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Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market☆

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ABSTRACT

This paper analyzes the effects of hurricane Sandy on the New York City housing market using a large parcel-level dataset that contains all housing sales for 2003–2017. The dataset also contains geo-coded FEMA data on which building structures were damaged by the hurricane and to what degree. Our estimates provide robust evidence of a persistent negative impact on flood zone housing values. We show the gradual emergence of a price penalty among flood zone properties that were not damaged by Sandy, reaching 8% in year 2017 and showing no signs of recovery. In contrast, damaged properties suffered a large immediate drop in value following the storm (17–22%), followed by a partial recovery and convergence toward a similar penalty as non-damaged properties. The partial recovery in the prices of damaged properties likely reflects their gradual restoration. However, the persistent price reduction affecting all flood-zone properties is more consistent with a learning mechanism. Hurricane Sandy may have increased the perceived risk of large-scale flooding episodes in that area.

1. Introduction

Currently, sea levels are rising about 3 cm per decade (Stocker et al., 2013) and this rate is likely to accelerate in the coming decades. Almost unanimously, the scientific community predicts that this will lead to a higher prevalence of extreme weather events and large flooding episodes. The cumulative rise in sea levels will pose important economic challenges in many regions around the world. Arguably, dense urban areas on the shore will face the largest economic threats because of infrastructure and housing stock that cannot be easily relocated.[1]

Fortunately, the factors behind rising sea levels are well understood (warming oceans, loss of ice in glaciers and the thinning of the ice sheets) and scientists have produced detailed projections of the resulting increases in the risk of large-scale flooding. This information provides an opportunity to adopt measures to mitigate the costs of future flooding episodes but it is also likely to affect real estate markets in coastal areas facing increased flood risk (Kahn, 2010). Nonetheless, there are plenty of impediments to a gradual response, ranging from psychological biases to coordination problems, misguided policies, and the expectation of financial assistance by the government in case of disaster.[2] In this context, large-scale flooding events may play an important role in nudging agents to update their beliefs and act accordingly.[3]

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[1] According to Climate Central, nearly 5 million people in the United States currently live at locations that are likely to be flooded by the end of the century. The challenges are even more severe for China, with several fast-growing coastal urban areas, such as Shanghai, Tianjin or Shantou. Other examples of large cities in coastal areas are Mumbai, Miami, and Osaka (Hanson et al., 2011).

[2] From a global perspective, adjustments to the rise in sea levels over the long run may also be constrained by restrictions to international migration. As argued by Desmet et al. (2018), the geographic world distribution of productivity and income in the future will be largely shaped by the evolution of international migration restrictions.

[3] In the words of Sean Becketti, the chief economist for Freddie Mac, *"It is only a matter of time before sea level rise and storm surges become so unbearable along the coast that people will leave, ditching their mortgages and potentially triggering*

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This paper analyzes the impact of hurricane Sandy on housing prices in New York City. Hurricane Sandy hit New York on October 29, 2012, and was the largest Atlantic hurricane on record and the second costliest in U.S. history (behind hurricane Katrina), with damages amounting to over $19 billion.[4] To do so we assemble a large parcel-level dataset with rich geographic data. The data contain all property sales in New York City for the period 2003–2017, along with FEMA data on which building structures were damaged by hurricane Sandy and to what degree. Methodologically, we present difference-in-difference estimates of the effect of Sandy on housing prices, along with some more flexible specifications. In essence, identification of these effects is based on the change in housing values in (narrowly defined) neighborhoods affected by hurricane Sandy relative to unaffected neighborhoods. Importantly, we distinguish between the direct effects of the storm in terms of flooding and related damage, and the indirect effects on the prices of properties that were not damaged but are located on flood-prone areas. We also pay close attention to the evolution of the effects of the storm over time, which provides important information to assess the merit of competing explanations.

Our main finding is that hurricane Sandy has persistently reduced housing prices by about 9% in the city's flood zone, relative to similar properties in the rest of the city. Our analysis also shows larger price drops immediately after the storm for properties that suffered damage, ranging from 17% to 22%. However, by 2017, the price discount on those properties has converged toward the same level as for non-damaged properties located in the areas affected by Sandy, about 8%. Importantly, we also show that the price wedge between properties affected by Sandy and similar units elsewhere in the city did not exist prior to Sandy.

Possibly, our most intriguing finding is the gradual emergence of a price penalty associated with properties located in affected areas that were not damaged by hurricane Sandy. We examine a variety of mechanisms that could account for this finding, such as neighborhood deterioration (of houses and infrastructures) and expectations of increases in flood insurance costs. While we find evidence that some of these mechanisms played a role, we argue that the hypothesis that better aligns with our findings is that hurricane Sandy led to a persistent increase in the perceived risk of extreme events in flood-prone areas, which can be formalized with the belief updating process in Kozlowski et al. (2015). Clearly, repairing the housing stock and public infrastructures after a catastrophic event takes considerable time. However, this type of inertia should generate a *shrinking* price penalty in tune with the pace of recovery. In contrast, we find that non-damaged properties located on the flood zone have experienced a gradually *increasing* price penalty that seems to have stabilized at around 8% and, five years after the storm, shows no signs of recovery.

It is natural to view flood-related damage in coastal areas as draws from a probability distribution. Under rational expectations, property prices should naturally be a function of the moments of this distribution but should not be affected by individual draws.[5] In contrast to this view, many studies have documented large negative price effects following hurricanes and other catastrophic events (Hallstrom and Smith, 2005; Atreya et al., 2013; Bin and Landry, 2013; Zhang, 2016) as well as spikes in flood insurance take-up rates (Gallagher, 2014). However, these effects tend to be short-lived (very often completely vanished within 5 years) and are typically interpreted as temporary behavioral responses. While it is too early to be sure, our estimates suggest a more persistent negative effect on housing values, suggesting that other mechanisms may be at play. Compared to these studies, our analysis is based on a much larger and richer dataset, with detailed information on which properties suffered damage, and to which degree. In this respect, our analysis is closely related to a recent study by McCoy and Zhao (2018) who use data on building permits to analyze the effects of hurricane Sandy on house improvements in New York city. As we argue later, their findings are strongly complementary with ours.

The low persistence of the effects of flooding episodes on housing prices documented in the previous literature is in stark contrast to the findings of two recent papers that document extremely persistent effects of large shocks using datasets that are similar to ours in nature. Ambrus et al. (2016) analyze a cholera outbreak in a neighborhood in London in the 19th century. These authors also build a panel for housing prices at the parcel level over a long period of time, and match it to housing maps and to the the number of deaths in each house. They find that housing prices fell significantly in the affected area, with a large, permanent reduction in values. They argue that the cholera episode triggered selective out-migration, which permanently lowered socioeconomic status and housing values in the neighborhood. Hornbeck and Keniston (2017) study the aftermath of the 1872 Great Boston Fire using a longitudinal dataset of (assessed) housing values linked to the exact burned area. They document large *increases* in property values following the fire and argue that this was due to the (well-employed) opportunity to redevelop the zone, breaking away from inefficient inertia.

Our work is also related to the vast literature documenting that housing values reflect local amenities (Oates, 1969; Black, 1999; Fack and Grenet, 2010; Schwartz et al., 2014; Schwartz et al., 2003; Thaler, 1978; Manelici, 2017; Saiz and Wachter, 2011; Billings and Schnepel, 2017, among many others). In this light, it is natural to expect that changes to the perceived flood risk associated with a particular location will capitalize into lower housing values. Our paper is also related to studies on the general economic effects of climate change. McIntosh (2008) examined the effects of Katrina-related migration of evacuees on the Houston metropolitan area labor market. Deryugina et al. (2018) use data on individual tax returns to analyze the long-term economic effects of Katrina on the population of New Orleans. They find evidence of persistent geographical displacement, but only transitory effects on income and employment. Deryugina (2017) studies the role of government transfer programs, such as unemployment insurance, and shows that the relief they provide is at least as large as that coming from emergency aid. Groen et al. (2015) estimate the effects of hurricanes Katrina and Rita on employment and earnings. Using individual panel data these authors also find evidence of a temporary reduction in income, followed by prolonged increase in earnings due to the increased labor demand in sectors related to rebuilding. There have also been important theoretical contributions to this literature, such as Desmet and Rossi-Hansberg (2015) who develop a dynamic spatial theoretical model of trade, innovation and growth to analyze the global effects of climate change. Desmet et al. (2018) go on to extend the previous framework by endogenizing migration, and use the model to simulate the effects of a rise in sea level. A number of studies analyze weather shocks in an international context. Gröger and Zylberberg (2016) analyze coping mechanisms through internal remittances and migration after catastrophic natural disasters. More closely related to our study, Kocornik-Mina et al. (2015) examine a large dataset of massive flooding events across the world and find that economic activity (measured by night lights) typically returns to pre-flooding levels after one year.

The rest of the paper is organized as follows. Section 2 describes the main data sources and presents descriptive statistics. Section 3 presents our main estimates and a detailed discussion of potential selection issues. Section 4 discusses the potential mechanisms behind our findings, and Section 5 concludes.

2. Data and descriptive statistics

Essentially, our analysis relies on a dataset that combines the universe of housing sales for New York City and FEMA data on the exact

another housing meltdown – except this time, it would be unlikely that these housing prices would ever recover." (The New York Times, 11/24/2016).

[4] Hurricane Sandy flooded 17% of the city and nearly 90,000 buildings.

[5] For theoretical frameworks designed to study the effects of flood risk on housing prices, see Frame (1998) and Bakkensen and Barrage (2017).

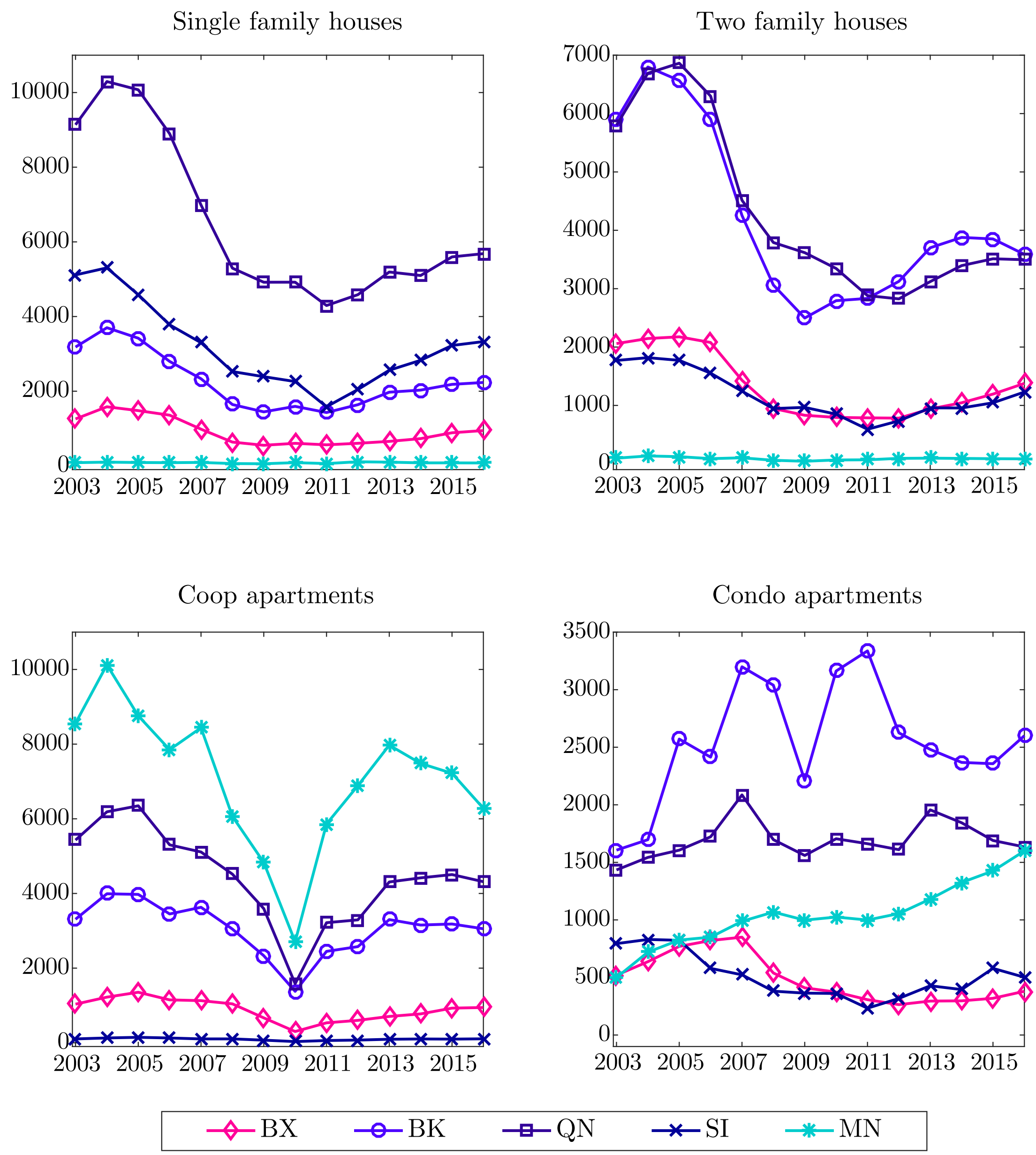

Fig. 1. Transactions (sales counts).
Notes: Transactions-based data from the NYC Department of Finance, 2003–2017. For each housing type we report data by borough: Bronx (BX), Brooklyn (BK), Queens (QN), Staten Island (SI) and Manhattan (MN).

structures that were damaged by hurricane Sandy. We merged these two datasets relying on the PLUTO dataset provided by the New York City Department of Planning, which contains shape files for the footprints of all building structures in the city as well as the associated tax lot numbers.

2.1. Data sources and definitions

2.1.1. Housing prices

Our main outcome variable is the sale price of a housing unit. Our data on housing prices is based on the universe of transactions (sales) for residential properties that took place in New York City between years 2003 and 2017 (NYC Department of Finance). Transactions-based datasets are very sparse because most housing units only appear only once in the data.[6] Besides sale price, the dataset also contains information on the parcel (tax lot) number of the property, the building class (e.g. single family home, condo, and so on), and the exact date the sale took place.

