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Hurricanes, flood risk and the economic adaptation of businesses

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Abstract

We use administrative data containing all business establishments in New York City to analyze how businesses reacted to flooding in the context of Hurricane Sandy (October 2012). We find that flooding led to reductions in employment (of about 4%) and average wages (of about 2%) among the affected businesses. The effects were substantially larger and more persistent in some parts of the city (Brooklyn and Queens) than others (Manhattan). Heterogeneity across boroughs reflects differences in the severity of flooding, building types and industry composition. The effects of flooding also vary by industry and businesses in sectors involved in rebuilding after the storm experienced employment growth. Flooding also led to establishment closings and relocation to other neighborhoods, which is a form of adaptation to increased flood risk.

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1. Introduction

Sea levels have been rising over the last few decades and this trend is expected to continue for the foreseeable future (Stocker et al., 2013). As a result, large-scale flooding episodes will become more frequent, with large associated economic costs and displaced populations (Hinkel et al., 2014).[1]

The costs due to rising sea levels will depend on how businesses adapt. According to Desmet et al. (2018), permanent coastal inundation will displace about 1.5% of the world population, but the loss in terms of GDP could be much lower (at 0.2%) if companies and people gradually adapt to the changing environment by relocating. Absent these adjustments, the economic and welfare costs could be an order of magnitude larger.[2]

The main goal of our article is to empirically analyze the economic effects of a large-scale flooding episode. Specifically, we focus on the effects of Hurricane Sandy on the employment, wages and location decisions of New York City's businesses. Hurricane Sandy hit New York on 29 October 2012, and caused $50 billion in damage (Abel et al.,

1 In the context of the USA, Neumann et al. (2015) estimate that the combined effect of sea-level rise and episodic storm surge could be close to 1 trillion dollars through year 2100.

2 Naturally, cities or countries that are more constrained in their ability to adapt to rising sea levels are expected to suffer much larger losses. Desmet et al. (2018) forecast a reduction of more than 7% in Vietnam's GDP.

2012), much of it attributed to the effects of storm surge. Our longitudinal establishment data allow us to identify which structures flooded during the hurricane, and to trace their evolution in terms of employment and wages.

Because companies and people can move, we expect the storm's main effects to result in a reduction of the income generated at the affected locations. Lots (parcels) that flooded may have experienced out-migration of businesses, remaining vacant or populated by less productive businesses. Alternatively, companies may have maintained those establishments but downsized them in favor of safer locations. Either way, the quantity and quality of employment (measured by wage income) in the lots affected by the storm may have fallen, entailing a negative income shock to the neighborhood.[3]

We estimate the effects of Hurricane Sandy on the employment and wage income of the *lots* that were flooded (or suffered damage) during the storm. In addition, we also examine whether the hurricane affected the exit rate of the companies established in those lots. Our analysis is based on the estimation of linear models that include lot fixed effects, which account for all time-invariant lot characteristics (such as location, elevation or natural amenities), and differential trends in the flood zone. Thus, identification is based on the within-lot change around the time of Hurricane Sandy in employment (and wage income) among lots that were affected relative to unaffected lots. Our analysis also produces estimates separately by borough, to account for heterogeneity in industry composition, building type and severity of flooding.

Our data merge a confidential version of the *Quarterly Census of Employment and Wages* (QCEW) containing the universe of establishments in New York City for years 2000–2019 with damage-point data from Federal Emergency Management Agency (FEMA) that identify which building structures suffered damage during Sandy. The data show that there were close to 200,000 establishments in New York City in the year 2019, housed in roughly 85,000 lots. Our data also show that 2.6% of the lots (housing at least one business) are located on a FEMA Special Hazard Flood Area and 5.9% of the lots citywide flooded during the storm.

Our analysis delivers several main findings. First, we estimate that employment fell by approximately 4% (in the 2013–2019 period) in lots that flooded during Sandy. However, the effects vary substantially across the city's boroughs. Employment in flooded lots fell by 8% in Brooklyn and Queens (and possibly the Bronx). In contrast, we do not find evidence of a drop in employment among affected lots in Manhattan and Staten Island, partly driven by disparities in building types across the flood zones of the different boroughs. We also find evidence of reductions in wage income and average wages in lots that flooded during the storm, suggesting declines both in the quality as well as in the quantity of employment. Our estimates also show that the effects of flooding vary across industries. In industries involved in rebuilding after the storm, such as construction, businesses that flooded actually grew in terms of employment, likely reflecting the increased demand for their services (Belasen and Polachek, 2008; Groen et al., 2020).

