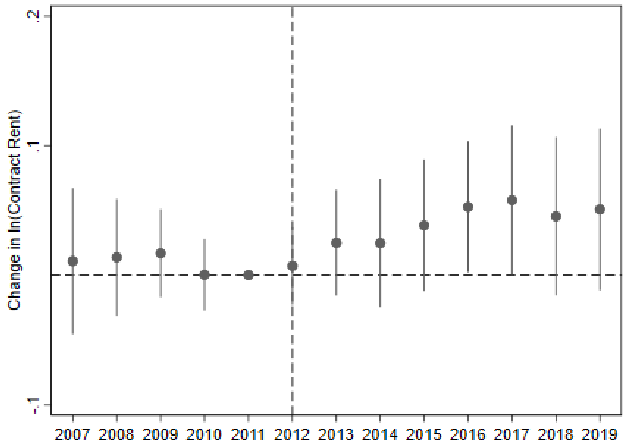
(d) High Surge, Above Median Income Neighborhoods



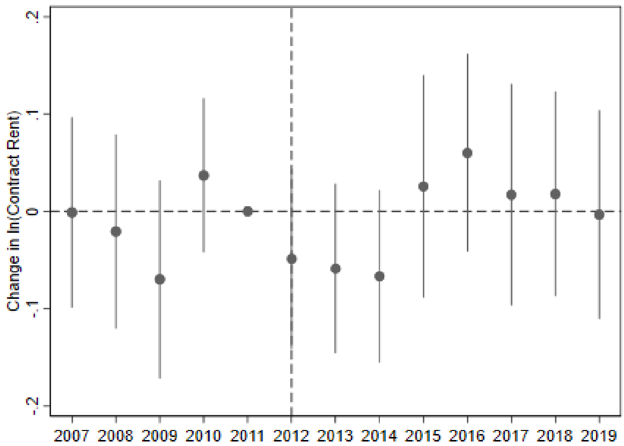
Notes: Figure 12 shows estimation of equation 2 on log voucher rents in Panels A and B and equation 3 in Panels C and D where the measure of heterogeneity in the triple interaction is an indicator for whether the unit is located in a census tract with above city median income. Panel C shows the impact for neighborhoods at or below median income, and Panel D shows the differential effect for above median income neighborhoods.

Figure 13: High Surge Voucher Rental Impacts by Tenure

(a) Sitting Voucher Units



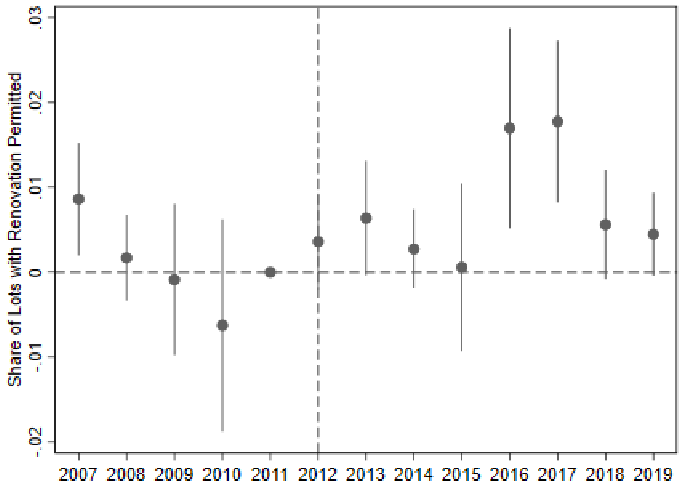
(b) "New" Voucher Units



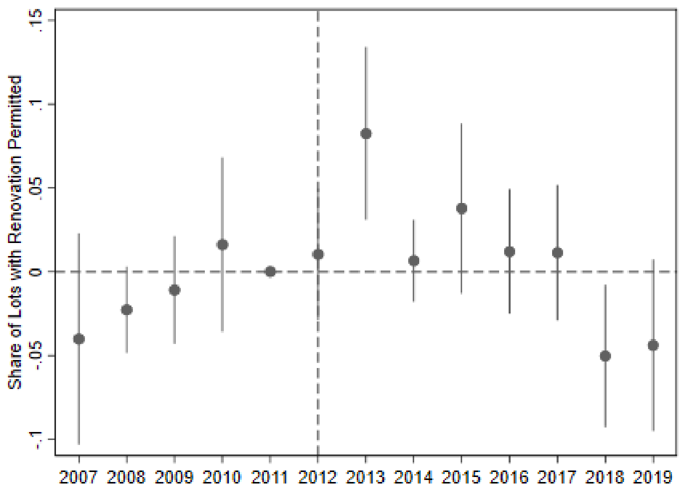
Notes: Figure 13 shows estimation of equation 2 on log voucher rents for the sample of voucher units where the tenant did not move (Panel A) and a repeated cross-section of units with a new tenant (Panel B).

Figure 14: Share of Lots that Filed for Renovation Permits in Below Median Income Neighborhoods

(a) Non Voucher Buildings



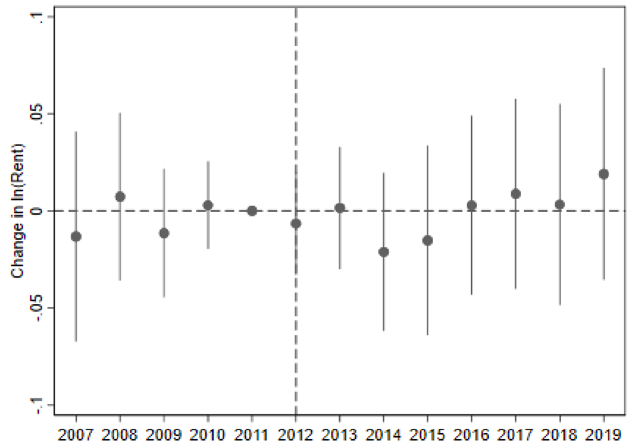
(b) Voucher Buildings



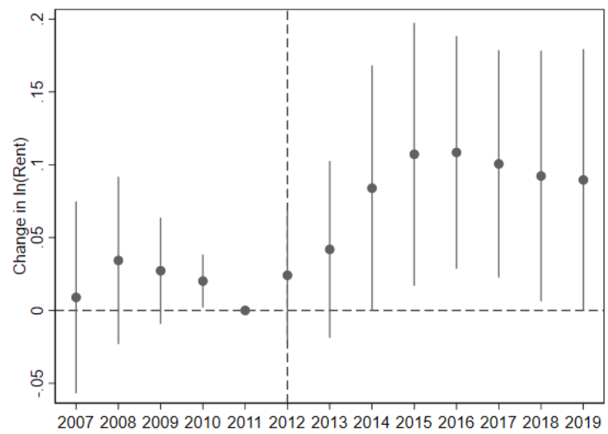
Notes: Figure 14 shows estimation of equation 3 on the share of lots that filed for renovation permits where the measure of heterogeneity is whether the building houses a voucher tenant in that year. Panel A shows the impact for buildings that do not house a voucher holder and Panel B shows the differential impact for buildings that do.

Figure 15: Differential Voucher Rental Impacts for 2013 Job Filings

(a) Buildings that did not file for a 2013 permit



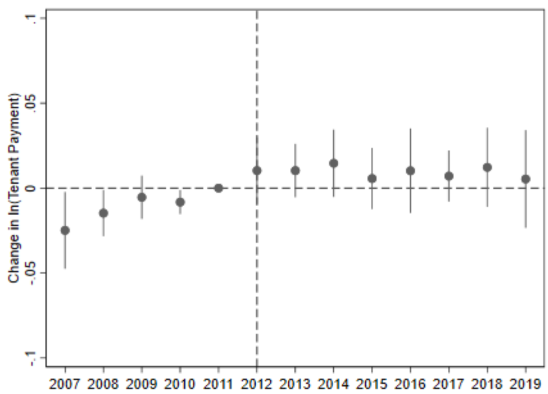
(b) Buildings that filed for 2013 renovation permit



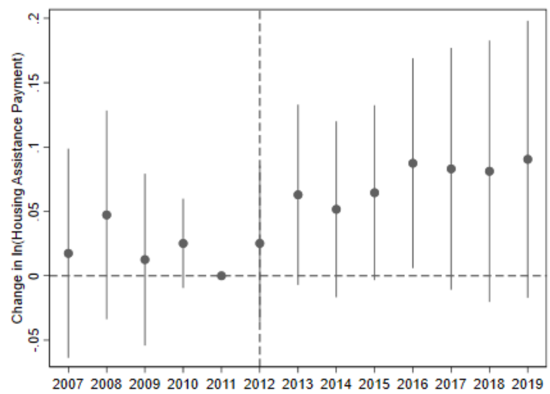
Notes: Figure 15 shows estimation of equation 3 on log voucher rents where the measure of heterogeneity is whether the building filed for a renovation permit in 2013. Panel A shows the impact for buildings that did not file for a permit and Panel B shows the differential impact for buildings that did.

Figure 16: Impacts on Tenant and Housing Assistance Payments in High Surge Areas

(a) Voucher Tenant Payments

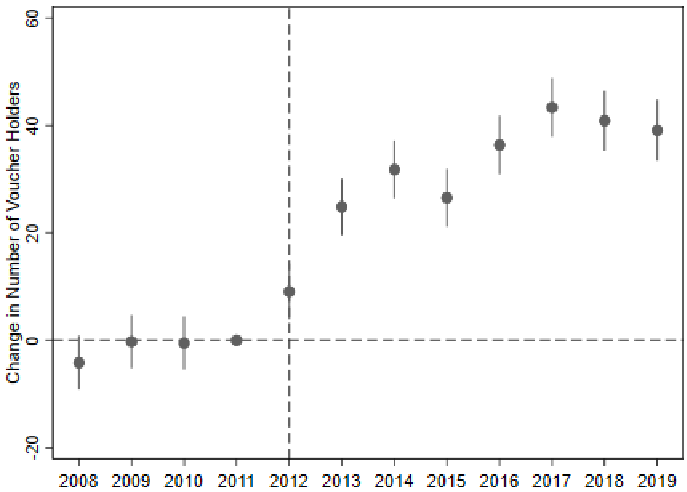


(b) Housing Assistance Payments



Notes: Figure 16 shows estimation of equation 2 on the total tenant payments (Panel A) and the housing assistance payments (Panel B).