We merge the data for all years (and boroughs) and do some minimal trimming. Specifically, we eliminate units with a sale price below $10,000 or above $15,000,000.[7] Fig. 1 reports the count of annual transactions by building class and borough, which reveals a very different geographical distribution for apartments and houses across the city boroughs. The first row summarizes the counts of sales for single-family and two-family homes, which prevail in Queens and Brooklyn. In both cases the trends clearly match the housing cycle with a dramatic slow down

[6] In fact, the majority of units do not appear in any given year because they were not sold in that year.

[7] In the raw data we had around 1.2 million observations. These two sample restrictions reduce the sample size to roughly 0.87 million observations by eliminating title changes not linked to sales, or sales of garages and other small constructions inside a lot. We also drop housing units that are sold 10 or more times during the 14-year period covered by our dataset.

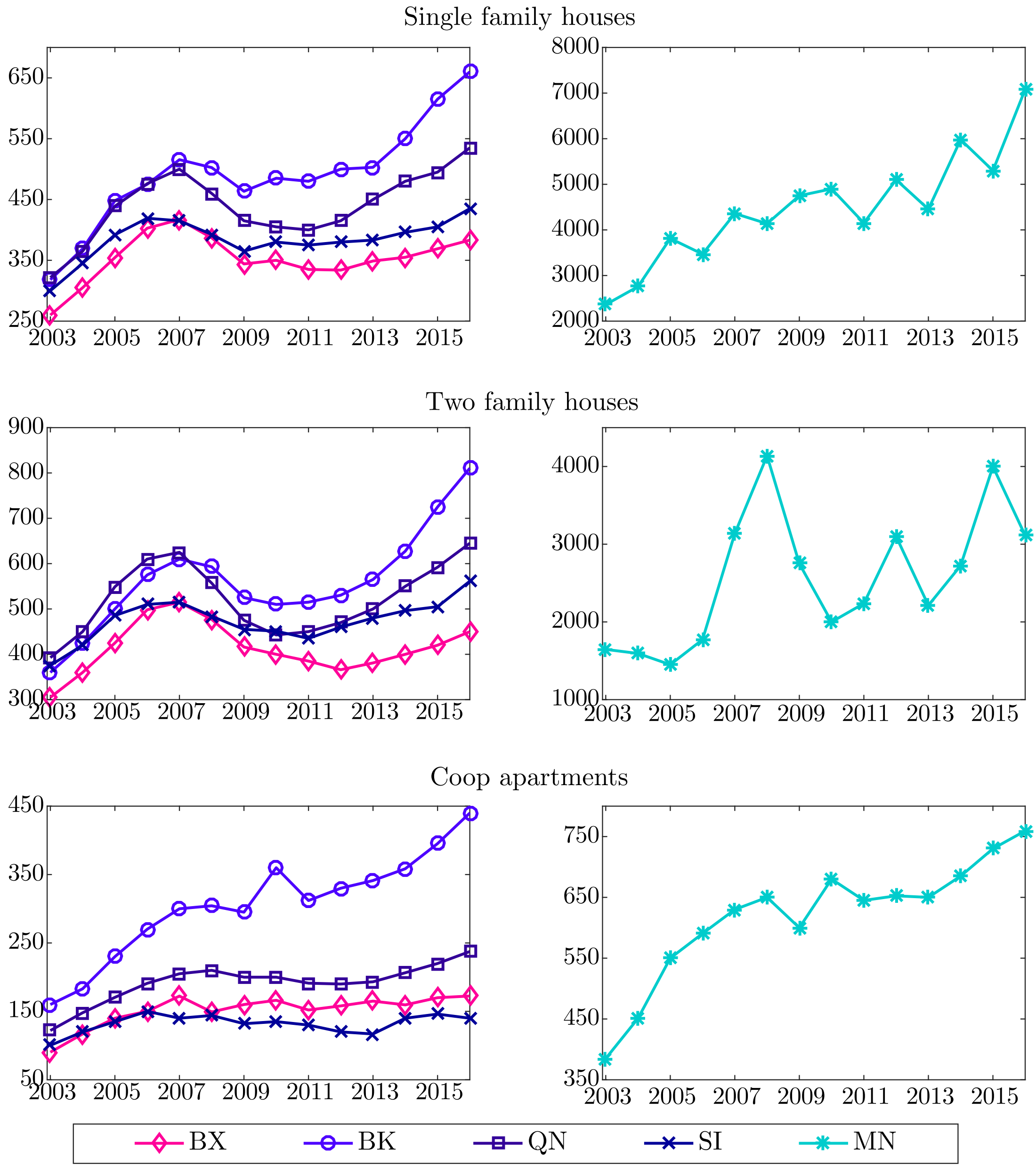

Fig. 2. Median Sale Prices by Housing Type and Borough (in thousands of $).
Notes: Transactions-based data from the NYC Department of Finance, 2003–2017. For each housing type we report data by borough: Bronx (BX), Brooklyn (BK), Queens (QN), Staten Island (SI) and Manhattan (MN).

in sales after 2006 that only started recovering after 2010. In contrast the sales of apartments (particularly in coop buildings) are uniformly higher in Manhattan. Turning now to sale prices, Fig. 2 reports median prices by borough and building type. The right column presents the data for Manhattan and the remaining four boroughs are collected in the left column (with a different scale). The top and middle figures on the left panel, corresponding to 1-family and 2-family homes in the outer boroughs, clearly trace the housing cycle, with prices rising up until 2007, then falling for four years and beginning their recovery around year 2012. In comparison, housing prices in Manhattan appear less sensitive to the economic cycle.

2.1.2. FEMA data

To measure the damage caused by hurricane Sandy we rely on building point-damage determination estimates provided by FEMA. These data, also recently used in McCoy and Zhao (2018), combine inundation measurements with field-verified aerial imagery by FEMA's Modeling Task Force.[8] This dataset contains damage estimates for each of the almost 320,000 buildings in the Sandy inundation zone and includes over 15,000 points outside that zone for which aerial imagery damage determinations were made.[9]

In this dataset each building point is identified by its longitude and latitude. Variable *DMGCOMBO*, which stands for combined measure of damage, provides a categorical measure of the damage suffered by each

[8] The Modeling Task Force is a group of experts specialized in impact assessments for earthquakes, hurricanes, and other natural disasters. This task force plays an important role in developing best estimates of the impacts before, during and after the events. Specifically, during hurricane Sandy the Modeling Task Force coordinated with the U.S. Geological Survey to deploy surge sensors and field teams to obtain surge assessments.

[9] Where available, the aerial imagery overrules the inundation-based damage assessment. In particular, "destroyed" determinations were only based on imagery.

Table 1
Summary statistics by borough. Sales-FEMA dataset.

Borough	Obs.	Sale price (median)	% HEZ AB	% Major damage	% Major flooding
1 Manhattan	113,766	655,707	6.07	0.00	0.24
2 Bronx	61,215	380,814	1.91	0.01	0.01
3 Brooklyn	173,897	518,836	19.46	0.86	0.66
4 Queens	245,419	411,934	8.26	0.78	0.47
5 Staten Island	68,854	404,107	16.30	0.00	3.06
NYC	663,151	456,390	11.07	0.52	0.71

Notes: Sales data for years 2003–2017. Pct. denotes percent. HEZAB is an indicator for being located in hurricane evacuation zones A or B. Column 4 reports percent of units that suffered major damage or were destroyed. Column 5 reports percent of units that suffered more than 5.5 ft of flooding. Condos are not included in this sample because they could not be matched.

property due to Sandy. According to FEMA, this is the best measure of damage for inundation events, like Sandy, because it complements aerial imagery with observed inundation depths for each structure. Importantly, this dataset provides damage estimates for all structures in the inundation area, rather than only those that applied for assistance, which would introduce serious issues of sample selection. The combined damage variable takes four values: affected (1), minor damage (2), major damage (3) or destroyed (4).[10] Appendix Table C.2 shows that over 13% of all buildings in New York's inundation zone suffered major damage, with Staten Island and Queens being the hardest hit boroughs.

In addition, we also use FEMA data on hurricane Sandy's storm surge.[11] These data provide the geographic boundary of the area that got flooded during hurricane Sandy at very high geographic resolution. In addition the data report the level of flooding at each point (coded in a variable named *Depth*). As noted earlier, the surge data are also an input into the point-damage estimates, inducing high correlation between the two measures. One reason we are interested in the storm surge data set because it allows us to build measures of the effects of Sandy that are not affected by idiosyncratic differences across properties in the level of preparedness for the storm.

2.1.3. Flood zone definition

We view all housing units located on New York's flood zone as potentially affected by hurricane Sandy. Some of those properties were flooded and suffered damage in ways that we can measure. However, other properties in the flood zone may have been affected in other ways, including disruptions in transportation, blackouts, or by a reduction in housing values at the neighborhood level, among other factors.

A common way to define flood zones in New York City is based on the hurricane evacuation zones (HEZ) defined by the city's Emergency Management department.[12] Specifically, the city is subdivided in 3 evacuation zones with decreasing flooding risk, with zone A being the one with the highest risk (depicted in Appendix Fig. C.1.). In our main analysis we define the city's *flood zone* as the combination of evacuation zones A and B, which we denote by HEZAB, but we will conduct sensitivity analysis regarding this choice.[13] As shown in Appendix Table C.1, about 13% of the city's parcels are located in HEZAB (and 4% in HEZA).

Table 2
Summary statistics. Sales-FEMA dataset.

Variable	Obs	Mean	Std. dev.	Min	Max
Year	663,151	2009	4.579	2003	2017
HEZ A	663,151	0.034	0.181	0	1
HEZ AB	663,151	0.111	0.314	0	1
HEZ ABC	663,151	0.265	0.441	0	1
DMGCOMBO	663,151	0.091	0.409	0	4
Dam0	663,151	0.061	0.239	0	1
Dam1	663,151	0.045	0.207	0	1
Dam2	663,151	0.005	0.071	0	1
Depth	663,151	0.181	0.884	0	14.004
Sur0	663,151	0.054	0.226	0	1
Sur1	663,151	0.05	0.217	0	1
Sur2	663,151	0.007	0.084	0	1
Sale price	663,151	665,142	1,024,013	10,000	1.50e+07
Bclass 1-fam	663,151	0.292	0.455	0	1
Bclass 2-fam	663,151	0.246	0.431	0	1
Bclass 3-fam	663,151	0.064	0.245	0	1
Bclass Coops	663,151	0.332	0.471	0	1
Bclass Condos	663,151	0	0.003	0	1
Bclass Rentals	663,151	0.064	0.244	0	1
Gross sqf.	441,160	3475	19036.11	1	3,750,565
Price sqf.	441,160	327	6254.745	0.013	1,350,000
Year built	659,942	1941	28.045	1798	2015
Year altered1	123,345	1992	12.208	1900	2014
Year altered2	12,155	2003	10.041	1921	2014

Notes: Data contains sales 2003–2017. HEZ corresponds to hurricane evacuation zones. *DMGCOMBO* is the FEMA categorical value establishing the level of damage suffered by each property, and it is the basis for the definition of the $Dam0 - Dam2$ indicator variables. *Depth* is the FEMA variable measuring the depth of the surge for each property, and it is the basis for the definition of the $Sur0 - Sur2$ indicator variables. Category *Bclass 1-fam* refers to building class 1-family houses. The other building classes we consider are 2-family homes, 3-family homes, apartments in Cooperative buildings, Condos and rental units. Condos are not included in our final dataset. Gross square footage and the price per square foot are conditional on a positive value for gross square footage.

2.2. Descriptive statistics

Next, we provide descriptive statistics on our estimation sample (Table 2), which contains 663,151 property (tax lot-apartment) by year observations. Besides the sale price, we build indicators for being located on the flood zone (defined on the basis of hurricane zones). Our

[10] For example, a building is declared to have suffered *major damage* if aerial imagery showed that more than 20% of the roof diaphragm was destroyed and some exterior walls collapsed. In terms of the inundation assessment, a classification of major damage requires a field verified flood depth greater than 5 ft. Our understanding is that when either of these conditions is met the property is considered to have suffered *major damage*. In comparison, a property is considered *destroyed* only if aerial imagery revealed that the majority of the exterior walls collapsed. For further details on the exact definition of the FEMA damage classification, visit http://www.arcgis.com/home/item.html?id=307dd522499d4a44a33d7296a5da5ea0.

[11] According to NOAA (the National Oceanic and Atmospheric Administration), *storm surge* is the abnormal rise in of water generated by a storm, over and above the predicted astronomical tide. The raw storm surge data contain 350,154 latitude-longitude observations in New York city.

[12] All city residents are familiar with the hurricane evacuation zones as they are used to communicate evacuation orders. Alternatively, one could use FEMA's flood maps, which overlap heavily with the city's HEZ map. FEMA's 100-year floodplain overlaps heavily with hurricane evacuation zone A.

[13] Analogously, we define HEZA as the set of properties in hurricane evacuation zone A.

main definition of the flood zone is *HEZAB*, the indicator for being in hurricane evacuation zones A or B, which is the case for 11% of the observations. We view set *HEZAB* as containing all units that are subject to high risk of coastal flooding in the event of a hurricane.