Second, in some city boroughs (Brooklyn and Queens), these effects are highly persistent and show no signs of convergence to pretrend values 7 years after the hurricane. Given that most Sandy-related damage was repaired fairly rapidly, this pattern suggests

3 These issues are also relevant for the public sector. A recent study by Balboni (2018) using data for Vietnam argues that, the projected changes in flood risk affect the optimal location of infrastructure, entailing a shift away from flood-prone coastal areas.

that the storm may have affected business location and investment decisions more permanently. Consistent with this idea, we document a significant increase in exit rates among firms located in lots flooded by Sandy. We estimate a 1 percentage point increase in the probability to exit a lot that flooded, which amounts to a 25% of the mean exit rate.[4] In addition, we show that companies that were affected by flooding during the storm were much more likely to choose different neighborhoods for their new establishments, compared to companies whose establishments did not flood.

A plausible interpretation for our findings is that businesses whose activity was disrupted by Hurricane Sandy revised upward their beliefs on the flood risk associated with their specific location, consistent with recent studies of the housing market (Ortega and Taspinar, 2018; Bernstein et al., 2019) and municipal bond markets (Goldsmith-Pinkham et al., 2020). Responding to the increase in perceived risk, these businesses reacted by downsizing those establishments and shifting operations toward safer locations.

Our article contributes to the growing literature analyzing the economic effects of hurricanes and large-scale flooding events. Typically, these studies find that these events depress housing values and disrupt economic activity, both at the individual (Deryugina et al., 2018; Groen et al., 2020) and city level. However, most studies find that these effects vanish quickly. In this vein, Belasen and Polachek (2008) use data from the QCEW to estimate the effects of the 19 hurricanes that hit Florida between 1988 and 2005 on county-level outcomes. They find reductions in employment (of 1–5%) in the first quarter after the hurricane but *increases* in average earnings (of 1–4%), relative to unaffected counties. When they disaggregate the analysis by industry they find *positive* effects on employment and earnings for construction and services, and *negative* effects on both outcomes for manufacturing and most other industries. According to their analysis, the reduction in employment peaks 6 months after the hurricane and vanishes quickly. The transitory nature of these effects is consistent with the observation that hurricanes are fairly common in Florida and, as a result, unlikely to reveal new information that might affect agents' beliefs. Along similar lines, Kocornik-Mina et al. (2020) analyze flooding events worldwide, measuring economic activity using night-lights data, and find that flooded cities typically recover rapidly. This finding is echoed in the housing literature, where most studies show that flooding events lower housing values, though the penalty vanishes within a few years (Harrison et al., 2001; Bin and Polasky, 2004; Bin et al., 2008; Atreya et al., 2013; Bin and Landry, 2013; Zhang, 2016) and the effects appear to be more profound in more disadvantaged neighborhoods (Varela, 2019).

It is worth noting that there are numerous instances of natural disasters or other large shocks with highly persistent effects, such as the negative effects of London's 19th-century cholera outbreak on housing values (Ambrus et al., 2016) or the *increases* in property values following the 1872 Great Boston fire (Hornbeck and Keniston, 2017). Both studies argue that the persistent shift in outcomes was due to multiple equilibria. The (cholera and fire) shocks triggered a shift from one equilibrium to another, without affecting the fundamentals of the economy. However, the empirical relevance of explanations based on shocks to a system with multiple equilibria remains in dispute (Davis and Weinstein, 2002, 2008; Vigdor, 2008).

4 This finding is in line with the evidence in Boustan et al. (2017), who show that large natural disasters trigger out-migration (of people).

In the context of hurricanes and flooding, several recent studies focusing on housing values suggest that large-scale events reveal new information regarding flood risk and, hence, change the fundamentals of the economy. Ortega and Taspinar (2018) analyze the effects of Hurricane Sandy on the New York housing market and provide robust evidence of a persistent, negative impact on the price trajectories of houses that were damaged by Sandy. The authors argue that rare events provide useful information on tail flood risk and entail persistent effects.[5] Using Zillow data for thousands of counties in the USA, Bernstein et al. (2019) show that coastal properties exposed to projected increases in sea-level rise sell at a discount and also argue it is evidence of a gradual updating of beliefs over long-run flood risk. In our context, it is likely that a reorganization of the physical structure of a firm's establishments requires a change in risk beliefs that is large enough to overcome the inertia stemming from sunk organizational costs. Last, several recent studies provide empirical evidence of spatial sorting by perceived flood risk (Bakkensen and Barrage, 2017) and how flood risk revisions impact financial and real estate markets (Billings et al., 2019; Del Valle et al., 2019; Hong et al., 2019; Schlenker and Taylor, 2019; Goldsmith-Pinkham et al., 2020).