Figure 17: Impact on Number of Voucher Holders in High Surge Areas



Notes: Figure 17 shows an estimation of equation 2 where the outcome is the number of existing voucher holders per block. Voucher holders that enter the program after 2012 are omitted from the analysis.

9 Tables

Table 1: Rental Listing/Unit Samples by Surge Area

Panel A: Street Easy Asking-Rent Listings				
2011	High Surge	Low Surge	Non-surge	Total
Listings	2,070	6,078	37,647	45,795
Blocks	110	222	2,043	2,375
ZIP codes	30	60	81	93
2017	High Surge	Low Surge	Non-surge	Total
Listings	6,042	16,265	123,306	145,613
Blocks	330	501	3,900	4,731
ZIP codes	45	79	88	98
Panel B: Voucher Units				
2011	High Surge	Low Surge	Non-surge	Total
Voucher Units	6,136	4,749	40,829	51,174
Blocks	394	499	4,093	4,986
ZIP codes	37	79	92	96

Notes: Table 1 shows the number of listings, blocks and ZIP codes included in the Street Easy sample for 2011 and 2017 and the number of voucher units, blocks and ZIP codes included in the voucher sample for 2011. Two years are included for the StreetEasy sample because it grows over time, while the voucher sample remains relatively constant.

Table 2: Summary Statistics for Market Units in 2011 by Surge Level

	High Surge	Low Surge	No Surge
Unit Level			
No. Bedrooms	1.36	1.25	1.25
	(0.97)	(0.89)	(1.02)
No. Bathrooms	1.25	1.33	1.22
	(0.53)	(0.64)	(0.59)
No fee	0.44	0.60	0.31
	(0.50)	(0.49)	(0.46)
Rent (in $2021)	4377.28	5364.10	4390.90
	(3313.40)	(9058.12)	(4460.26)
Building Level			
No. Res. Units	47.83	80.44	41.39
	(109.32)	(197.59)	(132.69)
Building Age	74.86	68.72	84.66
	(40.78)	(41.28)	(32.44)
Tract Level			
Tract Pov Rate	0.17	0.14	0.18
	(0.08)	(0.12)	(0.13)
Tract Share White	0.53	0.49	0.46
	(0.26)	(0.29)	(0.30)
Tract Share Black	0.11	0.16	0.15
	(0.19)	(0.24)	(0.23)
Tract Share Hispanic	0.16	0.22	0.25
	(0.14)	(0.20)	(0.23)
Tract Share Asian	0.17	0.10	0.12
	(0.13)	(0.12)	(0.15)
Tract Share College Degree	0.26	0.24	0.25
	(0.11)	(0.12)	(0.13)
Tract Share Foreign Born	0.44	0.34	0.32
	(0.18)	(0.15)	(0.15)
Tract Med Rent (in $2021)	1371.39	1518.26	1517.39
	(467.23)	(479.22)	(499.75)

Notes: Table 2 shows means and (standard deviations) from the StreetEasy sample prior to the hurricane (2011) by surge area designation. The table includes characteristics at the unit level, building level and census tract level.

Table 3: Summary Statistics for Voucher Units in 2011 by Surge Level

	High Surge	Low Surge	No Surge
Unit Level			
HH Head Black	0.03	0.05	0.04
	(0.16)	(0.22)	(0.20)
HH Head Hispanic	0.18	0.22	0.25
	(0.38)	(0.41)	(0.44)
HH Head White	0.48	0.35	0.38
	(0.50)	(0.48)	(0.49)
HH Head Over 65	0.46	0.33	0.28
	(0.50)	(0.47)	(0.45)
Has Children	0.28	0.36	0.39
	(0.45)	(0.48)	(0.49)
Contract Rent (in $2021)	1483.59	1605.83	1449.96
	(546.51)	(844.68)	(488.48)
HH Income/10000 (in $2021)	1.97	2.16	1.85
	(1.39)	(1.51)	(1.18)
Housing Assistance Payments (in $2021)	1026.11	1126.68	1065.66
	(506.63)	(808.20)	(475.51)
Tenant Rent Portion (in $2021)	490.37	532.59	445.97
	(352.43)	(383.85)	(289.28)
Share Below Payment Standard	0.57	0.73	0.80
	(0.27)	(0.31)	(0.34)
Building Level			
No. Res. Units	389.41	1193.76	142.83
	(471.68)	(2413.30)	(342.67)
Building Age	49.54	55.75	70.41
	(21.68)	(29.30)	(29.96)
Tract level			
Tract Poverty Rate	0.25	0.23	0.27
	(0.11)	(0.15)	(0.13)
Tract Share White	0.42	0.30	0.27
	(0.34)	(0.31)	(0.31)
Tract Share Black	0.30	0.31	0.24
	(0.25)	(0.28)	(0.23)
Tract Share Hispanic	0.20	0.31	0.40
	(0.15)	(0.26)	(0.27)
Tract Share Asian	0.06	0.06	0.08
	(0.09)	(0.10)	(0.12)
Tract Share College Degree	0.17	0.17	0.15
	(0.09)	(0.09)	(0.09)
Tract Share Foreign Born	0.42	0.34	0.35
	(0.19)	(0.14)	(0.14)
Tract Median Rent (in $2021)	1009.00	1182.58	1197.20
	(349.23)	(312.86)	(334.01)

Notes: Table 3 shows means and (standard deviations) from the voucher sample prior to the hurricane (2011) by surge area designation. The table includes characteristics at the unit level, building level and census tract level.

Table 4: Impact of Hurricane Sandy on Market Rents

	(1) Log Rent	(2) Log Rent	(3) Log Rent
No. Bedrooms	0.165***	0.170***	0.168***
	(0.017)	(0.018)	(0.018)
high surge × post=1	0.053***	0.018	0.021
	(0.018)	(0.021)	(0.020)
low surge × post=1	0.010	0.010	0.016
	(0.022)	(0.019)	(0.020)
Building Age		-0.005***	-0.004***
		(0.000)	(0.000)
Building Age Sq		0.000***	0.000***
		(0.000)	(0.000)
No. Bathrooms			0.012
			(0.011)
No Broker Fee			0.006
			(0.005)
No. Res Units			-0.000
			(0.000)
Res Units Sq			0.000
			(0.000)
Subsidized housing			-0.016
			(0.014)
Number of Floors			0.008***
			(0.001)
Flood Zone			0.046**
			(0.019)
Constant	7.886***	8.122***	7.931***
	(0.025)	(0.025)	(0.028)
N	1371538	1371538	1371536
Age Controls		X	X
Zipcode * Year		X	X
Zipcode * Surge	X	X	X

Notes: Table 4 shows results from regressions on log asking rents in $2021 using equation 1. Column 1 includes control for number of bedrooms, Column 2 adds building age, Column 3 includes all controls. All models include ZIP code-by-year and ZIP code-by-surge level fixed effects. Clustered standard errors in parentheses. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table 5: All Voucher Rent Results

	(1) Log Rent (2021)	(2) Log Rent (2021)	(3) Log Rent (2021)
No. Bedrooms	0.160***	0.160***	0.156***
	(0.004)	(0.004)	(0.004)
high surge × post=1	0.028	0.029	0.026
	(0.019)	(0.020)	(0.020)
low surge × post=1	0.042**	0.039*	0.042*
	(0.021)	(0.022)	(0.023)
Building Age		-0.002***	-0.002***
		(0.001)	(0.001)
Building Age Sq		0.000	0.000
		(0.000)	(0.000)
No. Res Units			-0.000***
			(0.000)
Res Units Sq			0.000***
			(0.000)
No. of Floors			0.007**
			(0.003)
Subsidized housing			-0.096***
			(0.022)
Flood Zone			-0.088*
			(0.048)
Constant	6.961***	7.060***	7.074***
	(0.009)	(0.016)	(0.022)
N	681247	680663	680663
Age Controls		X	X
All Other Controls			X
Zipcode * Year	X	X	X
Zipcode * Surge	X	X	X

Notes: Table 5 shows results from regressions on repeated cross-section of all voucher units rents in the program during time period in $2021 using equation 1. Clustered standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

A Appendix

Below I discuss the results for further possible drivers of heterogeneity.

A.0.1 Building Height

Since units on lower floors were more likely to be damaged by the storm surge than units on higher floors, it's possible that taller buildings and/or units on higher floors experienced different rental impacts. There is some evidence this is true in Figures B.16a and B.16b where, though not statistically significant, rents appear to have increased in buildings above median height (6 floors) and decreased in buildings below median height. However, I find no differential impacts for ground floor apartments, based on a rough approximation of the unit's floor. (Figure B.17) [19].

A.0.2 Renovations

Since neighborhood income heterogeneity in rental impacts appears to be related to the timing of renovations, I explore in the StreetEasy sample whether the renovated buildings in particular are driving the rent impacts. If landlords conducted renovations to repair damage and return their unit to its initial quality, we would not expect landlords to be able to pass on renovation costs into rents. However, some research suggests that landlords enjoy monopoly pricing power in New York City (Watson and Ziv (2021)), and, in the wake of a disaster, they may enjoy even more abnormal market power. In addition, if the landlord took the opportunity to improve the unit beyond its original condition, a well functioning market would allow those costs to be passed onto rents.

Figure B.18b plots the relative rental impacts for buildings in high surge areas that did not file for renovation permits in 2013 (r = 0) and B.18a plots the $\beta(s = high, r = 1)$ from equation 3 which represent the differential impact for buildings that did file for permits in 2013-2015. Interestingly, while rents decreased initially for buildings that did not file for renovation permits in the 3 years after the hurricane, and slightly increased for those that did, neither impact is persistent throughout the period. The fact that the buildings that filed for renovation permits do not drive the rental increases lends more credibility to the argument that their ability to recover faster lead to an increase in demand, and therefore rents, in those neighborhoods.