We define indicators for the level of damage suffered during Sandy. These indicators effectively partition the set of units located on *HEZAB*. Specifically, we define *Dam*0 as the indicator for units in *HEZAB* that were not damaged by hurricane Sandy according to FEMA. *Dam*1 is an indicator function for units in *HEZAB* that suffered at most minor damage while *Dam*2 is the indicator for the units in *HEZAB* that suffered major damage or were destroyed. The relative frequency of these categories in our dataset is 6.1% , 4.4%, and 0.5%, respectively. Given that 11% of the observations belong to the flood zone (*HEZAB*), almost half of the sales in the flood zone correspond to properties that suffered some degree of damage. We also build alternative measures of damage that are purely based on FEMA's storm surge data. We again define three indicators that partition the flood zone. *Sur*0 is an indicator for those units in *HEZAB* that were not flooded. In turn, *Sur*1 and *Sur*2 are indicators for being in *HEZAB* and having registered flooding below or above 5.5 ft, respectively.[14]

Table 2 also shows that the average sale price (in current dollars) was slightly over $665,000.[15] The table also reports the distribution of observations over building classes, where we distinguish between 1-, 2-, and 3-family homes, Coop apartments, Condos, and apartment buildings devoted to rental. By far the three most important categories are 1-family homes (29%), 2-family homes (25%), and Coop apartments (33%), which combined amount to 87% of all observations in our dataset. The table ends with some important control variables: (gross) square footage, which is only meaningful for houses, year built, and the last two years when a property was altered, according to city records.[16]

3. Main estimates

3.1. Specifications and identification

In essence we want to compare the price trajectories of housing units affected by hurricane Sandy to similar housing units that were not affected. One challenge we face is that the storm affected properties in several ways. While some properties suffered damage others were affected in more subtle ways through externalities or changes in flood risk beliefs, similar to the effects emphasized in Abadie and Dermisi (2008). For this reason we view all units in the flood zone (defined by *HEZAB*) as our treatment group. Using the FEMA point-damage data we can consider several types of 'treatment'. Specifically, we partition the set of observations located on the flood zone (*HEZAB*) into three groups: non-damaged properties, moderately damaged properties, and severely damaged properties. Each of these groups is identified by indicator variables *Dam*0, *Dam*1 and *Dam*2, respectively.

The second challenge in this type of analysis is the choice of the 'control group', which ideally would consist of observations pertaining to similar properties that were not affected by hurricane Sandy. In our regression models, the control group consists of sales of properties located outside the flood zone.[17] Clearly, properties inside and outside the flood zone differ in obvious ways: distance to the city center, elevation, type of building and age, and so on. In order to make the two groups as comparable as possible, we take advantage of the richness of our dataset and include fixed-effects for narrowly defined neighborhoods (city blocks).

Naturally, including property fixed-effects in our estimation would absorb even more unobserved heterogeneity. However, this would entail an enormous loss of information, given that the majority of properties in our dataset were sold only once during our sample period, and introduce serious concerns of selection bias. As argued below, in practice, city-block fixed-effects soak up a great deal of individual unobserved heterogeneity. These fixed-effects are a highly effective method to account for geographical heterogeneity, such as location and elevation, as well as differences in construction quality. The reason is that individual properties within a block tend to be fairly homogeneous in terms of materials and construction code. Furthermore, we control for each property's year of construction (and last alteration) and base our preferred set of estimates on the sub-sample of 1-family and 2-family homes.[18] Nevertheless, it is still possible that Sandy might have induced selection into the sample of properties being sold, and we will explicitly address these concerns later on by providing property-fixed effects estimates and analyzing the effect of the storm on sales activity.

Estimation of these effects lends itself nicely to a difference-in-difference estimator. Consider an observation (i, z, t), where i refers to an individual house or apartment, z to the neighborhood, and t to the sale period. Our empirical model for the log of the sale price is given by

$$\begin{aligned} \ln p_{izt} = {} & \alpha_z + \alpha_t + \gamma_0 Dam0_i + \gamma_1 Dam1_i + \gamma_2 Dam2_i \\ & + Post_t \times (\beta_0 Dam0_i + \beta_1 Dam1_i + \beta_2 Dam2_i) + \gamma' X_{iz} + \varepsilon_{izt}, \end{aligned} \tag{1}$$

where α_z denotes neighborhood fixed-effects that will absorb all time-invariant differences in prices across neighborhoods, α_t denotes quarter-year dummy variables, and X_{iz} collects property-specific controls, such as year built or last altered or square footage.[19] Indicator variables $Dam0_i$, $Dam1_i$, and $Dam2_i$ denote the level of damage caused by Sandy, as defined earlier, and the excluded category contains sales outside the flood zone. Note also that the coefficients accompanying the damage indicators will capture pre-Sandy differences in housing prices between the control and treatment groups. Ideally, these coefficients will be estimated to be close to zero.

The most important coefficients for our purposes are the interaction terms between the post-Sandy indicator ($Post_t$) and the damage indica-

[14] This cutoff is the 90th percentile of the *Depth* variable, conditional on positive values, and was chosen so that the distribution of the surge-based indicators roughly resembles that of the damage-based indicators.

[15] As we discuss in the Appendix, even though Staten Island was the borough that suffered the most damage, it is not part of our sales-FEMA dataset. The reason is that none of the damaged properties in Staten Island have been sold within the period 2003–2017. Consequently, Staten Island will not play any role in the identification of the damage treatments. However, the Staten Island sales do play a role when we define treatment on the basis of storm surge, or when we use the data on assessed market values (described later).

[16] Gross square footage is the sum of the surface of all construction in a lot, including basements, higher floors, and additional structures. In the analysis we combine year built and year altered into a single variable that replaces the year built by the most recent year of alteration. We then build categories for this variable and include them as dummy variables in our regression models.

[17] We exclude a very small number of sales pertaining to properties outside the flood zone that suffered damage during hurricane Sandy. In most cases the damage was due to strong winds rather than flooding. We also acknowledge that it is not strictly correct to assume that housing units outside the flood zone were not affected by the storm. After all, all housing units belong to New York's housing market. However, the flood zone is a relatively small part of the market, accounting for about 11% of the sales, and thus the effects of hurricane Sandy outside the flood zone were greatly diluted.

[18] By excluding apartments, the sub-sample of homes provides a more homogeneous sample and allows us to include additional controls, such as square footage. In addition, while one can argue that Sandy damaged some houses in a neighborhood while leaving others intact, this is not the case for apartments. Apartment buildings affected by Sandy experienced flooded common areas and damaged the electrical systems powering elevators. While obviously disruptive, it is unclear how this may have affected the prices of individual housing units.

[19] The reason that the building's age is relevant is that older buildings were typically subject to less demanding construction codes. As a result, older 1-family houses suffered the most severe structural damage. Specifically, these buildings accounted for only 18% of the buildings in Sandy's inundation zone. However, they accounted for 73% of all damaged buildings.

Table 3
Neighborhood fixed-effects models. Damage and surge indicators.

Dep. var. ln p Estimation	1 LSDV	2 LSDV	3 Within	4 Within	5 Within	6 Within	7 Within
Dam0	0	0.01	0	−0.01	−0.01	−0.03	0.01
	[0.03]	[0.04]	[0.05]	[0.03]	[0.03]	[0.05]	[0.03]
Dam1	−0.06*	0.04	−0.03	−0.02	−0.01	−0.02	0.04
	[0.03]	[0.08]	[0.06]	[0.03]	[0.03]	[0.05]	[0.04]
Dam2	−0.33***	−0.19**	−0.05	−0.01	−0.08*	−0.09	0.04
	[0.02]	[0.09]	[0.06]	[0.04]	[0.04]	[0.06]	[0.06]
Post × Dam0	−0.06	−0.06	−0.07***	−0.05***	−0.08**	−0.08*	−0.12***
	[0.04]	[0.04]	[0.01]	[0.01]	[0.03]	[0.05]	[0.01]
Post × Dam1	−0.07	−0.08**	−0.09***	−0.10***	−0.14***	−0.15***	−0.10***
	[0.07]	[0.04]	[0.01]	[0.01]	[0.04]	[0.05]	[0.02]
Post × Dam2	−0.15	−0.15	−0.17***	−0.18***	−0.08	−0.08	−0.14***
	[0.13]	[0.09]	[0.04]	[0.03]	[0.08]	[0.09]	[0.05]
Post × Sur0	−0.02	−0.02	−0.03*	−0.03***	−0.07**	−0.09*	−0.08***
	[0.06]	[0.04]	[0.02]	[0.01]	[0.04]	[0.05]	[0.02]
Post × Sur1	−0.09	−0.09**	−0.12***	−0.11***	−0.11***	−0.13**	−0.13***
	[0.05]	[0.03]	[0.01]	[0.01]	[0.04]	[0.05]	[0.01]
Post × Sur2	−0.21***	−0.22***	−0.20***	−0.17***	−0.06	−0.07	−0.16***
	[0.03]	[0.06]	[0.03]	[0.03]	[0.06]	[0.07]	[0.03]
Observations	660,211	660,211	660,211	354,310	354,310	113,436	354310
Nbh. FE	borough	zip code	block	block	block	block	block
N. clusters	5	183	24,236	22,062	22,062	6755	22,062
Clustered s.e.	borough	zip code	block	block	block	block	block
Building types	all	all	all	fam12	fam12	fam12	fam12
Sample	all	all	all	all	all	HEZ	all
Trends	city	city	city	city	block × year	block × year	city
Treated	HEZAB	HEZAB	HEZAB	HEZAB	HEZAB	HEZAB	HEZA

Notes: Models estimated on the Sales-FEMA dataset. Dependent variable is the log of the sale price. Included in all specifications, but not displayed in table: quarter-year dummies and year built or last altered categories. In specifications 4–7 we also control for the log of gross square footage. Post is defined as a sale occurring in November 2012 or later. *Dam*0 is a dummy variable for whether the unit is located in HEZAB but did not suffer any damage. *Dam*1 indicates if a unit located in HEZAB was affected but suffered at most minor damage. *Dam*2 indicates if a unit located in HEZAB suffered major damage or was considered destroyed. *Sur*0 is a dummy variable that takes a value of one if a unit is located in HEZAB but was not flooded. *Sur*1 is an indicator for whether a unit was located in HEZAB and experience storm surge depth between 0 and 5.5 feet. *Sur*2 indicates if a unit located in HEZAB experienced storm surge above 5.5 feet (90th percentile conditional on positive storm surge). Columns 5-6 include block-times-year dummies (and are based on the estimator by Correia (2016)). In column 7 the damage indicators (and their interactions with the post-Sandy dummy) partition HEZA, as opposed to HEZAB. The sample excludes the damaged properties outside of HEZAB, which reduces the sample by about 7,000 BBL-year observations. Standard errors clustered at the indicated neighborhood level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

tors.[20] These coefficients are the difference-in-difference estimates for our three treatments. We expect these coefficients to be negative, reflecting a price reduction in the post-Sandy period, and to be ordered in the following manner: $\beta_2 \leq \beta_1 \leq \beta_0 \leq 0$. Regarding the stochastic specification of the model, we assume that the error terms are uncorrelated across neighborhoods, but allow for correlation across properties within a neighborhood and over time. Consequently, we will report standard errors clustered at the neighborhood level.

In some specifications we will also include neighborhood-specific price trends, denoted by α_{zt}. These trends will absorb any time-varying neighborhood characteristics that may affect housing prices and may be hard to measure, such as changes in amenities or socio-demographic composition. However, these trends may also soak up some effects of hurricane Sandy, as would be the case if the hurricane increased the perceived risk of flooding or triggered business divestment in a neighborhood.

The key identifying assumption in difference-in-difference estimation is that of parallel trends. In short, we require that prices for units in the treatment group would have evolved similarly to the prices of units in the control group. Typically, the validity of this assumption is assessed by comparing price trends for the control and treatment groups in the pre-Sandy period. Fig. 4 (top panel) plots the year-by-year difference in the average sale prices for properties in and out of the flood zone (*HEZAB*) for the 1-family and 2-family sample, after controlling for city-block fixed-effects, year dummies, the log of square footage, and year built or last altered. Prior to 2013 the price gaps are small and fairly constant over time, providing strong support for the parallel trends assumption. The bottom panel allows us to assess this identifying assumption for our treatments that distinguish by damage levels. The treatment-control price gaps corresponding to treatments *Dam*0 and *Dam*1 are fairly constant over the pre-Sandy period, once again providing strong evidence in support of the parallel trends assumption for these treatments. The evidence is much less clear for treatment *Dam*2. In this case, the estimated price gaps vary widely over the 2004–2012 period, reflecting the small size of the group of severely damaged properties, but we cannot reject the hypothesis of a zero price gap in any of the years (as we discuss later).

3.2. Damage treatments

Table 3 reports the estimates for the model in Eq. (1). In all specifications the dependent variable is the log of the sale price and quarter-year dummies are included (but not displayed), along with categories for year built or last altered. Columns 1–3 report estimates based on the whole sample (660,211 observations), which includes both houses and

[20] Hurricane Sandy hit New York City on October 29, 2012. Hence, the first quarter that may display an effect is the first quarter of 2013. We define the $Post_t$ indicator as taking a value of one for sales in November 2012 or later.

apartments. As we move from columns 1 to 3 we employ increasingly narrower definitions of neighborhood, moving from borough (5), to zip code (183), and city block (over 24,000). Let us first focus on the point estimates for the damage indicators. In column 1 the coefficients of variables *Dam*1 and *Dam*2 are negative and significantly different from zero, indicating that, prior to hurricane Sandy, the average sale price for these types of properties was lower in the flood zone (*HEZAB*) than elsewhere in the city. However, as we adopt narrower definitions of neighborhood, the point estimates fall (in absolute value) and become statistically insignificant.

Next, we turn to our main coefficients of interest, the interaction terms between the damage indicators and the post-Sandy dummy variable. Across all specifications we find negative point estimates. Specifically, in column 3, these point estimates are negative and significantly different from zero, indicating a reduction in the prices for housing units in the flood zone in the aftermath of the storm. Note also that the price reduction is increasing in the damage caused by Sandy, ranging between 7 and 17 log points. In columns 4–7, we restrict to the subsample of 1-family and 2-family houses (354,410 sales) and include the log of gross square footage as a control. The difference-in-difference estimates of the three damage treatments in column 4 are practically the same as in the previous column, with price penalties ranging from 5 to 18 log points.[21]

Let us now consider a number of robustness checks. Column 5 introduces city-block-by-year neighborhood trends.[22] The point estimates for the *Dam*0 and *Dam*1 treatments increase (in absolute value), relative to column 4, as well as the associated standard errors. In contrast, the estimated effect for treatment *Dam*2 falls by half and becomes insignificantly different from zero. Column 6 restricts the sample to housing units located within one of the three hurricane evacuation zones, which effectively changes the control group from housing units outside hurricane evacuation zones A and B to units in evacuation zone C, which may provide a more homogeneous control group. The estimates are almost identical to those in column 5. Column 7 adopts a more restrictive definition of flood zone, defining it as hurricane evacuation zone A. As before, we partition the sales in this zone by damage levels.[23] The estimates reported in column 7 show a 12 log-point post-Sandy price decline for non-damaged properties relative to undamaged properties outside HEZA. This is about twice as large (in absolute value) as the estimate reported in column 4, suggesting that residents of evacuation zone A may have felt the effects of the hurricane much more vividly than those located in the lower risk evacuation zone B. As for damaged properties, the estimated price reductions range between 10 and 14 log points.