Our article is similar to the recent work by Meltzer et al. (2019). They also analyze the effects of Sandy on New York's establishments on the basis of a survey that ends in 2015 and contains only a small (possibly nonrandom) fraction of the city's establishments. They find that small retail establishments in heavily flooded blocks were more likely to close and reduce employment, but find no effects for larger establishments or in other industries. Our more comprehensive data allow us to exploit variation at the individual lot level, and carry out a more granular analysis by borough, industry and over time.

Lastly, our article is also related to the research on the link between temperature and economic activity (Jones and Olken, 2010; Dell et al., 2012; Zivin and Kahn, 2016; Addoum et al., 2020). Our article contributes to this literature by providing evidence of an *indirect* channel through which higher temperatures affect establishment outcomes: the increased prevalence of large-scale flooding episodes resulting from global warming.

The structure of the article is as follows. Section 2 introduces some useful notation, Section 3 describes the data sources, Section 4 discusses the empirical specification, Section 5 presents descriptive statistics, Sections 6 and 7 contain the main results, and Section 8 concludes.

2. Location-specific outcomes

It is helpful to introduce a bit of notation. Consider the set of companies in the city, with each company indexed by $i \in \mathcal{I} \equiv \{1, 2, \ldots, I\}$. Companies may operate in multiple locations and a given location may host several companies. We index locations by $\ell \in \ell \equiv \{1, 2, \ldots, L\}$ and we will refer to a pair (i, ℓ) as an *establishment*. In practice, companies will be uniquely identified by their employer identification number (EIN) and locations by their tax lots (parcels).[6] Let us define the matching function between companies and locations by $M : \mathcal{I} \times \ell \mapsto \{0, 1\}$, where $M(i, \ell) = 1$ means that company i is established at

5 Barr et al. (2017) develop an estimation approach aimed at identifying the informational content of storm surge on flood risk, using data for property values in New York City around Hurricane Sandy.

6 In most cases, a tax lot is simply a building.

location ℓ. We denote the pre-Sandy and post-Sandy matching functions by M_0 and M_1, respectively.

Clearly, if Hurricane Sandy triggered businesses to move out of their original locations, there may have been a reduction in the quantity or quality of employment in those lots. Those vacancies may have been filled up by smaller (in terms of employment) or less productive businesses (paying lower wages). However, even if there were no exits, companies may have downsized, either by reducing employment or diverting investment to their establishments in other (safer) locations. Importantly, these effects take place at the location level, rather than at the company level. To measure them, we build location-specific measures of employment and wages. Specifically, we define the employment and wage bills at location ℓ in period t by:

$$Emp_{\ell,t} = \sum_i Emp_{i,\ell,t} \tag{1}$$

$$Wagebill_{\ell,t} = \sum_i Wagebill_{i,\ell,t}, \tag{2}$$

where the summation is carried out over the set of companies at location ℓ: $\{i : M_t(i,\ell) = 1\}$. Several businesses may coexist at the same location. Hence, location aggregates may pool employees from companies belonging to different industries. We will also examine the effects of the hurricane on the average wage per worker in a given lot ℓ, defined as the wage bill over employment in the lot.

3. Data sources

We merge data from two sources: the Bureau of Labor Statistics' *QCEW* and FEMA's storm surge and damage-point estimates for Hurricane Sandy. In order to merge the two datasets, we geocoded the address of each establishment in the QCEW data and linked it to its tax lot number (using New York City's *PLUTO* dataset). Remarkably, we were able to do this for 95% of the establishments. Second, we spatially joined the FEMA data points to the footprints of all structures in the city, identified by their tax lot numbers, which resulted in a success rate of 98%. Last, we simply merged the two datasets by tax lot number (see Appendix A for more details). Next, we provide more details on each of the sources along with summary statistics.