A.0.3 Building Ownership

Given the evidence that prices fell in affected areas (Ellen and Meltzer (2024), Ortega and Taşpınar (2018)), it is possible that certain buyers aimed to take advantage of the price discounts, bought rental properties and adjusted management practices to alter rents. Consistent with Ellen and Melter (2024), I find no evidence of an increase in the share of lots or units sold in the years immediately after the hurricane (Figure B.19). In addition, the main results are unaffected by dropping listings from properties that were sold during this time period (Figure B.20).

A.0.4 Information

While the flood zone is less likely to be a salient boundary for renters than homeowners, it is still possible that households outside of the flood zone were less aware of the level of flood risk of their neighborhoods and that after the hurricane, renters in these neighborhoods updated their preferences accordingly: toward newer buildings they viewed as less prone to flood damage. The

[19] The sample does not include enough basement apartments to isolate the impacts on these units, which are most likely to be affected by flooding

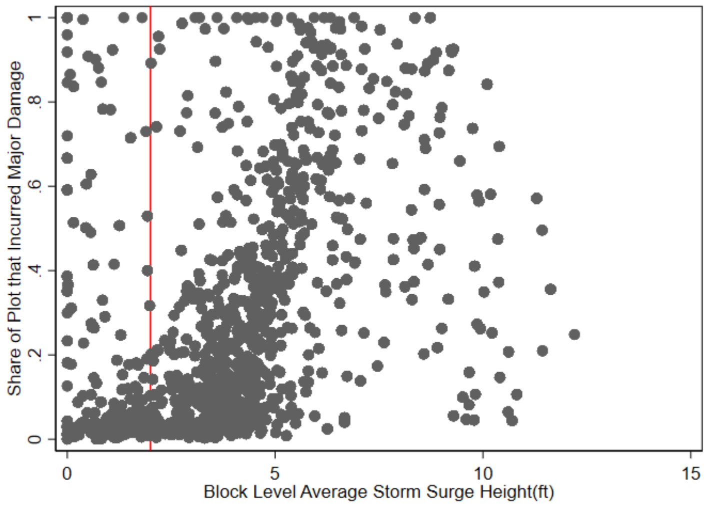
StreetEasy listings data is not powered for a full comparison of the impacts within and outside of the flood zone because in the pre-period there are less than 10 listings each year in the flood zone that did not experience surge[20]. However, roughly half of the listings in high surge areas are outside of the flood zone.

When limiting the sample to those listings outside the flood zone, Figure B.22a shows that the relative negative rental impacts between high surge and non-surge areas are larger. However, rents do still recover back to non-surge levels by 2016. Stratifying the results by higher and lower income neighborhoods also shows more dramatic impacts: rents increased by more in higher income neighborhoods (Figure B.22b) and experience larger negative impacts in lower income neighborhoods (Figure B.22c) than for the full sample. It is difficult to fully interpret these results without the analogous comparisons of listings within the flood zone, however they offer suggestive evidence that climate risk information may play a small, short term role in housing decisions for renters, but a marge larger role for home owners.

[20]There are a substantial number of blocks that were in the flood zone that did not experience surge, but the buildings on these blocks do not appear to use StreetEasy.

B Appendix

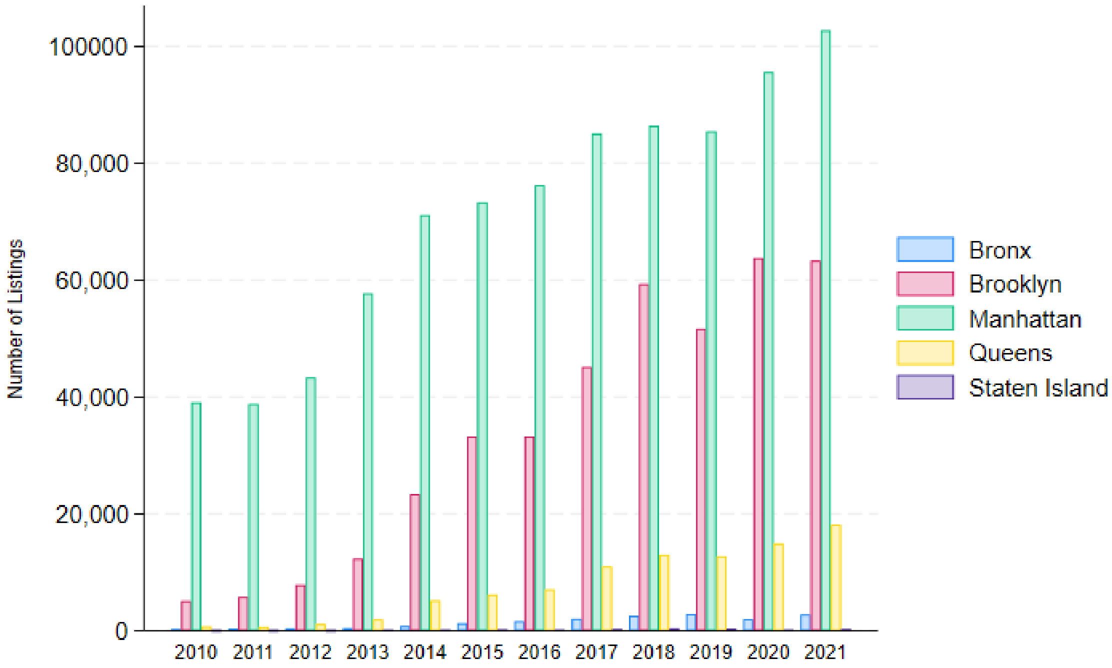
Figure B.1: Percentage of Plot Incurred Major Damage by Surge Height



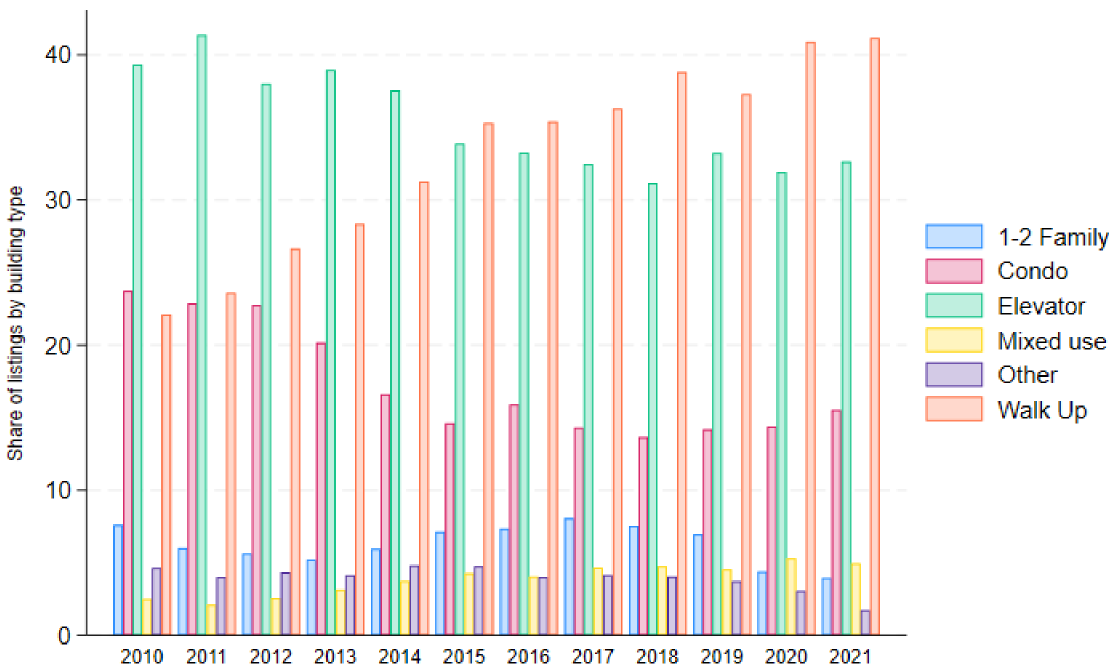
Notes: Figure B.1 plots the relationship between major damage and surge height and the lot level. Red line indicates cut off of 2ft of surge height for high surge areas.

Figure B.2: Composition of StreetEasy Sample over Time

(a) Number of Listings by Borough over Time



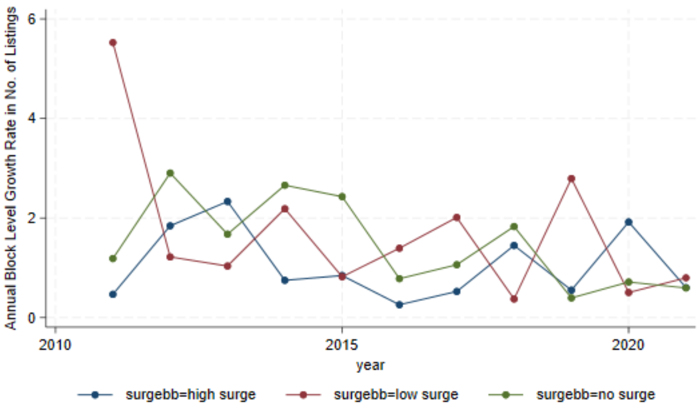
(b) Share of Listings by Building Type



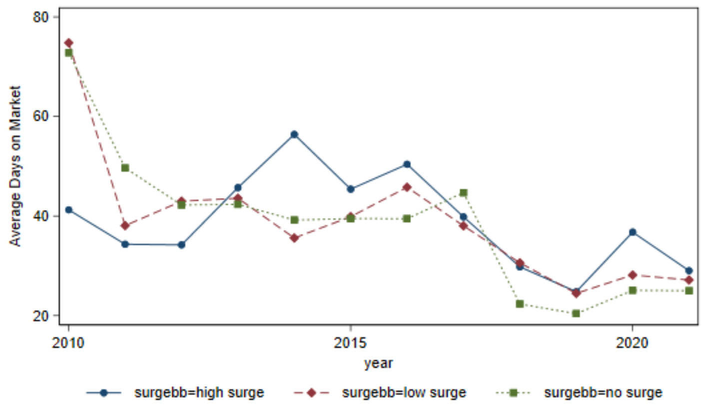
Notes: Figure B.2 shows the number of listings by borough and the share of listings by building type from 2010-2021.