3.3. Surge treatments and endogenous mitigation

One potential concern behind our previous estimates is that the actual damage incurred by a house during hurricane Sandy may have been a function of the idiosyncratic value of the property, possibly biasing our estimates because of endogenous mitigation efforts. One way to address this concern is to define 'treatments' on the basis of the level of flooding due to Sandy's storm surge (also collected by FEMA). Accordingly, we partition the flood zone (*HEZAB*) into three groups. The first group identifies sales pertaining to properties on the flood zone that did not experience flooding (*Sur*0). Indicator variables *Sur*1 and *Sur*2 identify sales pertaining to properties that experienced a storm surge of less or more than 5.5 ft, respectively, during hurricane Sandy.[24]

Difference-in-difference estimates of the surge-based treatment effects are reported in the bottom panel of Table 3. Our preferred estimates refer to the sample of 1-family and 2-family homes and are collected in column 4. These estimates suggest price penalties that are very similar to those based on measured damage, with 3, 11 and 17 log points, respectively, pertaining to treatments *Sur*0, *Sur*1 and *Sur*2.[25]

Our surge-based estimates are also informative regarding the nature of the price reduction for non-damaged properties on the flood zone (*Dam*0). One plausible interpretation for this finding is that the storm affected these properties in ways that are not captured by our damage measures. For instance, some of the properties identified by indicator *Dam*0 may have suffered water damage and developed mold, which would have reduced their value. However, this is less of a concern for the *Sur*0 treatment group, which contains properties that were not flooded and thus much less likely to develop mold, for which we estimate a 3 log-point price reduction. Thus, while mold may partly explain the 5-log point price reduction for *Dam*0 properties, other factors were also at play. It is also worth noting that the inclusion of city-block trends (in columns 5 and 6) raises the estimate for treatment *Sur*0 to 7–9 log points, and in line with the estimated effect for *Dam*0.

3.4. Selection

The main limitation of the estimates in the previous section arises from the fact that we are not able to account for all potentially relevant dimensions of property-level heterogeneity. As a result, we are concerned that properties sold before and after Sandy in the affected neighborhoods may differ systematically. For example, it could be the case that only the relatively better properties were sold after Sandy, inducing positive selection into sales and leading us to *underestimate* the price reductions caused by the storm.

We address the selection concerns in two ways. First, we estimate models including property-fixed effects (on the subsample of repeat sales and on a new dataset that contains imputed market values for all properties) and, secondly, by analyzing whether Sandy affected the volume of sales on the basis of measured damage. Our property fixed-effects specifications are the following:

$$\ln p_{it} = \alpha_i + \alpha_t + \beta HEZAB_i \times Post_t + \varepsilon_{it} \quad (2)$$

$$\ln p_{it} = \alpha_i + \alpha_t + \left(\beta_0 Dam0_i + \beta_1 Dam1_i + \beta_2 Dam2_i\right) \times Post_t + \varepsilon_{it}, \quad (3)$$

[21] Estimating the model on the sub-sample of apartment units does not produce any significant estimates. As argued earlier, this is because there is not enough variation in the effects of Sandy across apartments within the same building. In addition, the cooperative ownership structure ties together the values of the individual units in the same building.

[22] The estimation of the models with city-block trends was implemented using the estimator developed by Correia (2016).

[23] Thus, *Dam*0 is now an indicator for undamaged properties located on hurricane evacuation zone A. Likewise, *Dam*1 and *Dam*2 are moderately and severely damaged units, respectively, located on hurricane evacuation zone A. This choice has two immediate implications. First, there will be a higher prevalence of heavily damaged units (*Dam*2) relative to moderately or non-damaged units, relatively speaking. Second, the control group, now includes most of the units in hurricane evacuation zone B, along with the units in evacuation zone C and in the rest of the city. Intuitively, these two changes act in opposite directions regarding the post-Sandy price changes in the flood zone (now defined by HEZ A) so it is not clear how the main results will be affected.

[24] These surge indicators are based on the *Depth* variable summarized in Table 2. As expected, the damage and surge indicators are strongly correlated. The pairwise correlation coefficients for (*Dam*0, *Sur*0), (*Dam*1, *Sur*1), and (*Dam*2, *Sur*2) are, respectively, 0.86, 0.83, and 0.47.

[25] We have also experimented with an instrumental-variables approach where we instrument the damage treatments using the storm surge indicators. More specifically, we have restricted our estimation sample to the flood zone (defined as *HEZAB*), defined a single damage treatment (*Dam*), identifying units that suffered some degree of damage, and used a single measure of storm surge as an excluded instrument. The results are reported in column 7 of Table 7. The difference-in-difference estimate of the effects of suffering damage during Sandy is highly significant and implies a 13 log-point price reduction, which is roughly twice as large as the estimate that assumes that damage is exogenous (conditional on our control variables and block fixed-effects) reported in column 6. Thus the estimated effects of damage from Sandy presented earlier may be too conservative.

Table 4
Property fixed-effects. repeat sales (columns 1–5) and imputed market values (columns 6–8).

Dep. var. ln p	1	2	3	4	5	6	7	8
Post × HEZAB	−0.09***	−0.06***				−0.16***		
	[0.01]	[0.01]				[0.001]		
Post × Dam0			−0.04***		−0.02		−0.12***	
			[0.01]		[0.01]		[0.001]	
Post × Dam1			−0.09***		−0.07***		−0.22***	
			[0.02]		[0.03]		[0.001]	
Post × Dam2			−0.15***		−0.14***		−0.23***	
			[0.05]		[0.05]		[0.003]	
Post × Sur0				−0.04**				−0.09***
				[0.02]				[0.001]
Post × Sur1				−0.09***				−0.23***
				[0.02]				[0.001]
Post × Sur2				−0.05				−0.26***
				[0.03]				[0.004]
Obs.	310,335	158,502	158,502	158,502	158,502	11,389,285	11,389,285	11,389,285
Properties	131,037	66,364	66,364	66,364	66,364	668,943	668,943	668,943
R-squared	0.19	0.158	0.158	0.158	0.183	0.803	0.804	0.804
FE	BBL-Apt	BBL	BBL	BBL	BBL	BBL	BBL	BBL
Sample	All	Fam12	Fam12	Fam12	Fam12	Fam123	Fam123	Fam123
Trends	City	City	City	City	Zip code	City	City	City

Notes: All models contain property (BBL) fixed-effects. In model 1 properties are identified by BBL and apartment number. Models 1–5 are estimated on the Sales-FEMA final dataset, the dependent variable is the log of the sale price, and include (but not displayed in the table) quarter-year dummies. In addition, column 5 includes zip-code-specific linear time trends. Models 6–8 estimated on the dataset using assessed market values. The definitions for dummy variables HEZAB, Dam0-Dam2 and Sur0-Sur2 are the same as in the previous tables. The sample excludes the damaged properties outside of HEZAB. Standard errors clustered at the city block level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

where α_i are fixed-effects that remove time-invariant differences across properties, α_t are quarter-year dummies, and we also include interaction terms for post-Sandy sales ($Post_t$) with damage indicators. The property-level characteristics included in our dataset are time-invariant and, hence, would be redundant because of the property fixed-effects. As before, we cluster standard errors at the city block level.[26] That is, we assume that price shocks across city blocks are uncorrelated, but allow for arbitrary correlations across individual properties within the block and over time.

3.4.1. Repeat sales

Let us now restrict to the sample of sales pertaining to properties that were sold more than once during period 2003–2017. Naturally, this reduces our sample size substantially but allows us to estimate the more demanding fixed-effects specification. Close to 55% of the properties (defined by borough-block-lot-apartment) in our sample were sold just once and 29% were sold exactly twice.[27] Thus our repeat sales sample contains less than half of the sales included in our full sample. Furthermore, some observations refer to properties that have been sold only before Sandy or only after. These properties do not contribute to the identification of the difference-in-difference estimates, further reducing the set of observations that drive identification of the effects.

Table 4 presents the estimates of the coefficients in Eqs. (2) and (3). The first column considers the general treatment of being located in the flood zone, estimated on the sample including all building types (apartments and houses). The estimates reveal a 9 log-point price reduction in the period after hurricane Sandy. Column 2 restricts the estimation to the sample of 1-family and 2-family houses, which reduces the estimated price reduction to 6 log points. Column 3 considers the various damage treatments on the sample of houses. The estimates show price reductions of 4, 9 and 15 log points for flood-zone properties that were non-damaged, lightly damaged, or severely damaged, respectively. Interestingly, these coefficients are fairly similar to the ones reported in the previous section (column 4 in Table 3), suggesting that those estimates were not affected by selection bias. Last, column 4 presents estimates based on the storm surge treatments. The estimated effects for treatments $Sur0$ and $Sur1$ are very similar to the analogous estimates in column 3. However, the estimated effect for heavily flooded properties is now much smaller and not statistically significant, which may reflect the relatively small number of observations contributing to identify this effect in the repeat sales sample.

All in all the results of the repeat sales analysis largely confirm the findings of the previous section, suggesting that selection on unobservables among the properties sold after Sandy has not been very pronounced.

3.4.2. Imputed market values

We now proceed to estimate models with property fixed-effects on a new dataset that addresses some of the shortcomings of the repeat sales analysis but faces other limitations. The city's Department of Finance (DoF) produces market-value estimates on a yearly basis for all properties in the city – the property assessment roll database. Thus this dataset is a balanced panel for all housing units in the city. The downside of these data is that they are heavily imputed because only a small fraction of properties are exchanged in the market in any given year, which introduces spatial correlation and complicates inference. The market value of unsold properties is estimated (by DoF) on the basis of spatial models that match each property to recent nearby sales of comparable units.

We focus on data for fiscal years 1999–2015 and restrict to 1-to-3 unit houses (tax class one), which we match with our FEMA storm surge and damage-point data. The final dataset is almost 20 times larger than our sales-based dataset, containing 11.4 million property-year observations that correspond to 658,000 properties, and the average market value across all years and properties is about $513,000.[28]

[26] While we can also cluster at the property level (Borough-Block-Lot), this would require assuming that price shocks are uncorrelated across individual properties within a neighborhood. In addition, clustering standard errors by block turns out to be a more conservative choice that gives rise to larger standard errors.

[27] Regarding 1-family and 2-family homes, the distribution is similar: 57% of the houses were sold only once and 27% were sold exactly two times.

[28] As a share of all properties, Queens accounts for 44%, Brooklyn for 29%, Staten Island for 17%, the Bronx for 9%, and Manhattan only for 1%. The small

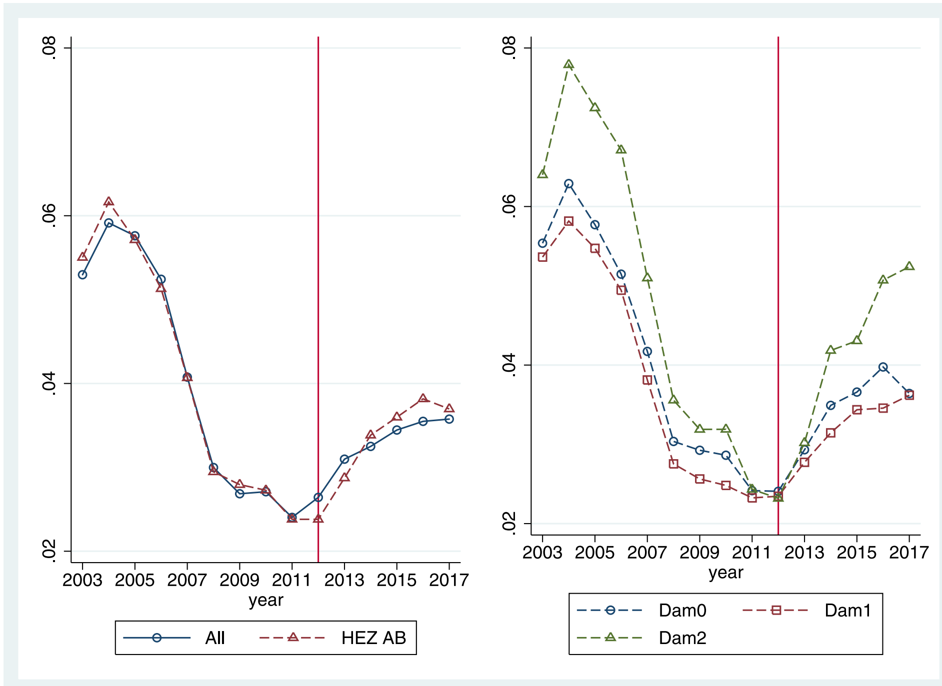

Fig. 3. Data. Fraction of properties sold. Tax class 1 (houses).
Notes: Fraction of properties in each category sold in any given year. Tax class 1 (houses only). Transactions-based data from the NYC Department of Finance, 2003–2016, merged with complete list of parcels from the PLUTO dataset.

Property fixed-effects estimates based on these data are reported in columns 6–8 in Table 4. Column 6 estimates the price effect of the general treatment of being located in the flood zone at 16 log points, which is substantially higher than our earlier estimates. Column 6 considers the various damage treatments, which imply reductions in value of 12, 22 and 23 log points, respectively, for flood zone properties that suffered no damage, minor damage, and major damage.[29] These estimates are qualitatively similar to those obtained with the sales data, but imply much larger price effects. While this could indicate positive selection into sales in the post-Sandy period, we cannot rule out that this finding may be an artifact of the imputation method used by the NYC Department of Finance, and are hesitant to give too much weight to the specific estimates obtained with these data.