3.1. Establishment data

Our establishment data are based on the QCEW, which provides quarterly information on establishment employment and wages, covering more than 95% of jobs in the USA.[7] We obtained a confidential version of these data from the New York State Department of Labor containing the exact location (address) and EIN for all establishments in New York City. Our data cover the period 2000Q1 through 2019Q4.

In our dataset, companies are uniquely identified by their EIN. Each company can have multiple *establishments*, defined as a company–lot combination. Restricting to establishments with positive employment and wage bill, our data for 2019 contain 194,949

7 The data are based on workers covered by federal and state unemployment insurance programs. More details on the QCEW can be found at https://www.bls.gov/cew/cewover.htm.

Table 1. Summary statistics establishments

Year	Establishments	Employment	Wage bill ($Mn annual)	Wage income per worker ($ annual)
2000	166,132	17.4	1.02	58,396
2001	168,098	17.4	1.04	59,912
2002	165,768	17.4	1.03	59,254
2003	166,808	17.2	1.02	59,189
2004	168,744	17.3	1.10	63,626
2005	172,964	17.4	1.18	67,798
2006	176,736	17.3	1.27	73,025
2007	181,784	17.5	1.40	79,991
2008	184,330	17.6	1.42	80,613
2009	183,498	17.1	1.27	74,313
2010	186,804	17.0	1.33	78,434
2011	190,870	17.0	1.35	79,620
2012	194,368	17.1	1.37	80,373
2013	198,238	17.2	1.37	80,044
2014	203,721	17.3	1.46	84,563
2015	209,648	17.5	1.50	85,416
2016	210,945	17.7	1.52	85,773
2017	212,045	18.0	1.62	89,874
2018	205,240	18.1	1.69	93,381
2019	194,949	18.8	1.81	96,011
Average	187,084	17.5	1.34	76,480

Notes: Unbalanced dataset at the establishment (EIN-BBL) level. Employment refers to the average employment across the four quarters in the corresponding year. The wage bill has been annualized. Average wage income is computed by dividing the wage bill (column 4) by employment (column 3). This table is computed on the basis of establishment-quarter observations with positive employment and wage bill.

establishments for New York City with an average employment of 18.8 workers and an annual wage bill of $1.8 million, which results in an average annual salary of $96,011 (as shown in Table 1).[8] The data also indicate a fairly stable level of employment per establishment, averaging 17.5 employees. It is helpful to examine the aggregate trends graphically. Figures 1and 2 plot the annual average employment and wage income (in millions of current dollars) citywide, exhibiting a highly pro-cyclical behavior.[9] Similarly, Figure 3 shows that the annual average wage per worker increased between 2003 and 2008, fell in 2009 and then resumed its upward trend (in nominal terms).[10]

3.2. Storm surge and damage point data

Our second data source is FEMA's storm surge and damage-point estimates for Hurricane Sandy. These data contain information on the water depth (above ground) and the resulting

8 Our data match well the official summary data by the BLS based on the same source. According to the BLS, total employment in New York City was 4.36 million workers, average employment per establishment was 16.4 employees and the annual wage per worker was $96,834.

9 Employment and the wage bill fell between 2000 and 2003 and again between 2008 and 2010, in line with the NBER recessions.

10 Over the 20-year period in our data, the average annual wage per worker has risen from $58,396 to $96,011, a 2.73% nominal average annual increase.