Figure B.3: Average Growth Rate in Listings and Time on Market by Neighborhood Income

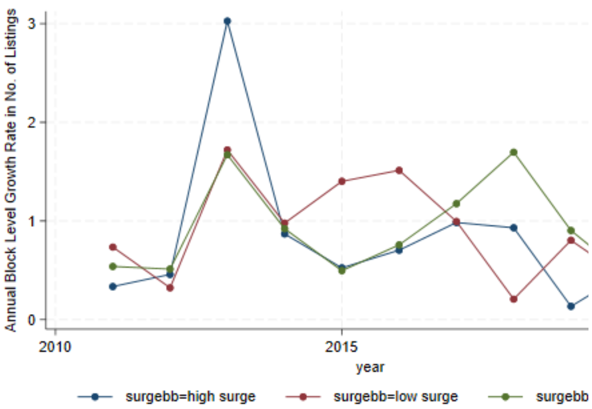
(a) At or Below Median Income:
Listings Growth Rate



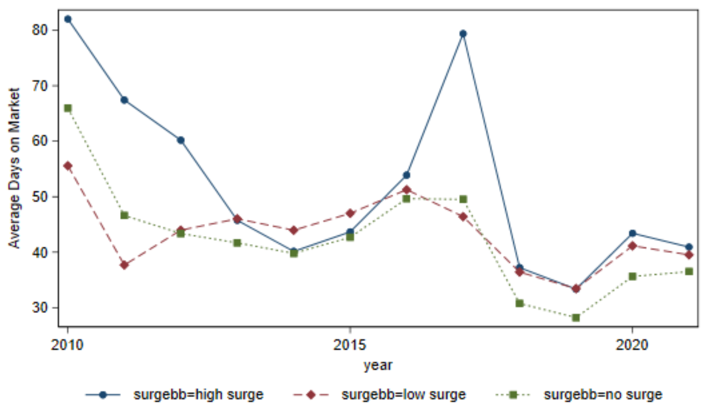
(b) At or Below Median Income:
Time on Market



(c) Above Median Income:
Listings Growth Rate



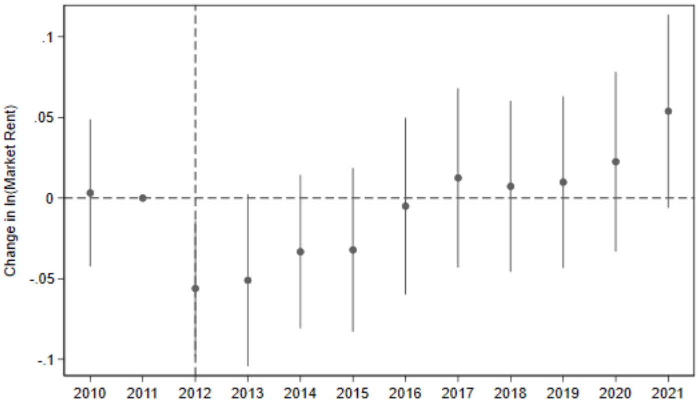
(d) Above Median Income:
Time on Market



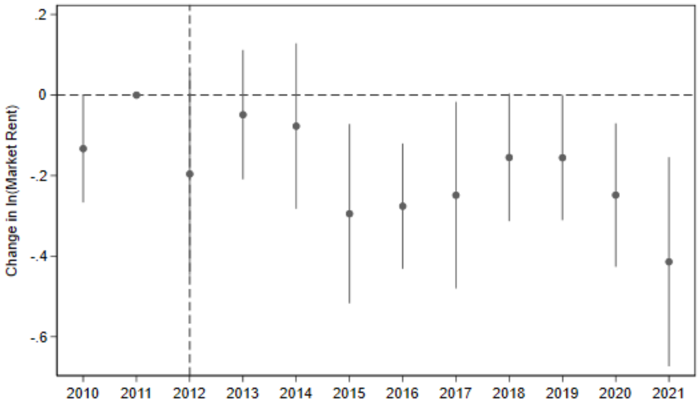
Notes: Figure B.3 shows binscatter plots of the annual block level growth rate in listings and the average number of days on the market for below and above median income neighborhoods.

Figure B.4: Impacts on Asking Rents on High Surge blocks by BW-12 Qualification

(a) BW-12 Non-Qualified Buildings



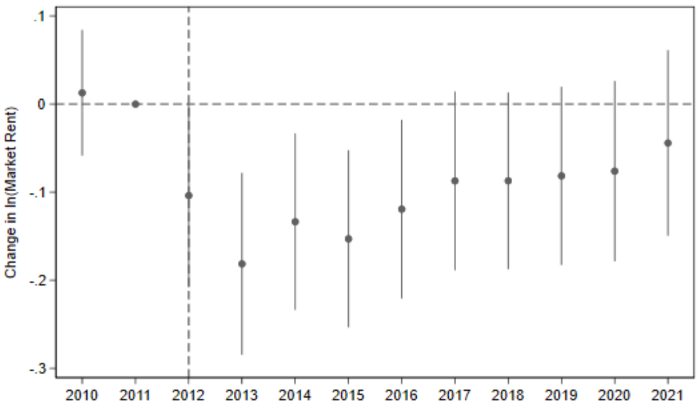
(b) BW-12 Qualified Buildings



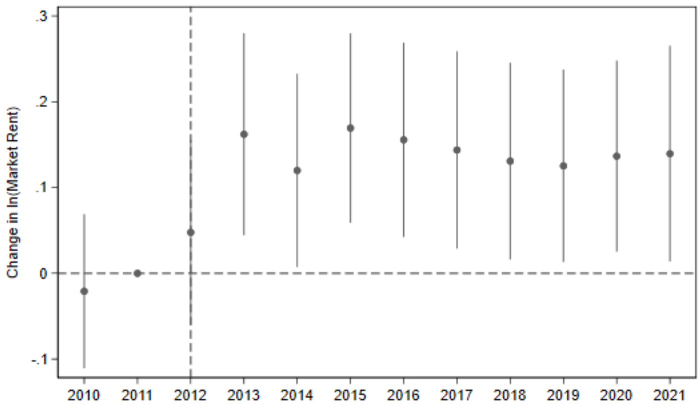
Notes: Figure B.4 shows estimation of equation 3 where the measure of heterogeneity in the triple interaction is an indicator for whether the building would have qualified for a higher insurance premium under the Biggert Waters Act of 2012. Buildings that qualified were located in the 100 year flood plain *and* were built before 1983. Panel A shows the impact for buildings that would not have qualified, and Panel B shows the differential effect for those that did.

Figure B.5: Impacts on Asking Rents for BW-12 Non-Qualified Buildings by Neighborhood Income

(a) At or Below Median Income



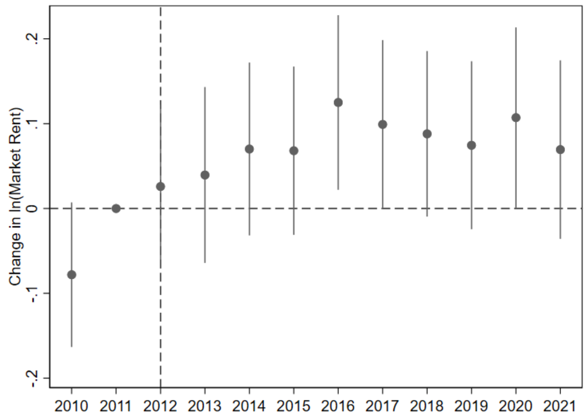
(b) Above Median Income



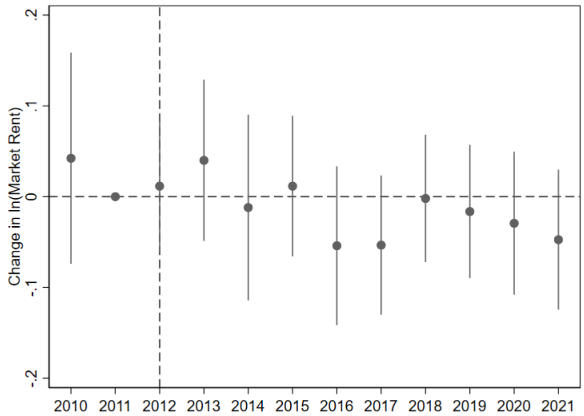
Notes: Figure B.5 shows estimation of equation 3 where the measure of heterogeneity in the triple interaction is an indicator for whether the unit is located in a census tract with above city median income. Panel A shows the impact for neighborhoods at or below median income, and Panel B shows the differential effect for above median income neighborhoods. The sample omits buildings that would have qualified for increased insurance premiums under BW-12.