3.4.3. Sales activity

Given that our data are based on transactions (sales), it is important to gauge whether Sandy impacted the composition of sales in the affected areas. To understand whether this is the case, it is helpful to examine the effects of Sandy on the *volume* of sales. For instance, evidence of a chilling effect on sales activity would increase concerns about sample selection. These concerns would be aggravated if, in addition, we found that the reduction in sales is more intense for properties that were damaged by the hurricane.

Specifically, we examine whether Sandy affected the probability that a specific housing unit sells in a given year, and whether these changes vary as a function of the degree of damage caused by Sandy. To conduct the analysis, we built a balanced panel with yearly observations for all (1-to-3 unit) houses in the city. We then created an indicator variable identifying the years in which a specific house was sold, and taking a value of zero otherwise, and merged these data with the FEMA damage-point information.

We begin by examining the fraction of properties sold in each year, which we refer to as sales activity. The solid line in the left panel of Fig. 3 reports citywide sales activity. We clearly observe the end of the housing boom and the subsequent bust. At the peak, 6% of all properties were sold in year 2004, compared to fewer than 2.5% in year 2011. The dashed line reports the sales in the flood zone (*HEZAB*). Up until 2011, the two lines are remarkably similar but, from 2012 onward, their behavior diverges, suggesting that hurricane Sandy had an effect on sales activity in the flood zone. However, this effect appears to be short-lived. In 2012, Sandy's year, and 2013, sales slowed down in the flood zone. However, they recovered vigorously in 2014–2016. By 2017, sales activity in the flood zone matches again the level in the rest of the city. Turning now to the right panel in Fig. 3, we observe that in the pre-Sandy period sales activity was higher among *Dam*2 properties, although the three treatment groups clearly trace the housing cycle and converge to a minimum of activity in 2012. In the post-Sandy period, sales activity recovers for all groups but, once again, the share of sales among *Dam*2 properties surpasses the levels of the other two treatment groups.

We explore this issue further using regression analysis, which will allow us to control for time-invariant property-specific factors. Specifically, we now estimate the following linear-probability-model specifications where the dependent variable takes a value of one if property i was sold in year t:

$$Sold_{it} = \alpha_i + \alpha_t + \beta Post_t \times HEZAB_i + \varepsilon_{it} \quad (4)$$

$$Sold_{it} = \alpha_i + \alpha_t + Post_t \times \left(\beta_0 Dam0_i + \beta_1 Dam1_i + \beta_2 Dam2_i\right) + \varepsilon_{it}, \quad (5)$$

where α_i denotes property fixed-effects. The results are presented in Table 5. Columns 1 and 2 do not include the fixed-effects in order to mimic the data presented in the figure. The estimates in these columns confirm the post-Sandy increase in sales activity in the flood zone relative to the rest of the city. More importantly, we note that the increase

weight of Manhattan is due to the fact that we are focusing on houses and leaving apartments out of the sample, largely accounting for the lower housing values in the imputed dataset.

[29] The surge-based estimates in column 8 provide very similar estimates. We also attempted to estimate specifications including linear zip-code trends, but it proved computationally infeasible.

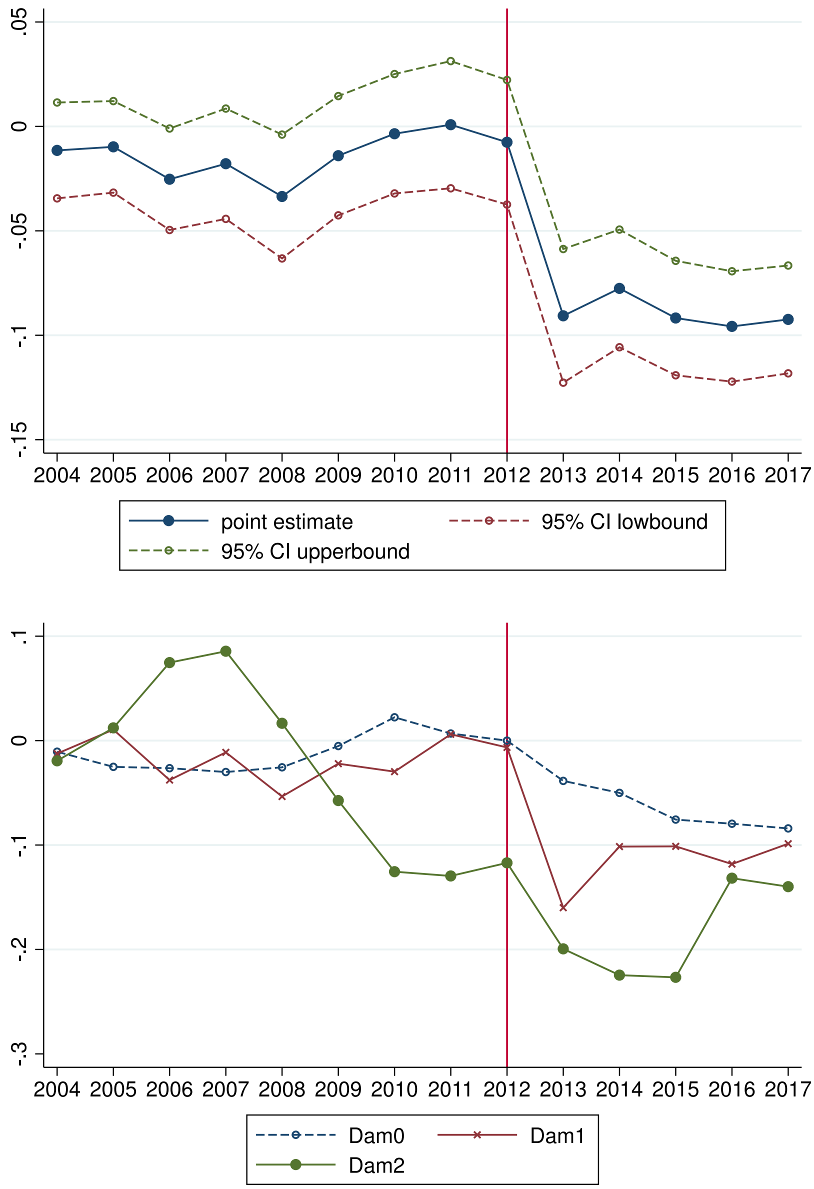

Fig. 4. Event study flood zone (HEZAB) versus rest of the city. Only 1-family and 2-family homes.
Notes: Top panel reports the estimated time-varying coefficients (annually) of the *HEZAB* indicator for the sample of 1-family and 2-family homes. Bottom panel reports the estimated coefficients of the time-varying *Dam*0, *Dam*1 and *Dam*2 indicators. All models include year dummies, year built or last altered, and the log of square footage.

in sales is similar across the three treatment groups.[30] We note also that the inclusion of property fixed-effects in columns 3 and 4 (and the clustering of standard errors at the block level) render the estimates rather uninformative.

3.4.4. Selection summary

All in all, our analysis in this section suggests that our main estimates of the effects of hurricane Sandy (based on neighborhood fixed-effects models estimated on the sales dataset) are not biased by changes in the composition of sales due to the hurricane. The property fixed-effects estimates based on the repeat sales sample were very similar to our main estimates. In addition, our analysis of the effects of the storm on sales activity suggests that the storm temporarily slowed down the recovery of sales activity in the flood zone, relative to the rest of the city. However, this effect was short-lived and did not appear to be driven by properties with systematically higher or lower levels of observed damage.

[30] A test of equal coefficients cannot be rejected at the usual significance levels.

3.5. Persistence

Our main finding so far is that hurricane Sandy reduced housing prices in the flood zone. The reduction was more pronounced for properties that were more severely damaged by the storm, but also affected non-damaged properties in the affected areas. The goal of this section is to analyze the dynamic effects of each of the treatments, which will provide useful information regarding the merits of alternative interpretations for our findings. We are particularly interested in determining whether the effects of hurricane Sandy on housing prices appear to be short-lived or display persistence.

We consider a flexible specification that allows for time-varying effects:

$$\ln p_{izt} = \alpha_z + \alpha_t + \beta^t HEZAB_i + \gamma X_{iz} + \varepsilon_{izt} \tag{6}$$

$$\ln p_{izt} = \alpha_z + \alpha_t + \beta_0^t Dam0_i + \beta_1^t Dam1_i + \beta_2^t Dam2_i + \gamma' X_{iz} + \varepsilon_{izt}, \tag{7}$$

Table 5
Sales activity. Linear probability model.

Dep. var. sold	1	2	3	4
Post × HEZAB	0.1478***		0.1009*	
	[0.0369]		[0.0592]	
Post × Dam0		0.1385***		0.0664
		[0.0478]		[0.0827]
Post × Dam1		0.1531***		0.1416*
		[0.0551]		[0.0726]
Post × Dam2		0.2272		0.1964
		[0.1909]		[0.2868]
Observations	9,856,991	9,856,991	9,856,991	9,856,991
R-squared	0.004	0.004	0.004	0.004
Fixed-effects	No	No	Block	Block
Groups	1	1	23,364	23,364
Clustered s.e.	No	No	Block	Block
Sample	fam12	fam12	fam12	fam12

Notes: Balanced panel containing all houses in tax class one (1-to-3 family units) for years 2003–2017. The dependent variable is an indicator for whether the property was sold in that year (multiplied by 100). Most cooperatives and condominiums are excluded from tax class one. Year dummies included in all specifications. The number of tax lots (properties) in the dataset is around 0.7 million. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

where the dependent variable is the log of the price of housing unit i in neighborhood z and period t. The right-hand-side contains neighborhood fixed-effects, year fixed-effects, and unit-specific controls (square footage and year built or last altered). Eq. (6) includes an indicator for being located in the HEZAB, with a coefficient β^t that is allowed to vary period by period.[31] Similarly, Eq. (7) allows for time-varying coefficients for each of the treatment variables (indicators *Dam*0, *Dam*1 and *Dam*2).

Table 6 presents the estimates for the sample of 1-family and 2-family houses. Column 1 provides estimates for the generic treatment of being located in the flood zone (corresponding to Eq. (6)). As we already discussed earlier, the estimates provide strong support for the parallel trends assumption. We do not find evidence of systematically different pre-treatment price trends for properties in and out of the flood zone (*HEZAB*). In fact, we are unable to reject the null hypothesis of equal price *levels* for almost all pre-Sandy years. In sharp contrast, the estimates corresponding to years 2013–2017 are large (in absolute value) and significant at the usual significance levels, converging toward a fairly stable 9 log-point price reduction for properties located on the flood zone that shows no signs of recovery, as clearly illustrated in Fig. 4 (top panel).[32]

To gain a deeper understanding, we turn to the estimation of the various damage treatments as per Eq. (7). The estimates are reported in columns 2 through 4 of Table 6. Once again, the estimates clearly show the absence of differential pre-treatment trends for all treatment groups relative to the control group. In contrast, the estimates for all years 2013 and beyond are economically large and statistically significant for the three damage treatments. Two other features of the evolution of these price effects are worth noting. First, the price penalty for non-damaged properties in the flood zone (*Dam*0) *increases* gradually after Sandy, reaching 8 log points in year 2017. In contrast, large penalties for damaged properties appear immediately after the hurricane – 16 and 20 log points for treatments *Dam*1 and *Dam*2, respectively – and gradually fall over time. In fact, Fig. 4 (bottom panel) suggests that the price penalty for damaged properties may be converging to that of non-damaged properties in the flood zone. As we discuss in greater detail later on, one possible interpretation for these price dynamics is that as homeowners repaired damaged properties, their prices gradually recovered but converged to a new, lower level.[33]

Table 6
Time-varying coefficients by year.

Model Treatment	Model 1 HEZAB	Model 2 Dam0	Model 2 Dam1	Model 2 Dam2
T × 2004	−0.01	−0.01	−0.01	−0.02
	[0.01]	[0.01]	[0.02]	[0.06]
T × 2005	−0.01	−0.03*	0.01	0.01
	[0.01]	[0.01]	[0.02]	[0.05]
T × 2006	−0.03**	−0.03*	−0.04*	0.07
	[0.01]	[0.02]	[0.02]	[0.06]
T × 2007	−0.02	−0.03*	−0.01	0.09
	[0.01]	[0.02]	[0.02]	[0.06]
T × 2008	−0.03**	−0.03	−0.05*	0.02
	[0.02]	[0.02]	[0.03]	[0.06]
T × 2009	−0.01	−0.01	−0.02	−0.06
	[0.01]	[0.02]	[0.02]	[0.06]
T × 2010	0	0.02	−0.03	−0.13
	[0.01]	[0.02]	[0.02]	[0.09]
T × 2011	0	0.01	0.01	−0.13
	[0.02]	[0.02]	[0.02]	[0.09]
T × 2012	−0.01	0	−0.01	−0.12
	[0.02]	[0.02]	[0.02]	[0.08]
T × 2013	−0.09***	−0.04**	−0.16***	−0.20**
	[0.02]	[0.02]	[0.03]	[0.10]
T × 2014	−0.08***	−0.05***	−0.10***	−0.22***
	[0.01]	[0.02]	[0.02]	[0.07]
T × 2015	−0.09***	−0.08***	−0.10***	−0.23***
	[0.01]	[0.02]	[0.02]	[0.07]
T × 2016	−0.10***	−0.08***	−0.12***	−0.13**
	[0.01]	[0.02]	[0.02]	[0.06]
T × 2017	−0.09***	−0.08***	−0.10***	−0.14**
	[0.01]	[0.02]	[0.02]	[0.06]
Observations	354,310		354,310	
R-squared	0.143		0.143	
Number of BB	22,062		22,062	
Fixed-effects	Block		Block	

Notes: T denotes dummy for the corresponding treatment, HEZAB or a Damage level indicator. Models 1 and 2 include block FE, year dummies, year built or last altered, and square footage. The sample includes only 1-family and 2-family houses. Standard errors clustered by block in both models. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Mechanisms

Our main findings can be summarized as follows. First, hurricane Sandy has led to a persistent reduction in housing prices on the flood zone of about 9 log points (or 9.4%) and, 5 years after the storm, shows no signs of vanishing. Secondly, the evolution over time of prices in the flood zone differs substantially for properties that were damaged by the storm and properties that were not, as illustrated by Fig. 4. Damaged properties experienced a sharp reduction in prices right after the storm, followed by a partial recovery, and eventually settling down at a roughly 9 log-point price penalty. In contrast, non-damaged properties in the flood zone have experienced a gradual reduction in price between 2013 and 2017, eventually converging to a price penalty that is similar to that of damaged properties.