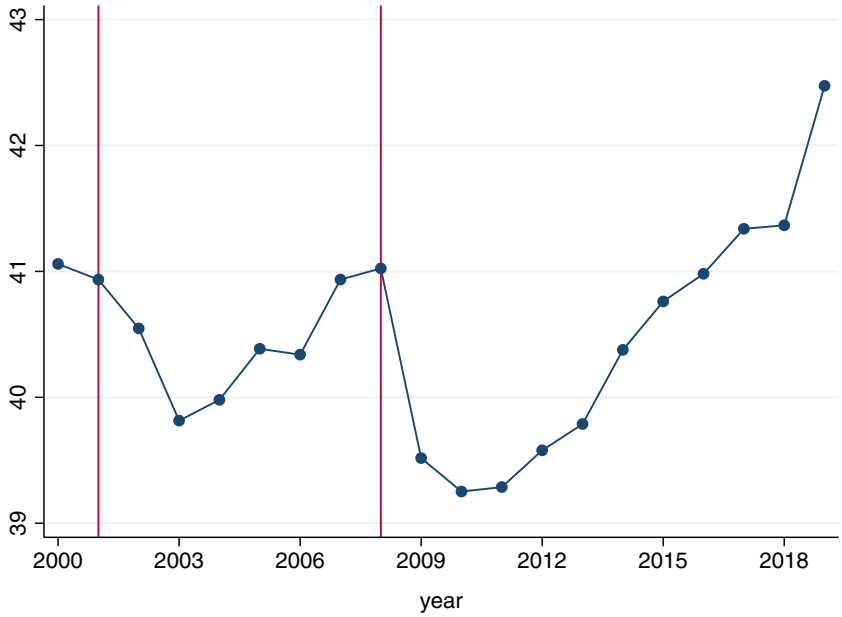

Figure 1. Average employment per lot.
Notes: We restrict to lots with positive employment and in the corresponding year. Vertical lines for NBER recession years 2001 and 2008.

Figure 2. Annual wage income per lot.*Notes:* We restrict to lots with positive wage bill in the corresponding year. Vertical lines for NBER recession years 2001 and 2008.

damage level experienced by each structure in the storm's inundation area. Each structure is identified by a latitude–longitude point, corresponding to its centroid.

Let us first discuss the *storm surge* data, which we use to a build property-level indicator for having been flooded during Sandy. Figure 4 illustrates Sandy's inundation area

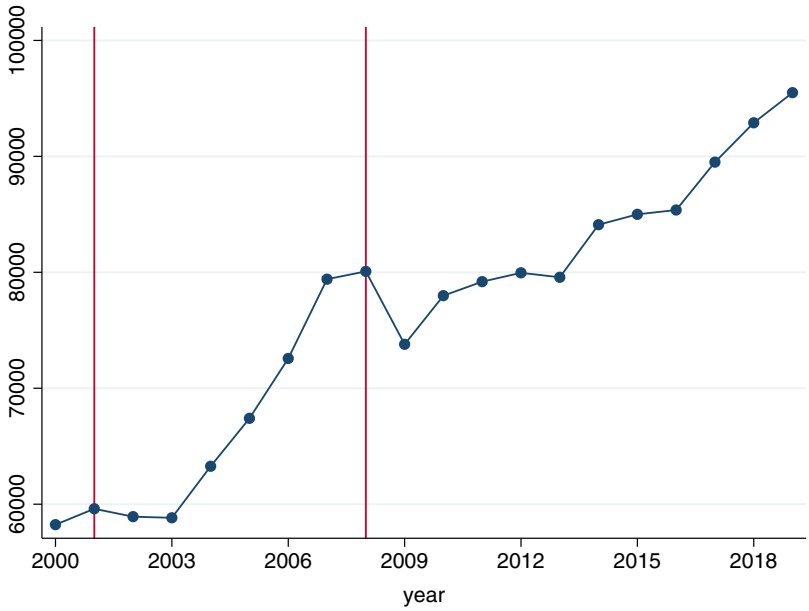

Figure 3. Annual wage income per worker.
Notes: The average annual wage per worker is the ratio between the annual wage bill and employment by lot, restricting to lots with positive employment and wage bill in the corresponding year. Vertical lines for NBER recession years 2001 and 2008.

within New York City, which contains all buildings that were flooded during the storm. The figure shows the storm surge (defined as feet of water above ground), with darker values denoting greater depth. The highest surge values were attained in Staten Island and the South-facing coastal areas in Queens and Brooklyn, with estimated depths often between 6 and 10 feet and, occasionally, above 10 feet.

The storm surge data are used by FEMA to build a more comprehensive measure of the *damage* suffered by each building structure during Hurricane Sandy using air imagery. This combined measure provides an assessment of wind-related damage (e.g. missing roofs or walls) as well as flooding.[11] Figure 5 plots the damage-point variable on New York City's map. Not surprisingly, the areas that suffered greater damage largely coincide with those that experienced the deepest inundation: Staten Island and Queens were the boroughs that were hit the hardest, followed by Brooklyn. In contrast, many fewer buildings were damaged in the Bronx and Manhattan. Clearly, the damage variable contains more information and provides a richer assessment of the impact of the storm on a property. However, realized damage may be affected by the adoption of protective measures by property owners, possibly introducing correlation with unobservable factors. Since property-level measures of the storm surge are less likely to suffer from endogeneity bias, we will rely on them more heavily in our analysis.[12]

11 Aerial imagery is based on images obtained by NOAA, Civil Air Patrol and media captured on 29 October through 6 November in year 2012. In areas of high-rise development, storm surge is determined using modeled results rather than field-verified flooding. For more details, see Appendix B.