Figure B.6: Impacts on High Surge Rents by Share of Building Units Rent-Stabilized

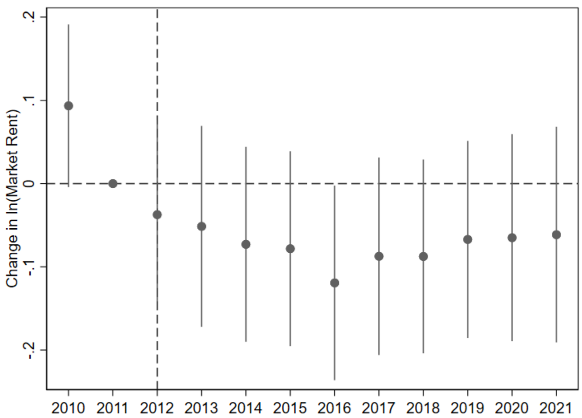
(a) Less than 25% Rent-Stabilized



(b) 25-75% Rent-Stabilized



(c) More than 75% Rent-Stabilized

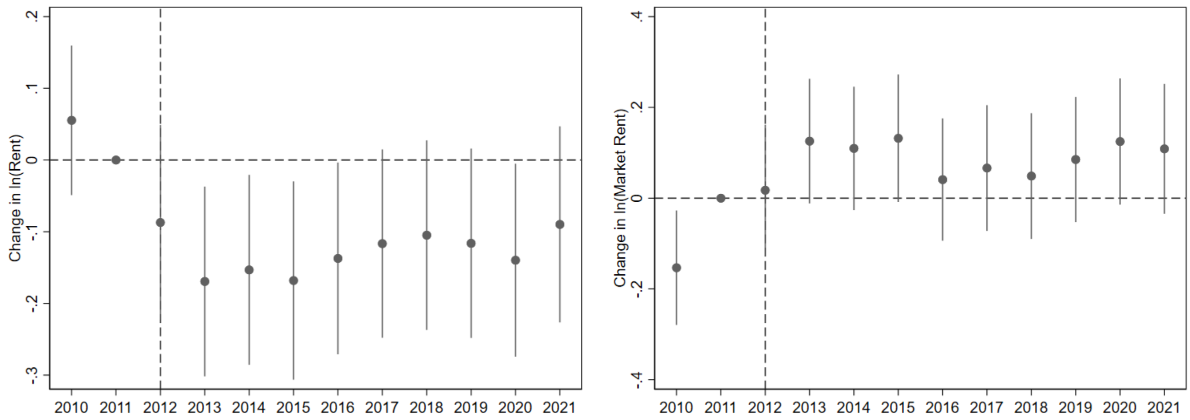


Notes: Figure B.6 shows estimation of equation 2 stratified by whether the building has less than 25% of its units rent-stabilized, 25-75% and more than 75%.

Figure B.7: Impacts on Rents for Buildings with Less than 25% of Units Rent-Stabilized by Neighborhood Income

(a) At or Below Median Income

(b) Above Median Income

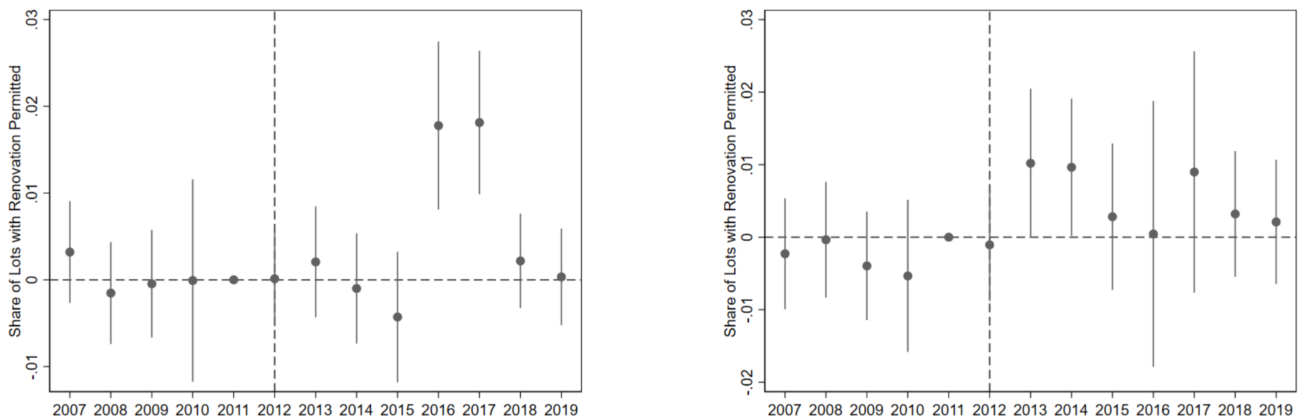


Notes: Figure B.7 shows estimation of equation 3 on asking rents where the measure of heterogeneity in the triple interaction is an indicator for whether the unit is located in a census tract with above city median income. Regressions are run just for the sample of buildings with less than 25% of their units rent stabilized. Panel A shows the impact for neighborhoods at or below median income, and Panel B shows the differential effect for above median income neighborhoods.

Figure B.8: Impacts on the Share of Lots with Renovation Permits for Buildings with Less than 25% of Units Rent-Stabilized by Neighborhood Income

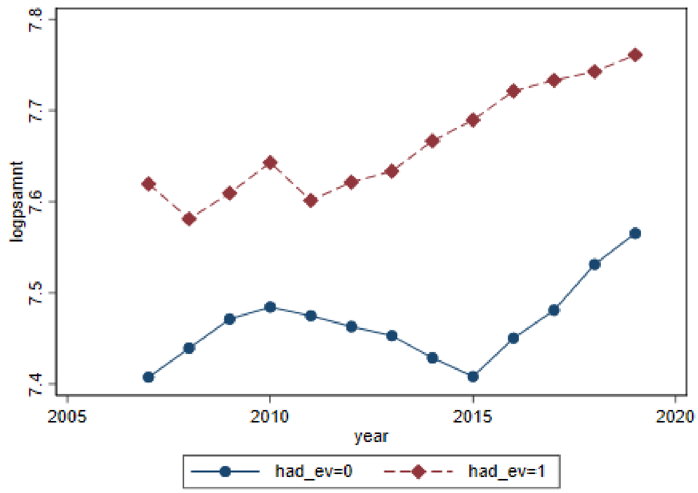
(a) At or Below Median Income

(b) Above Median Income



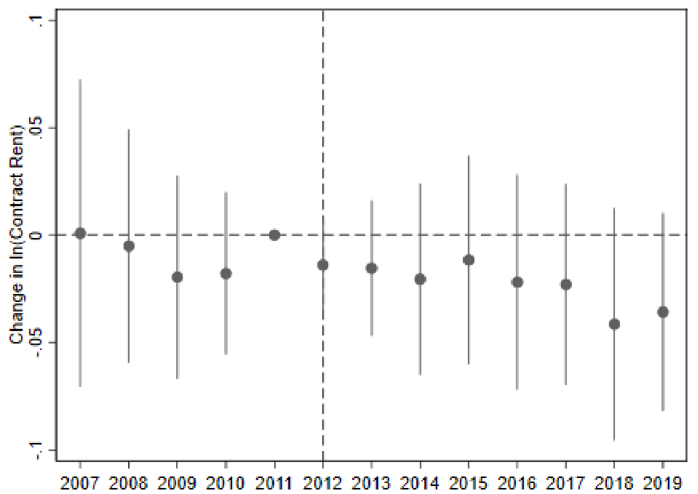
Notes: Figure B.8 shows estimation of equation 3 where the measure of heterogeneity in the triple interaction is an indicator for whether the unit is located in a census tract with above city median income and the outcome is the block-level share of lots with renovation permits. Regressions are run just for the sample of buildings with less than 25% of their units rent stabilized. Panel A shows the impact for neighborhoods at or below median income, and Panel B shows the differential effect for above median income neighborhoods.

Figure B.9: Average Log Payment Standard for Households with Enhanced Vouchers and With Regular Vouchers



Notes: Figure B.9 shows a binscatter plot of the average log payment standard for households with enhanced vouchers and those with regular vouchers over time.

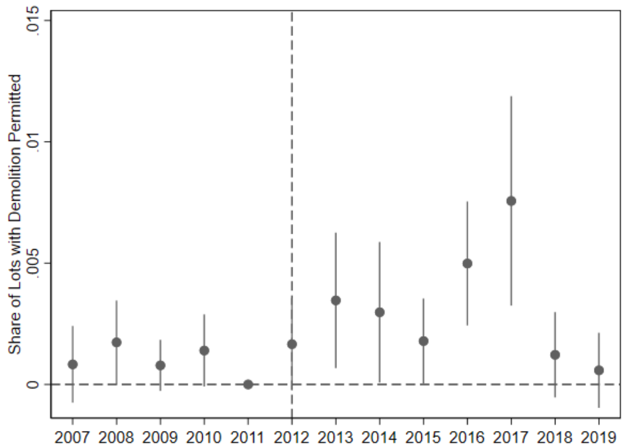
Figure B.10: Impact on Voucher Rents without Households below Payment Standard Or with Enhanced Vouchers that had Renovations in 2013



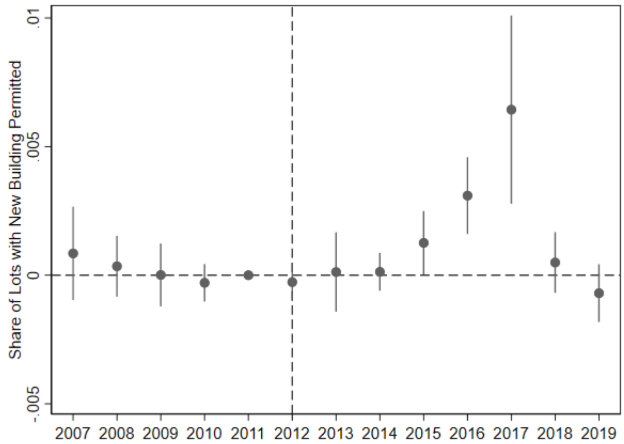
Notes: Figure B.10 shows an estimation of equation 3 on log asking rents where the measure of heterogeneity is whether the building filed a renovation permit in 2013, omitting enhanced vouchers and households whose rents were below in the payment standard in 2011 from the analysis.