The goal of this section is to discuss three potential explanations that could account for these results. The first explanation is based on neighborhood blight (affecting residential properties, businesses and infras-

[31] Specifically, we include a series of interactions between year dummies and an indicator for HEZAB.

[32] We note that the pattern reported here is robust to defining the flood zone using FEMA's 100-year floodplain (also known as special flood hazard areas), as reported in Indaco et al. (2018) (Fig. 4), and to the inclusion of linear price trends by neighborhood (defined by zip code). These figures are available from the authors upon request.

[33] About 22,000 homeowners applied for assistance through the federally funded *Build Back* program. According to the Wall Street Journal, around 75% of these projects were completed by the end of 2016.

Table 7
Additional analysis: heterogeneous effects, damaged neighbors, and endogenous damage.

Dep. var. ln p	1	2	3	4	5	6	7
Post × Dam0	−0.05***	−0.06***	−0.06***		−0.05***		
	[0.01]	[0.01]	[0.01]		[0.01]		
Post × Dam1	−0.10***		−0.10***	−0.11***	−0.09***		
	[0.01]		[0.01]	[0.02]	[0.01]		
Post × Dam2	−0.18***		−0.23***	−0.16***	−0.07		
	[0.03]		[0.05]	[0.04]	[0.05]		
Post × Dam						−0.06***	−0.13***
						[0.01]	[0.01]
Post × Damblock					−0.80**		
					[0.33]		
Observations	354,310	333,083	322,926	314,728	354,310	48,766	48,766
Number of BB	22,062	21,023	19,973	19,831	22,062	3098	3098
R-squared	0.148	0.15	0.148	0.147	0.148	0.153	–
Excludes	No	HEZAB	HEZAB	HEZAB	No	Outside	Outside
blocks		Any dam.	No dam/all dam	All dam.		HEZ AB	HEZ AB

Notes: Regression models include (but not reported) quarter-year dummies, year built or last altered, log of square footage, indicators of damage (Dam0, Dam1 and Dam2), as well as indicators for severe damage among neighbors in the block (column 5). Column 1 reproduces one of our main findings and provides a benchmark. Column 2 excludes observations pertaining to blocks in HEZAB with any damaged units. Column 3 excludes observations from blocks in HEZAB with all units either non-damaged or damaged by hurricane Sandy. Column 4 excludes observations pertaining to blocks in HEZAB with all units damaged. Variable *Damblock* in column 5 is the (distance-weighted) average of severely damaged properties in the block (excluding own damage). In columns 6 and 7 we combine properties that experienced some degree of damage into a single category ($Dam = Dam1 + Dam2$). Column 6 reports OLS estimates. Column 7 reports 2SLS estimates where the vector of instruments is (Sur, $Post \times Sur$), where $Sur = Sur1 + Sur2$ is an indicator for whether the property suffered flooding. The sample includes only 1-family and 2-family houses. Standard errors are clustered by block. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

tructures), coupled with time lags in repairing the damage. The second explanation has to do with the response to news of higher flood insurance premia that were announced around the time of Sandy. Last, we consider the implications of a belief updating model where economic agents learn about flood risk from experience.

4.1. Neighborhood blight

Hurricane Sandy caused widespread damage in the affected areas, both to residential properties and to businesses and infrastructures. Naturally, this is likely to negatively affect the prices of all properties in the affected areas, including non-damaged properties. Because it takes time to rebuild, these price effects can persist over time. We begin by parsing out the different dimensions of neighborhood blight and trying to provide evidence for them.

4.1.1. Damaged neighbors

It has been shown in a number of studies that the perceived quality of neighboring properties acts as an externality with an effect on housing prices. Thus it is plausible to expect that housing prices may be negatively affected by the presence of damaged properties in the neighborhood, which may also provide an explanation for the price penalty for non-damaged properties (Sturm and Redding, 2016). Additionally, the effects of Sandy on individual property levels may be heterogeneous and differ by the extent of neighborhood blight.

To address these questions we computed the fraction of damaged properties in each city block in the flood zone (*HEZAB*).[34] According to our calculations, within the flood zone, the average number of damaged properties in a city block was 17%, or 41% of the properties in the block. It is worth noting that some blocks in the flood zone had zero damaged properties, while in others all properties were damaged in some degree. In fact, the data indicate a large degree of polarization: almost 2 in 3 blocks on the flood zone were either completely undamaged or completely damaged. More specifically, 44% of the blocks in *HEZAB* had no damaged properties, whereas all properties were damaged in 20% of the blocks.

To analyze whether or not the effects of Sandy on individual property levels differed by the extent of neighborhood blight, we re-estimated our models on three sub-samples and report the findings in Table 7. In each of these sub-samples, the control group was the same – non-damaged properties outside of the flood zone – but each one differed in the treatment groups. In the first sub-sample the treatment group contains only observations pertaining to completely undamaged blocks within the flood zone (column 2). Obviously, in this case we are only able to identify the effect of the $Dam0$ treatment. The estimated effect is practically identical to our baseline results (reported in column 1). The treatment group in the second sub-sample contains observations pertaining to city blocks within the flood zone with some, but not all, units damaged (column 3). The estimated effects of the three treatments are almost identical to those obtained using the whole sample. Last, the treatment group in the third sub-sample contains only observations pertaining to flood zone blocks where *all* properties experienced some degree of damage. Once again, the estimated effects of the ($Dam1$ and $Dam2$) treatments coincide almost exactly with the estimates based on the whole sample (column 1). In sum, our findings indicate that the treatment effects estimated on the whole sample do not seem to vary by the extent of damage in the neighborhood.

Let us now turn to whether the presence of damaged neighboring properties had an effect on a property's sale price (after Sandy) that is separate from the own-damage effect. To do so we consider the following specification:

$$\ln p_{izt} = \alpha_z + \alpha_t + \gamma_0 Dam0_i + \gamma_1 Dam1_i + \gamma_2 Dam2_i + \gamma_3 Damblock_i + Post_t \times \left(\beta_0 Dam0_i + \beta_1 Dam1_i + \beta_2 Dam2_i + \beta_3 Damblock_i\right) + \gamma' X_{iz} + \varepsilon_{izt}, \quad (8)$$

where $Damblock_i$ measures the average damage in property i's city block. Thus the externality effect is captured by coefficient β_3.

Column 5 in Table 7 presents the results. The estimated effects for treatments $Dam0$ and $Dam1$ are practically the same as in the baseline model (reproduced in column 1). In contrast, the estimate for the severe damage treatment $Dam2$ falls substantially (to −0.07), reflecting the strong correlation (0.54) between severe own damage ($Dam2$) and the prevalence of damage among neighbors in the same block ($Damblock$). Importantly, the estimated externality effect is highly significant, imply-

[34] Specifically, for each property in the flood zone, we computed the number of (moderately or severely) damaged properties in the same city block (excluding own damage) as a fraction of the overall number of homes ($Damblock_i$). We built this variable on the basis of all lots in the block, not just those that were sold over our sample period, restricting the analysis to 1-family and 2-family homes.

ing that the presence of damaged properties in one's neighborhood does have a significant negative effect on housing values.

To the extent that rebuilding damaged properties takes time, the external effect from damaged neighbors will generate a persistent reduction in the prices of non-damaged properties in blocks with a significant prevalence of damaged neighbors. The persistence induced by this mechanism will depend on the time lags due to rebuilding. A recent study by McCoy and Zhao (2018) finds that hurricane Sandy led to an immediate surge in building permit applications in New York's flood zone (defined by FEMA's special flood hazard areas). Their data can also be used to gauge the time needed to rebuild the damage properties.[35] On the basis of their estimates, the volume of building permits in the flood zone returned to its pre-Sandy levels approximately 14 quarters (i.e. 3.5 years) after the hurricane. This suggests that the majority of damaged properties had been repaired by the end of 2016 or shortly after. Our estimates (plotted in Fig. 4) show that the price effects of Sandy have already outlasted this period, and present no signs of vanishing, suggesting that factors other than reconstruction time lags may be at play.

4.1.2. Damaged infrastructures

This is another dimension of neighborhood blight. Hurricane Sandy also caused extensive disruption to transportation, utilities, and fuel supply. Virtually all subways, commuting trains, buses and tunnels were shut down due to the hurricane. However, in a matter of a few weeks most of the city's transit network was functioning at or near normal capacity (with only a few exceptions), and all schools re-opened one week after the storm.[36] In terms of utilities, the largest problem was loss of electricity. Close to 2 million people lost power at some point during the storm, with service being restored to most houses in less than a month. The supply of liquid fuels was also severely disrupted and regular service in the affected areas remained limited for several weeks. These factors are difficult to quantify.[37] However, we have shown that our main estimates are robust to the inclusion of neighborhood time trends, which should capture many of these factors. Thus, it seems unlikely that the negative effects arising from service interruptions and damaged infrastructures can account for reductions in housing prices that extend for over 5 years. Nonetheless, this experience may have caused a lasting effect on individuals who suffered or witnessed the consequences, resulting in a reduced willingness to live in these areas.

4.1.3. Reduced amenities and unmeasured damage

Hurricane Sandy may have also deteriorated houses and neighborhoods in ways that are more difficult to measure. For example, in the aftermath of the storm, some businesses may have relocated to other parts of the city. This reduction in amenities and local economic activity may have negatively affected housing prices. Unfortunately, our current data do not allow us to measure these effects. However, we can take them into account by including neighborhood-level trends in our regression models, as we did in columns 5 and 6 in Table 3. As discussed earlier, the results were qualitatively unchanged, suggesting that reduced amenities are probably not the reason for the persistent reduction in housing values in the flood zone.

Yet another explanation for the emergence of a price penalty for non-damaged properties in the flood zone is that hurricane Sandy may have affected those properties in ways that are not captured by FEMA's point-damage estimates. For instance, properties in treatment group *Dam*0 may have been affected by mold, which is costly to remove and could negatively affect their value. However, it is important to keep in mind that companies that offer mold removal are widely available. Consequently, we would expect the number of mold-affected houses to fall over time, as more and more homeowners restore their properties. However, this pattern is at odds with the gradual *decrease* in the prices of undamaged properties documented in Fig. 4. Thus unmeasured damage caused by Sandy, such as mold, is unlikely to account for this pattern.

4.1.4. Out-migration

One way to measure neighborhood deterioration is to examine if families have fled from the flood zone toward other parts of the city. In fact selective out-migration has the potential to generate very persistent changes to the character of a neighborhood and to its housing prices, as illustrated in the study of the 1854 London cholera outbreak by Ambrus et al. (2016). Using plot-level data similar to ours, these authors show that the average property within the affected area suffered a persistent reduction in housing values, regardless of whether any cholera deaths occurred in that particular building. They argue that the persistence of these effects lasted for decades, and provide evidence of selective out-migration that resulted in permanent reduction in the average household income of the residents. Rosenthal (2008) provides also accounts of neighborhood dynamics, with instances of decline and renewal.

Because of the very fine geographical granularity required in our analysis, obtaining data to try to quantify within-city migration is rather challenging. To do so we obtained administrative data from the New York City department of education about enrollment in all public schools in the city. These data contain information on each school's total enrollment (by grade) as well as the socio-economic composition of the student body.[38] Thus we can analyze if the level and composition of enrollment has changed in the post-Sandy period. The econometric specification we consider is

$$y_{szt} = \alpha_s + \alpha_t + Post_t \times \left(\beta_0 avHEZAB_s + \beta_1 avDam_s\right) + \varepsilon_{szt}, \tag{9}$$

where the dependent variable alternates from total enrollment in the school, to enrollment in earlier grades (second or earlier), percent of the students that are black or Hispanic, and percent of the students in poverty. The subindices refer to school *s*, neighborhood (block) *z* and year *t*. The key right-hand side regressors are the average number of properties in the school's catchment area that are located in the flood zone ($avHEZAB_s$) and the fraction of units in the school catchment area that were damaged ($avDam_s$). The key coefficients of interest are β_0, which captures the effect of a marginal increase in the fraction of properties in the catchment area that are part of the flood zone, and β_1, which captures the additional effect of damage.

Unfortunately, our estimates of this model do not deliver any statistically significant treatment effects for any of the outcomes considered (as can be seen in Table C.3). Thus, we do not find any significant evidence for out-migration. However, it is also important to keep in mind that households with young children are perhaps the least mobile type of household. Thus we cannot rule out out-migration of households with older or no children.

4.1.5. Summing up

While hurricane Sandy created a great deal of disruption on neighborhoods located in the flood zone, our findings suggest that the resulting impact on housing prices was short-lived. Infrastructures, transportation and utilities were back to nearly normal service within a few

[35] See Fig. 6 in McCoy and Zhao (2018).

[36] See the report "A Stronger, More Resilient New York," by the NYC Special Initiative for Rebuilding and Resiliency, p. 94.

[37] Kousky and Shabman (2013) analyze the use of the relief funds approved by Congress. They note that "*a large share of the Sandy supplemental is funding projects designed to reduce damages from the next storm, not for emergency response and rebuilding.*" Some of these investments are ambitious multi-year projects that may, potentially, reduce the price penalty that we have uncovered. But we have not found any evidence of city infrastructures that were damaged by Sandy and remained out of service until the end of 2017.

[38] Merging the school-level data into our dataset required mapping school addresses into latitude-longitude points, which was done using Google's API. The dataset contains 1857 schools but we focus our analysis on the 722 elementary schools.

months of the storm, damaged properties were largely rebuilt over a 4-year period, and we have found no evidence of out-migration. In addition, our finding of a gradual emergence of a price *penalty* for non-damaged properties within the flood zone appears at odds with the expected dynamic effects of unmeasured damage. All in all, these observations suggest that other mechanisms must be at play to explain the persistence of the reduction in flood zone housing values five years after the hurricane.

4.2. Flood insurance reform

During the first half of 2013, FEMA released detailed information entailing upcoming steep increases in flood insurance costs for properties on New York's flood zone. The announcements made the public aware of the new, preliminary FEMA flood maps for New York city, which substantially increased the number of properties subject to mandatory flood insurance requirements. As quickly recognized (Dixon et al., 2013), the new flood maps had the potential to affect housing values in flood-prone areas, triggering an immediate backlash among homeowners in those neighborhoods (Checker, 2016).

4.2.1. A brief history of flood insurance

Congress created the National Flood Insurance Program (NFIP) in 1968, which is administered by FEMA, with the goal of providing affordable (i.e. subsidized) flood insurance to homeowners. An integral part of the program is the Flood Insurance Rate Map, which establishes risk zones. These zones determine flood risk for each property and, importantly, properties located on the high-risk zone are required to purchase flood insurance if they have federally backed mortgages (or if they have received FEMA assistance in the past).[39]

Largely because of hurricane Katrina, the NFIP accumulated a large amount of debt – over 25 billion dollars. In order to make the program financially stable Congress passed the *Biggert-Waters Flood Insurance Reform Act* in 2012 (but prior to hurricane Sandy), which basically eliminated subsidies to flood insurance rates and phased out a number of exemptions. However, as a result of vigorous public opposition in affected areas, Congress passed the 2013 *Homeowner Flood Insurance Affordability Act*, allowing for a more gradual adjustment by capping annual rate increases to 18%.

In addition to these legal changes, revised Flood Insurance Rate Maps were commissioned for all flood-prone areas in the country. The preliminary map for New York was released in June 2013, although the press had already publicized early releases as early as January 2013 (New York Times, 1/28/2013). The new map expands the high-risk zone, doubling the number of properties that may be subject to mandatory flood insurance.[40] In addition the new map also increases the required elevations for the buildings already located in high-risk zones. Properties that fail to do so will face steep increases in flood insurance premia.

As of 2018, the 2013 preliminary flood map has not yet become effective because New York City filed an appeal, arguing that the proposed map overestimates flood risk in some parts of the city. In October 2016, FEMA announced that the appeal was accepted and, therefore, flood insurance rates are still based on the 1983/2007 map. Nonetheless, the release of the preliminary map may have affected housing values. According to a 2013 study commissioned by the City of New York (Dixon et al., 2013), the expanded flood map and the phase-out of the flood insurance subsidies will lead to large increases in the cost of flood insurance in the city's flood zone. Interestingly, the highest increases will not concern the properties that face the highest risk of flooding. Rather, the highest increases in flood insurance costs will be suffered by the properties that were just outside the high-risk zone under the old map but are located in the high-risk zone of the 2013 map, which is the case for more than 20,000 structures.[41]

4.2.2. Our test

Separately identifying the effect of flood insurance reform from the effect of hurricane Sandy is complicated by the fact that both events overlapped in time and space. To try to accomplish this task, we obtained the geo-coded data for the 1983/2007 (effective) flood map, and for the 2013 (preliminary) map from FEMA, and matched them with our sales dataset. Next, we classified all properties in the city on the basis of their risk category in each of the two flood maps, and created an indicator for parcels that were not in the high risk zone according to the 1983/2007 map but are considered to be at high risk of flooding under the preliminary 2013 map. For short we will refer to these properties as *new risks*.

The rationale behind our test is to investigate whether the values for new-risk properties have fallen disproportionately more. It is important to keep in mind that the flood insurance reforms will affect all homeowners that carry flood insurance, as subsidies are gradually removed. However, *new-risk* properties are likely to suffer from a larger increase in flood insurance costs (or the need to invest heavily in their property to meet the more demanding building code requirements for the high-risk zone). Within *HEZAB*, 74% of properties have the same risk levels under both flood maps, but 25% (or 17,314) are considered at high risk of flooding in the 2013 map but were deemed to be at low risk in the 1983/2007 flood map.

Table C.4 presents the results of our test. In column 1 we reproduce estimates already discussed earlier, where the post-Sandy reduction in housing prices is estimated to be 7 log points for the properties located in HEZAB. Column 2 replaces indicator HEZAB for an indicator for *new-risk* properties, along with its interaction with the post-Sandy indicator. The interaction term is highly significant and the point estimate entails a 6 log-point price reduction for new-risk properties, closely matching the finding in column 1. In order to disentangle the roles played by having been affected by Sandy (measured by HEZAB) and being reclassified as a high flood risk in the 2013 flood map, we estimate a model that includes both sets of indicators. The estimates for this horse-race model are reported in column 3. The point estimate for the coefficient of the interaction term for HEZAB falls only slightly, to −0.06, relative to column 1. In contrast, the coefficient of the interaction for *new risks* falls to −0.01 and becomes statistically insignificant. Thus, the drop in housing prices from the beginning of 2013 onward appears to be linked to being located in the hurricane evacuation zones, rather than to being a *new risk*. Last, column 4 disaggregates HEZAB by the level of damage

[39] High-risk areas are defined as areas in the 100-year floodplain. According to a study by RAND (Dixon et al., 2013), when New York City was hit by hurricane Sandy, 3 out of 4 properties in the high-risk zone in New York City were required to have flood insurance, but only slightly more than half of all properties had it. Among homeowners not required to have flood insurance, take up rates were found to be low.

[40] The Flood Insurance Map currently in effect was adopted in 1983 and has suffered only very minor updates since then, with the latest update dating back to 2007. The 1983/2007 map contains approximately 21,000 residential parcels (with mostly 1-to-4 family houses) in the high-risk zone. The 2013 preliminary map contains over 47,000 residential parcels in the high-risk zone, which amounts to more than 6% of all city parcels.

[41] Since these properties were not considered to be at risk of flooding, they were not build according to the elevation requirements of the properties in the high-risk zone. As a result, when they become subject to the new mandatory requirements their rates will be much higher than for the typical properties that had been in the high-risk zone all along. According to Dixon et al. (2013), a typical increase in flood insurance premiums will entail an increase in the annual premium from $500 to $5000 in order to keep constant the level of coverage. Rule-of-thumb capitalization rules for such a permanent increase in mandatory flood insurance could lead to reductions in the value of the property of approximately $90,000. Given that the typical house in these areas has an assessed market value of approximately $500,000, thus the resulting reduction in value would be around 18%.

suffered by each property. The results again confirm the previous interpretation: *new-risk* properties do not seem to have suffered a reduction in value.

Summing up, flood insurance reform does not appear to be responsible for the price declines documented earlier. However, we expect that once the new flood map becomes effective, housing prices on the flood zone will adjust in response to the higher premiums.

4.3. Learning about flood risk

The mechanisms discussed above do not provide satisfactory explanations for the persistent reduction in housing values in New York's flood zone following hurricane Sandy. This section presents a mechanism that does appear to be consistent with our empirical findings. In a nutshell, hurricane Sandy may have revealed important information regarding the risks of living in flood-prone areas and, more specifically, about the probability of extreme events that had previously been considered practically impossible. This idea has been formalized by Kozlowski et al. (2015) in the context of macroeconomic fluctuations. These authors argue that it provides a plausible explanation for the slow recovery from the Great Recession.[42]

For decades, urban economists have recognized that households do not have perfect information regarding the likelihood of hazard events and, therefore, update their beliefs on the basis of new information and this may affect housing values (Rubin and Yezer, 1987). However, individual occurrences of *common* events typically will have much smaller effects on beliefs than unexpected or unusually large ones (Yezer, 2010). This important observation helps account for the short persistence of the effects of flooding episodes documented in many studies. For instance, Kocornik-Mina et al. (2015) examined a large dataset of massive flooding events across the world and concluded that economic activity (measured by night lights) typically returned to pre-flooding levels after one year. In the context of the effects of hurricanes on housing prices, Hallstrom and Smith (2005), Bin and Landry (2013), Atreya et al. (2013) and Zhang (2016) reported temporary reductions in the prices of houses located on the flood plain, with the effects vanishing rapidly, often within 2 or 3 years. Complementing these studies, Gallagher (2014) documented that flooding events are typically followed by spikes in flood-insurance take-up rates. These sudden increases are short-lived, peaking 1 or 2 years after the flood and converging rapidly to baseline levels. In a recent study, Bakkensen and Barrage (2017) build a model of the housing market where flood risk beliefs are endogenously updated. Their analysis highlights that belief heterogeneity can magnify substantially the negative price effects of sea level rise.

In contrast, as formalized by Kozlowski et al. (2015), extreme shocks, such as the Great Recession or hurricane Sandy, can lead to highly persistent changes in beliefs and in the economic outcomes affected by those beliefs. The key to modeling this type of learning is to consider flexible specifications for beliefs, where new observations lead to updates of the density locally around those observations. Because extreme events are typically infrequent, their influence on that region of the distribution of beliefs is highly persistent. In our context, hurricane Sandy may have led to an increase in the probability of massive flooding events, reducing the willingness to pay for living in flood-prone areas.[43]

Additional evidence in favor of an information-based mechanism is provided by the recent study by Bernstein et al. (2018). The goal of this study is to estimate the effects of exposure to rising sea levels on home prices using a nation-wide data (from Zillow). In contrast to us, their analysis does not focus on the aftermath of any specific flooding event. The main finding is that flood-prone houses sell at a 7.5% discount relative to observationally equivalent properties that are at the same distance from the coast but face a much lower risk of flooding. The authors argue that the effect on home prices is driven by sophisticated buyers and communities that are concerned about and aware of the consequences of climate change.

5. Conclusion

Our analysis has provided robust evidence that hurricane Sandy led to an important, and highly persistent, reduction in prices in the affected neighborhoods. Our findings suggest that properties damaged by the hurricane suffered a large immediate drop in value, and recovered only part of their original value. In contrast, non-damaged properties in the flood zone experienced a gradual reduction in prices over the 5-year period following the storm. Our findings suggest that, by 2017, the penalty associated with being located in the affected areas converged to approximately 9%, regardless of the degree of damage caused by the storm.

In our view, the partial recovery in the values of properties that were damaged by the hurricane reflects the gradual process of repairing and rebuilding. However, the most likely explanation for the persistent price penalty, which affects even properties that were not damaged by Sandy, is that the storm triggered an upward revision of the risk of massive flooding events. More research is needed to try to document the various ways in which households and businesses located in flood-prone areas try to adjust to the increased perception of the risk of living in those areas.

Appendix A. Merging process

Each dataset uses a different system of geographic coordinates. The housing dataset identifies observations by exact address and tax lot identifiers; FEMA data employ spherical latitude and longitude; and the hurricane evacuation zones (HEZ) are geocoded using the cartesian approximation for New York State.

Our strategy was to map the FEMA and HEZ datasets into tax lots, which could then be merged with the housing data. To do so we used an additional dataset as cross-walk. This dataset is called PLUTO and is a compilation of variables maintained by different New York City agencies that contains a wealth of information.[44] Using the PLUTO shape files, we were able to map each of the points in the HEZ and FEMA datasets into the corresponding polygons of the tax lots. We refer to this dataset as FEMA-HEZ, which contains the hurricane evacuation zone and the extent of damage for all tax lots in New York City.[45] The accuracy of this merge was extremely high. Furthermore, PLUTO identifies each parcel polygon by its center-point coordinates (based on the New York State plane approximation) along with its borough, block and lot (or BBL), which allows us to match the FEMA-HEZ data with the housing dataset by BBL.

A.1. More details on merging of datasets

We describe in more detail the merging process.

[42] This mechanism is also similar to the explanation proposed by Abadie and Dermisi (2008) to account for the reduction in the demand for downtown office space in Chicago following the attacks of 9/11.

[43] This mechanism is further supported by the analysis in Conte and Kelly (2017) who provide evidence of thick tails regarding the distribution of damages arising from a hurricane. Naturally, an upward revision in flood risk will negatively affect rents and housing prices, as is the case in Frame (1998).

[44] PLUTO contains information on over 857,000 tax lots, corresponding to three types of data: tax lot characteristics, building characteristics, and district-level data. In PLUTO all apartments belonging to the same Coop will display the exact same information (e.g. year built) because they belong to the same tax lot (BBL). Unlike other city datasets, in PLUTO all Condo apartments in the same building appear under a common tax lot and thus are treated symmetrically to coop apartments.

[45] We note that the variables in this dataset (storm surge, damage determination points, and hurricane evacuation zones) do not vary over time.