Figure B.11: Impacts on the Share of Buildings with Demolition, New Building and Renovation Permits

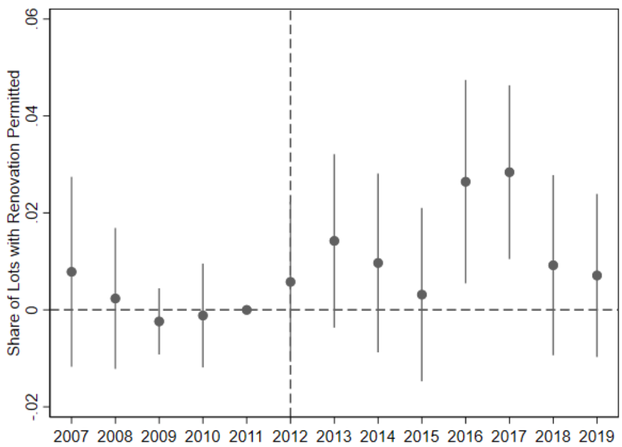
(a) Demolition Permits



(b) New Building Permits



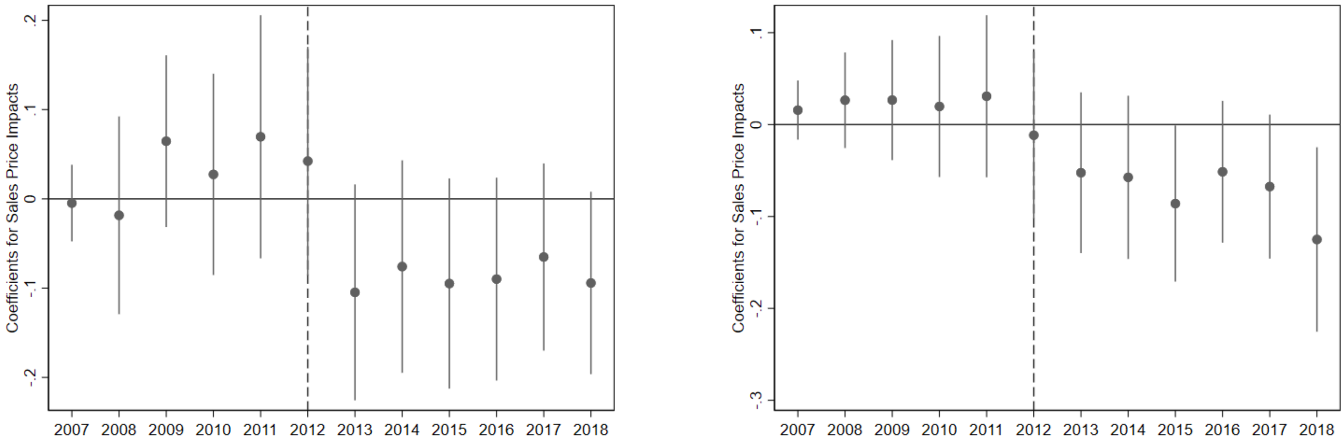
(c) Renovation Permits



Notes: Figure B.11 shows an estimation of equation 2 where the outcomes are the share of buildings with demolition permits (Panel A), new building permits (Panel B) and renovation permits per block (Panel C). is the number of existing voucher holders per block.

Figure B.12: Impacts on Sales Prices

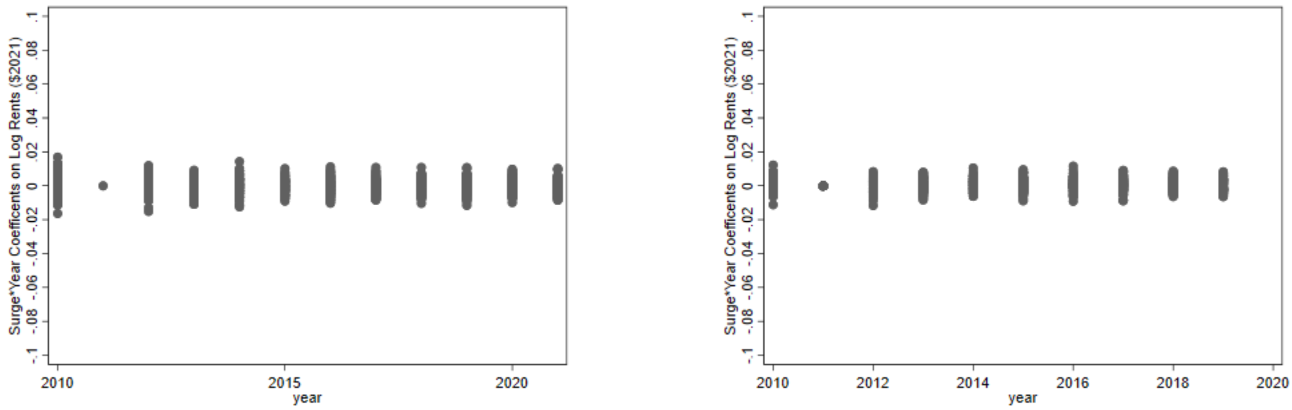
(a) High Surge Blocks (b) Low Surge Blocks



Notes: Figure B.11 shows an estimation of equation 2 where the outcome log sales prices.

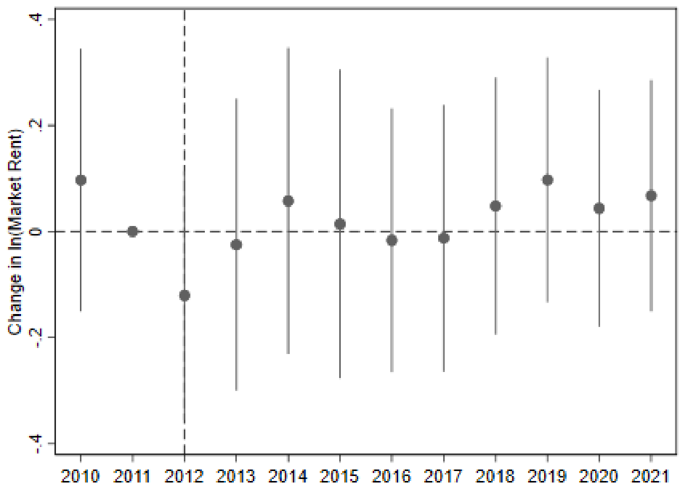
Figure B.13: Rental Impacts of Randomly Split Comparison Group

(a) Market Rents (b) Voucher Rents



Notes: Figure B.13 shows the results of a simulation generating random comparison groups and re-estimation of the main analysis with equation 2 for both market rents (Panel A) and voucher rents (Panel B).

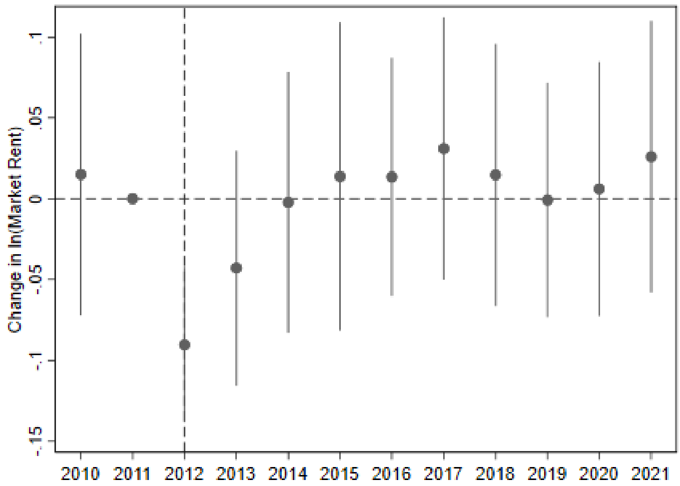
Figure B.14: Rental Impacts with Non-affected Coastal ZIP code Comparison Group



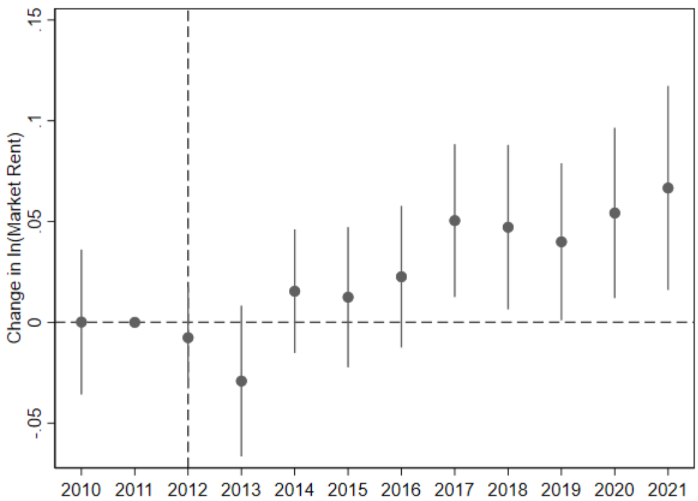
Notes: Figure B.14 shows the results of an estimation of equation 2 where the comparison group is coastal ZIP codes that did not experience any surge.

Figure B.15: High Surge Rent Impacts with Census Tract Fixed Effects

(a) Quality Adjusted Rents



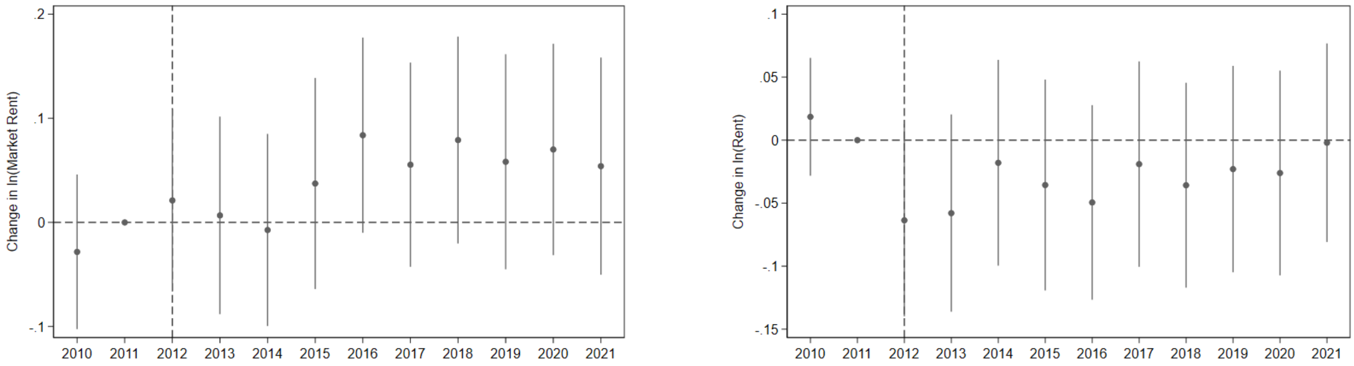
(b) Average, non-adjusted Rents



Notes: Figure B.15 shows estimation of equation 2 for the outcomes log asking rents using census tract-by-year and census tract-by-surge level fixed effects instead of ZIP code-by-year and ZIP code-by-surge level fixed effects. The figure includes an estimation with all controls (Panel A) and without building level controls (Panel B).