1. *FEMA Damage-Point Estimates and PLUTO.* In the FEMA data, each observation is characterized by its longitude and latitude in spherical coordinates. In total we had more than 55,000 individual points corresponding to New York City (and 319,000 for the overall Sandy inundation zone). We first mapped spherical coordinates to Cartesian XY (New York state) coordinates. Next we mapped these into New York City tax lots using the shape files provided by PLUTO. In the resulting dataset each observation is identified by its BBL (and its longitude and latitude).
   Then we proceeded to check the quality of the merge between the FEMA and PLUTO datasets. About 99.7% of the cases in the FEMA data mapped into a NYC tax lot. Next, we randomly sampled 50 cases and manually checked that their spherical coordinates landed in the correct tax lot.[46] The matches were correct in 98% of the cases (49 out of the 50).[47] In short the mapping from FEMA to tax lots in PLUTO was extremely accurate.
2. *Multiplicity of FEMA cases within a BBL.* In the FEMA data, each observation is uniquely defined by an administrative ID, which is not useful for our purposes, and a latitude-longitude (Cartesian) pair. However, not all of these observations are uniquely matched to a single BBL.[48] Specifically, 14% of all FEMA cases correspond to multiple determinations points within the same tax lot.[49] We adopt the simplest option: we average damage values across all cases within the same BBL.
3. *FEMA-PLUTO and HEZ.* We checked the quality of this match in a similar manner as before. Again the success rate was very high: only 0.4% of the cases (fewer than 200) in the FEMA-PLUTO data were not matched to a tax lot. We again randomly sampled 25 cases from the FEMA-PLUTO-HEZ dataset. We checked the spherical coordinates for each of those points using the NYC City Map to locate the resulting tax lot, and the NYC Hurricane Evacuation Zone Map to check the evacuation zone assigned to that point. The success rate was 100%.
4. *FEMA Storm Surge and PLUTO.* The raw storm surge data contains 350,154 observations covering the 5 boroughs of the city. Each observation refers to a longitude-latitude pair and the data has high geographic resolution. Hence, not surprisingly, many points map into the same BBL and therefore there are many duplicates (about 2000 on average but ranging from 1 to 30,089). Since our unit of analysis is based on BBLs in the final dataset, we now collapse by BBL. The resulting data contains 7,675 observations. We then proceed to merge with PLUTO and obtain a perfect match (except for one observation). Some of those BBLs are among the small number that cannot be assigned to a hurricane evacuation zone (including the non-evacuation zone). In the end 6449 BBLs can be matched with the PLUTO-HEZ dataset. We view this list of BBLs as the complete list of BBLs that were located in the Sandy surge area.

The PLUTO-HEZ-FEMA Data. This dataset encompasses all the data that is time-invariant: the inclusion or not of each tax lot in a hurricane evacuation zones and the level of damage (if any) suffered during Sandy. The unit of observation is the BBL.[50] We then merge these data with the property sales dataset, where the unit of observation is the BBL-Apartment and year. The merger proceeds in several steps. First, we begin with the PLUTO-HEZ dataset, which contains 857,000 tax lots. However, in 27,000 cases the hurricane evacuation zone is missing. We drop these observations so that the resulting dataset has about 830,000 tax lots. Second, we merge with the PLUTO-FEMA dataset, which contains roughly 48,000 cases (tax lots). This dataset contains all the tax lots (buildings) affected by Sandy. The vast majority (98%) of the tax lots in PLUTO-FEMA are successfully matched to the (much larger) set of tax lots in the PLUTO-HEZ dataset. The crucial step now is that we assign a zero value for the damage variable to all tax lots that were in the PLUTO-HEZ dataset but were not in the PLUTO-FEMA dataset. That is, we rely on the fact that the FEMA dataset contained all buildings affected by Sandy and that any building not included in the dataset was not damaged. The combined PLUTO-HEZ-FEMA dataset contains over 830,000 tax lots.

Details on HEZ. Table C.1 in Appendix B reports the distribution of tax lots (BBLs) across hurricane evacuation zones. About 4% of the parcels are located in HEZA and HEZAB accounts for 13% of the city's parcels. The city borough with the highest share of tax lots on HEZAB is Brooklyn with 21%.

Details on damage-point estimates. Table C.2 reports the classification of damage levels across buildings in the overall Sandy inundation zone and in the subset that is located within New York City. Column 1 reports damage levels for the buildings in the whole Sandy inundation area (close to 319,000 observations), with almost 7% of all buildings having suffered major damage. Column 2 reports on the points of the Sandy inundation zone located in New York City. Over 13% of all buildings in this area suffered major damage. Columns 3 through 7 report the damage distributions for each of the five boroughs. Focusing on the category of major damage, Staten Island and Queens were the boroughs that were hit the hardest, with 26% and 17% of the buildings having suffered major damage, followed by Brooklyn (8%). The Bronx and Manhattan were the boroughs for which major damage was much less prevalent (2.40% and 0.31%, respectively).[51]

Appendix B. More details on sales-FEMA dataset

We begin by verifying that the final dataset retains the key features of the original data in terms of differences across boroughs in average housing prices and average damage inflicted by Sandy. Table 1 reports summary statistics for these data. First, Manhattan remains as the borough with the highest median sale prices (640,000 dollars), followed by Brooklyn (369,000 dollars), Queens (400,000 dollars), the Bronx (369,000 dollars), and Staten Island (395,000 dollars). In comparison the median sale price (across all years and boroughs) for New York City is 440,000 dollars.[52] Next, we focus on the share of properties in each borough that are located in hurricane evacuation zones A or B (HEZAB). Brooklyn and Staten Island are the city boroughs with with the highest share of properties on HEZAB, at 19% and 16%, respectively, followed by Queens (8%), Manhattan (6%), and at a large distance behind, the Bronx (2%).[53] Finally, we turn to average damage levels caused by hurricane Sandy. In our combined dataset, Brooklyn and Queens are the boroughs that suffered the most damage. Respectively, 0.85% and 0.76% of all properties in these boroughs suffered major damage or were destroyed, compared to a city-wide average of 0.51%. Although the figures are not directly comparable because of the different denominators (citywide versus inundation zone), the ranking is consistent with the high levels of damage in these boroughs reported in the original FEMA data (Table C.2).

[46] To do this we used the NYC City Map (http://maps.nyc.gov/doitt/nycitymap).

[47] In the unsuccessful match the procedure identified the neighboring lot.

[48] The 55,534 observations correspond to 47,879 unique BBLs.

[49] Specifically, 3.80% of the observations appear exactly twice in a BBL, 1.08% appear exactly three times in a BBL, 0.66% appear four times, and 8% appear 5 or more times. The most extreme case is a BBL for which we have 1911 observations, which corresponds to the Breezy Point Cooperative in Queens that contains many one-family houses.

[50] Recall that in the FEMA dataset we collapsed all cases by BBL so that instances of multiple cases with the same BBL got averaged into a single value.

[51] We note that these percents do not refer to all buildings in the city or borough but, rather, only to the buildings that were part of the inundation zone.

[52] Condo apartments could not be merged into our dataset due to a recoding in the PLUTO dataset.

[53] For New York City as a whole, 11% of observations in our final dataset are located on HEZAB.

Appendix C. Tables and Figures

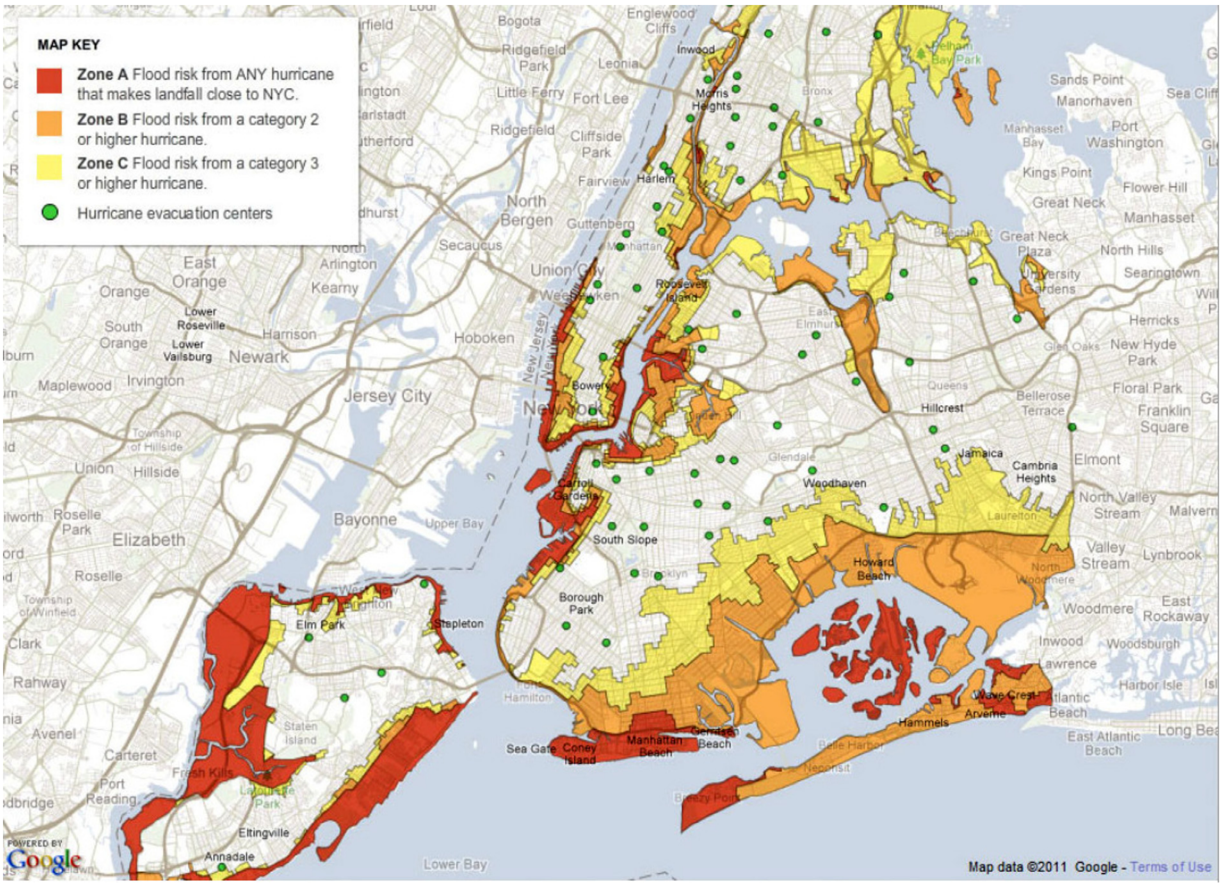

Fig. C.1. Hurricane evacuation zones.
notes: New York City Office of Emergency Management. July 2011 version.

Table C.1
Hurricane evacuation zones.

Borough	HEZ A	HEZ B	HEZ C	Rest of city
1 Manhattan	0.02	0.10	0.23	0.65
2 Bronx	0.00	0.02	0.16	0.82
3 Brooklyn	0.04	0.17	0.24	0.54
4 Queens	0.01	0.08	0.12	0.79
5 Staten Island	0.12	0.02	0.10	0.76
NYC	0.04	0.09	0.17	0.70

Source: The table reports the distribution of tax parcels of each of the five boroughs across the hurricane evacuation zones. Calculations are based on PLUTO-HEZ dataset. Zone A is the highest risk and zone C the lowest risk.

Table C.2
FEMA damage determination estimates.

Sample	All	NYC	Manhattan	Bronx	Brooklyn	Queens	SI
% Affected	50.01	39.10	39.88	69.87	43.50	32.20	35.74
% Minor	43.10	46.95	59.80	27.73	48.74	50.38	37.46
% Major	6.90	13.56	0.31	2.40	7.75	17.40	26.15
% Destroyed	0.26	0.39	0.00	0.00	0.02	0.01	0.66
Obs.	318,735	67,302	2254	1958	29,916	21,420	11,576

Notes: Own calculations based on FEMA's building point damage determination estimates data. Specifically, we use the variable DMG_COMB that is based on a combination of visible aerial imagery and field-verified inundation observation damage. Sample "All" refers to all buildings in the Sandy Inundation area (318,735) as well as points where visible aerial imagery damage determinations were made outside the inundation zone. Sample "NYC" refers to the subset of buildings that are in one of New York City's five boroughs (Manhattan, Bronx, Brooklyn, Queens and Staten Island). Each column adds up to 100 as it reports the distribution over damage levels for each of the samples.

Table C.3
Enrollment in public schools.

Dep. Var.	1 lnenrol	2 lnenrolpkk12	3 pctblackhisp	4 pctpoverty	5 lnenrol	6 lnenrolpkk12	7 pctblackhisp	8 pctpoverty
Post × AvHEZAB	−0.01	0.01	0	−0.01*				
	[0.02]	[0.02]	[0.00]	[0.01]				
Post × AvDam0					0.02	0.02	0.01	−0.01
					[0.03]	[0.03]	[0.01]	[0.01]
Post × AvDam1					−0.05	−0.03	0	−0.01
					[0.03]	[0.04]	[0.01]	[0.02]
Post × AvDam2					0.08	0.16	0.01	−0.05
					[0.09]	[0.11]	[0.02]	[0.10]
Obs.	3178	3173	3178	3178	3178	3173	3178	3178
Groups	646	646	646	646	646	646	646	646
R-squared	0.003	0.021	0.042	0.071	0.004	0.022	0.042	0.071
Fixed-effects	school DBN	school DBN	school DBN	school DBN	school DBN	school DBN	school DBN	school DBN
Clustering s.e.	Block	Block	Block	Block	Block	Block	Block	Block

Notes: The dependent variables in columns 1–4 are: log of enrollment in elementary schools, log of enrollment in pre-K, first and second grades, percent of black or hispanic students, percent of poor students. The dependent variables in columns 5–8 are the same as in columns 1–4. All regressions are weighted by total school enrollment. School DBN is the official numerical identification number assigned to each school. The $avHEZAB_s$ is the fraction of properties in school district s that lie within HEZAB. $avDam0_s$ is the fraction of properties in school district s that were located on HEZAB but were not damaged. Analogous definitions apply for $avDam1_s$ and $avDam2_s$. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table C.4
Horse race between HEZAB and 'New risks'.

Horse race Dep. var.	1 lnp	2 lnp	3 lnp	4 lnp
Post × HEZAB	−0.07***		−0.06***	
	[0.01]		[0.01]	
Post × Newrisk		−0.06***	−0.01	0.01
		[0.01]	[0.02]	[0.02]
Post × Dam0				−0.05***
				[0.01]
Post × Dam1				−0.09***
				[0.02]
Post × Dam2				−0.16***
				[0.04]
Observations	192,055	192,055	192,055	192,055
R-squared	0.141	0.141	0.141	0.141
Number of BB	18,455	18,455	18,455	18,455
Quarter dummies	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Sample of 1-family and 2-family houses. A property is classified as *New Risk* if it is located on the floodplain according to the 2013 Preliminary Flood Insurance Rates Map but was not on the floodplain under the 2007 (effective) Flood Insurance Rate Map. Estimated on transactions-based dataset. Controls include the log of the gross square footage and the year built or last altered. Dummy variables for quarter-year and for HEZAB, *New Risk* and Dam0, Dam1 and Dam2, included in the relevant specifications.

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