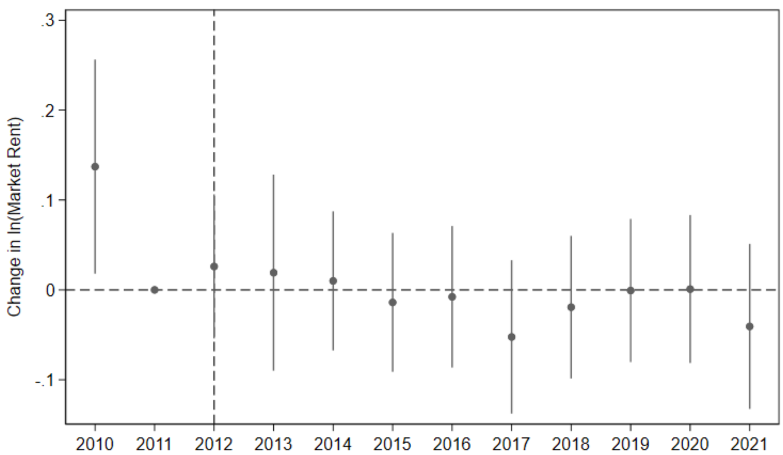
Figure B.16: High Surge Rent Impacts By Building Height

(a) Buildings Above Median Height (b) Buildings Below Median Height



Notes: Figure B.16 shows estimation of equation 3 for the outcome log asking rents where the measure of heterogeneity is whether the building was above sample median height (6 floors).

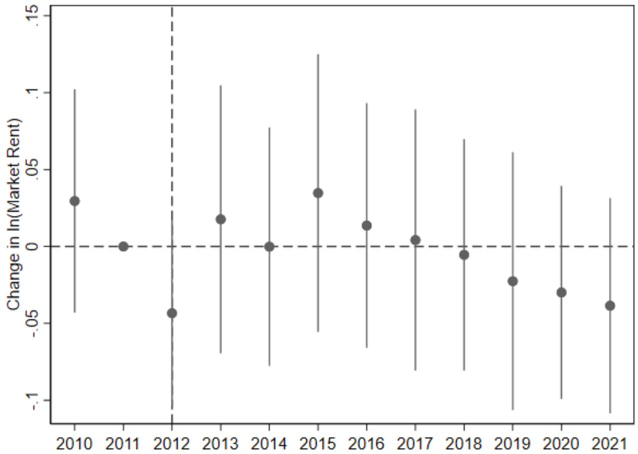
Figure B.17: Differential Rental Impacts for Ground Floor Apartments



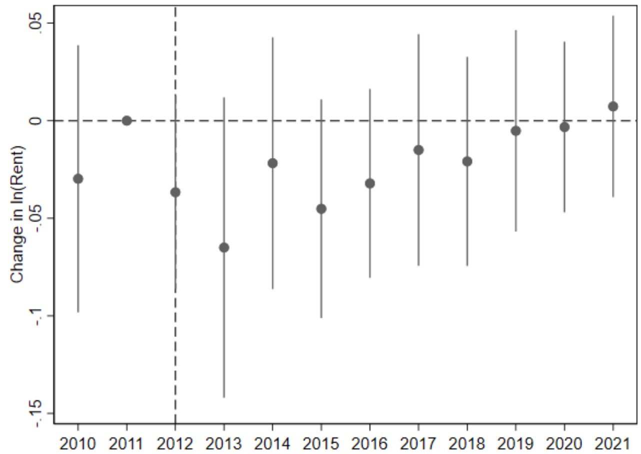
Notes: Figure B.16 shows estimation of equation 3 for the outcome log asking rents where the measure of heterogeneity is whether the unit was a ground floor apartment.

Figure B.18: Differential Asking Rental Impacts for 2013-2015 Job Filings

(a) Buildings that filed for 2013-2015 renovation permit



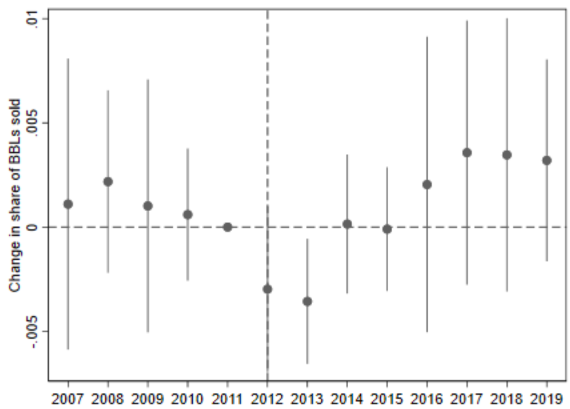
(b) Buildings that did not file for 2013-2015 permit



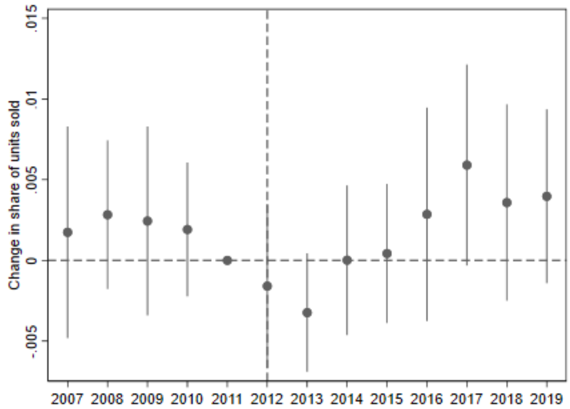
Notes: Figure B.18 shows estimation of equation 3 where the measure of heterogeneity in the triple interaction is an indicator for whether the building filed for a renovation permit in 2013-2015. Panel A shows the impact for those that filed a permit and Panel B shows the impact for those that did not.

Figure B.19: Impact on the Share of Residential Sales on High Surge Blocks

(a) Share of BBls on block sold

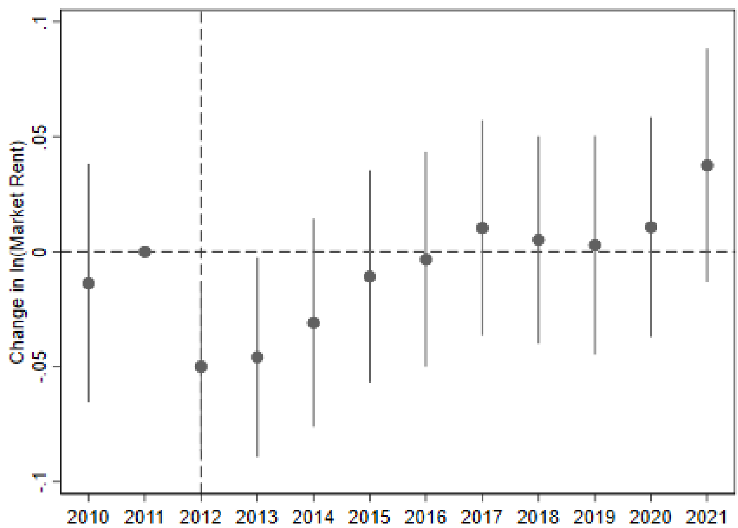


(b) Share of units on block sold



Notes: Figure B.19 shows estimation of equation 2 where the outcomes are share of BBLs sold on a block (Panel A) and share of units sold on a block (Panel B).

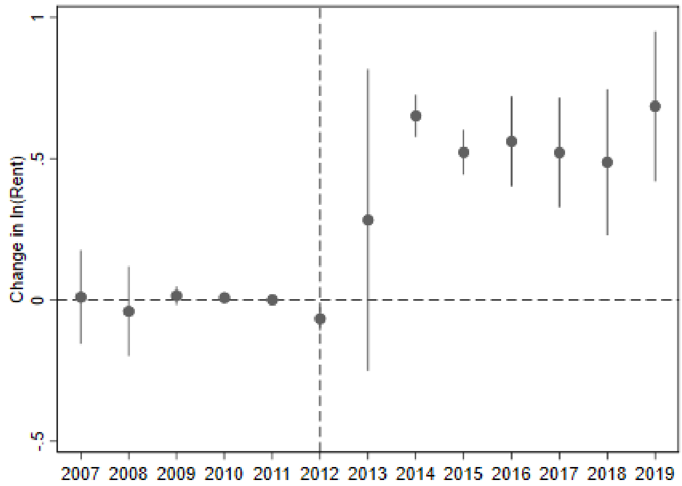
Figure B.20: High Surge Asking Rent Impacts without Properties that sold 2010-2021



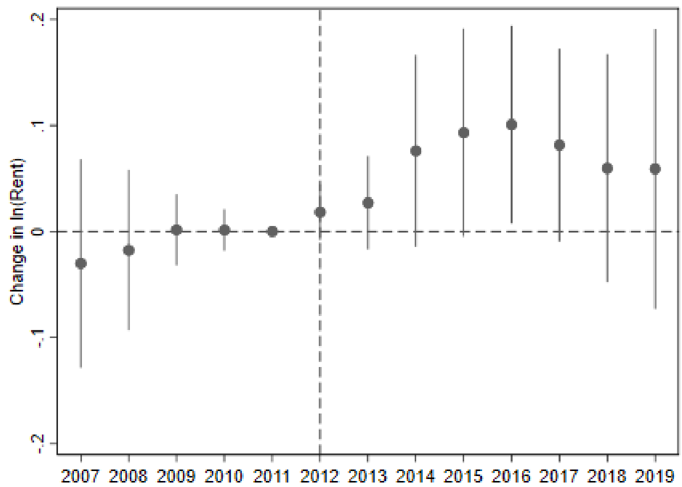
Notes: Figure B.20 shows estimation of equation 2 on asking rents, omitting properties that sold during the time period.

Figure B.21: High Surge Voucher Rent Impacts by Renovation Type

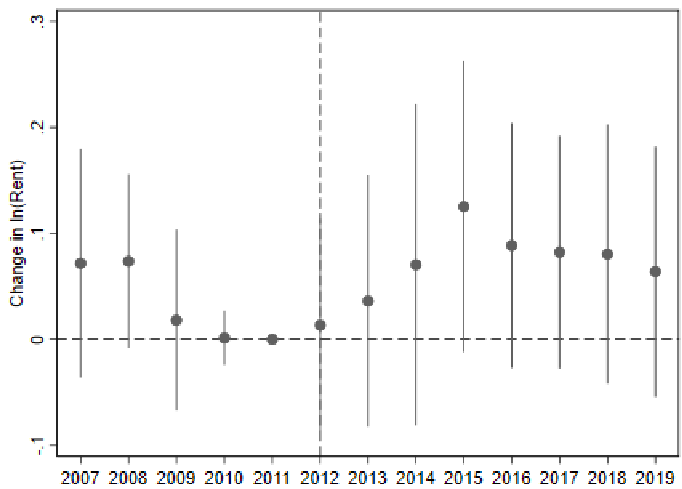
(a) A1 Renovations



(b) A2 Renovations



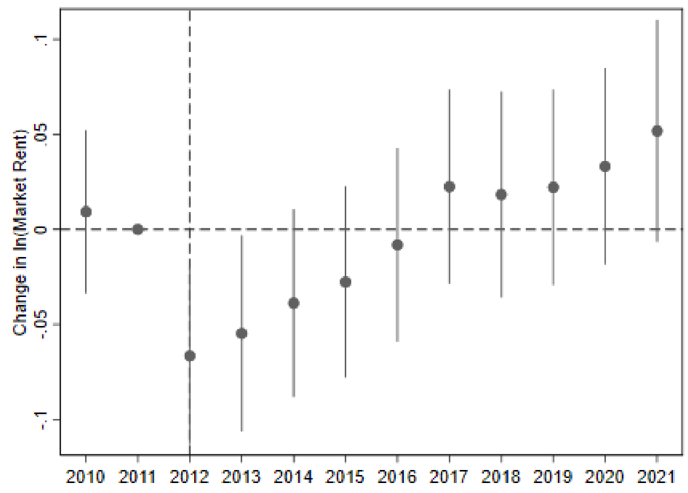
(c) A3 Renovations



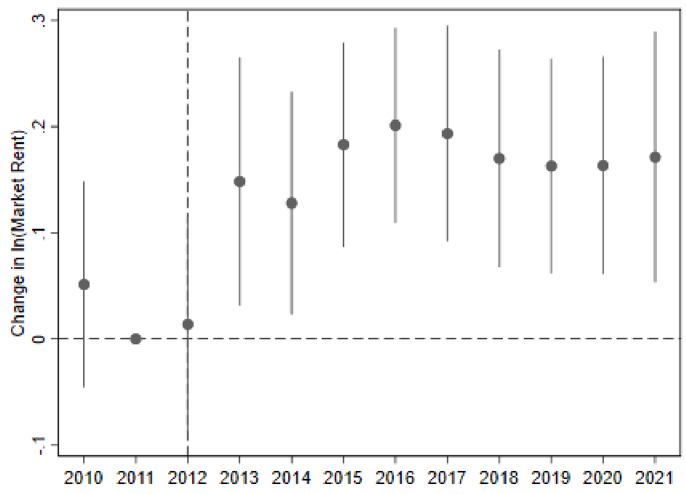
Notes: Figure B.21 shows estimation of equation 3 on voucher rents, stratified by the type of renovation: A1 (most substantial), A2 and A3 (least substantial) renovations.

Figure B.22: Rental Impacts for High Surge Areas Outside the Flood Zone

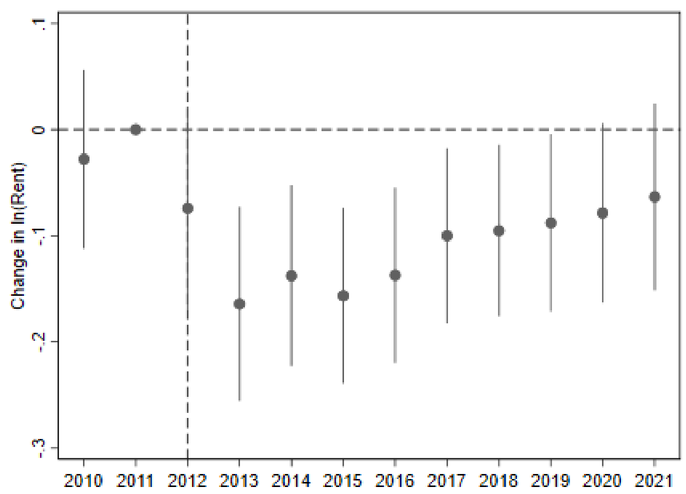
(a) All Listings Outside the Flood Zone



(b) Above Median Income Neighborhoods



(c) At or Below Median Income Neighborhoods



Notes: Figure B.22 shows estimation of equation 2 (Panel A) and 3 (Panels B and C) on asking rents, limiting the analysis sample to units outside of the flood zone.

Table B.1: Key Quality Adjusted Rental Impact Coefficients using Continuous Surge and Different Thresholds for High Surge

	(1) Log Rent	(2) Log Rent	(3) Log Rent	(4) Log Rent	(5) Log Rent	(6) Log Rent	(7) Log Rent	(8) Log Rent
post=1 × surge	0.003	-0.017**						
	(0.007)	(0.008)						
post=1 × high_inc1=1 × surge		0.045***						
		(0.014)						
high surge (1ft) × post=1			0.027	-0.072*				
			(0.027)	(0.040)				
high surge (1ft) × post=1 × high_inc=1				0.122**				
				(0.054)				
high surge (2ft) × post=1					0.021	-0.058*		
					(0.020)	(0.034)		
high surge (2ft) × post=1 × high_inc=1						0.120***		
						(0.042)		
high surge (3ft) × post=1							-0.003	-0.073**
							(0.024)	(0.036)
high surge (3ft) × post=1 × high_inc1=1								0.118**
								(0.048)
Zipcode * Year	x	x	x	x	x	x	x	x
Zipcode * Surge	x	x	x	x	x	x	x	x
N	1371537	1371537	1371537	1371537	1371536	1371536	1371537	1371537

Table B.1 shows key coefficients from regression estimations of the DID version of equation 3 on log average rental income per unit, where the measure of heterogeneity is neighborhood income. The table shows an estimation using a continuous measure of surge height, and then three different variations categorizing high surge as more than 1ft of flooding, more than 2 ft of flooding and more than 3 ft of flooding. Clustered standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.2: FEMA Damage Assessment by Type of Alteration

	A1	A2	A3	Total
Major Damage/Destroyed	0.02	21.61	10.24	31.87
Minor Damage	0.01	39.33	10.01	49.36
Affected	0	3.17	8.78	11.95
No damage	0	0.20	6.61	6.82
Total	0.04	64.31	35.65	100.00

Notes: Table B.2 shows the percentage of voucher holders in high surge areas by the FEMA Damage Assessment classification and the type of alteration permit the building filed for in 2013.

Table B.3: Key Rental Impact Coefficients for High Surge Heterogeneity by Neighborhood Income

	(1) Street Easy	(2) Vouchers
high surge × post=1	-0.055	0.030
	(0.034)	(0.022)
high surge × post=1 × high_inc1=1	0.117***	-0.005
	(0.042)	(0.049)
N	1370102	680663
All Controls	X	X
Zipcode * Year	X	X
Zipcode * Surge	X	X

Notes: Table B.3 presents key heterogeneity coefficients for the broader market and voucher sample. Column 1 presents results from estimation with Street Easy sample and Column 2 with voucher sample. Full heterogeneity interactions are included in the regressions, as well as standard unit, building, flood zone controls. Clustered standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$

Table B.4: NOPV Summary Statistics (2005)

	High Surge	Low Surge	No Surge
Building Age	74.53	76.92	80.49
	(26.81)	(24.38)	(19.73)
Number of Res. Units	61.60	54.94	28.04
	(142.31)	(325.42)	(85.97)
Number of Floors	6.03	5.34	4.89
	(4.50)	(4.68)	(3.28)
Monthly Rental Income/Unit ($2021)	1768.16	1658.86	1618.50
	(1232.35)	(1568.16)	(1396.65)
Number of buildings	687	1639	29,562

Table B.4 shows means and (standard deviations) for the NOPV sample in 2005 by surge category.

Table B.5: Key Coefficients for NOPV DID High Surge Estimates

	(1) Log Avg Inc/Unit	(2) Log Avg Inc/Unit
high surge $\times$ post=1	-0.018	-0.035
	(0.014)	(0.028)
high surge $\times$ post=1 $\times$ high_inc=1		0.016
		(0.051)
Zipcode * Year	X	X
Zipcode * Surge	X	X
N	311827	311827

Table B.5 shows key coefficients from regression estimations of the DID version of equation 3 on log average rental income per unit, where the measure of heterogeneity is neighborhood income. The model also includes controls for the age and size of the building, whether it includes affordable housing, and whether it is located in the flood zone. Clustered standard errors in parenthesis. * $p < 0.10$ ** $p < 0.05$ *** $p < 0.01$