12 Because surge depth data are used in the construction of the damage variable, both will be highly correlated. In fact, in the cross section, this correlation is 0.90.

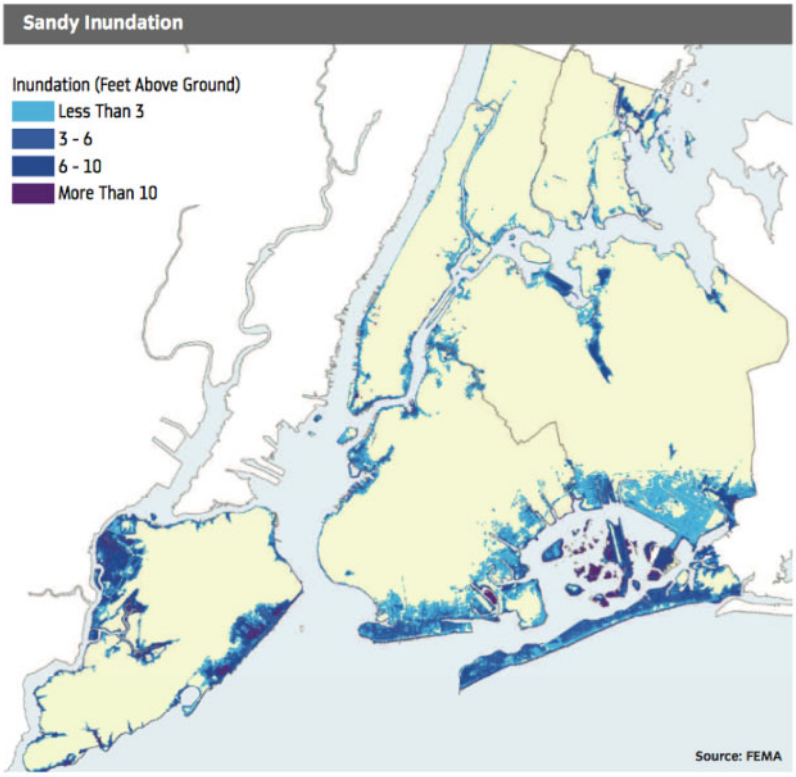

Figure 4. Sandy inundation zone.
Notes: The source for the figure is FEMA MOTF; Inundation defined as depth (in feet) of water above ground.

We created indicators of flooding and damage severity. Specifically, property-level dummy variable *Flooded* takes a value of one for all properties (lots) within Sandy's inundation zone. Furthermore, we build indicators *Flooded*1 and *Flooded*2, which identify properties in the storm surge that experienced flooding below or above median depth (5.5 feet), respectively.[13] We also created indicator variables to identify locations on the FEMA 100-year flood zone (*Special Flood Hazard Areas* or SFHA).[14]

3.3. Data by parcel

As discussed already, our main unit of analysis is the tax lot (parcel). Thus, we add the employment and wage bill across all business establishments located in the same lot in

13 Similarly, we define property-level indicators *Damaged*1 and *Damaged*2, which identify properties in the inundation zone that suffered at most minor and major damage (or were destroyed), respectively. Note that these definitions imply that every flooded property will be classified as suffering some damage. However, a property may be classified as damaged without having been flooded. For instance, this will be the case properties for properties that suffered wind-related damage but were not flooded. The data show that 6.1% of the properties in New York City suffered damage during Hurricane Sandy, but only 5.7% were flooded.

14 The flood zone is a fairly narrow strip, containing only 2.72% of the city's parcels, but naturally concentrates most of the buildings damaged during Hurricane Sandy. Despite its small size, because of its proximity to the waterways and amenity value, the flood zone is an important part of the city for residential and commercial purposes.

Figure 5. Sandy damage-points map.
Notes: The figure depicts damage-point estimates. Damage level defined on the basis of storm surge (depth) and aerial imagery. From lower to higher damage level: Affected, Minor Damage, Major Damage and Destroyed.

any given quarter. The resulting dataset has 6.4 million parcel-quarter observations for the period 2000Q1–2019Q4. In the average year, in our sample, there are almost 187,000 establishments housed in approximately 79,000 unique lots.[15] The data show that most lots house just one business (68%), 15% contain two businesses, 6% contain three businesses, and 5% contain four or five businesses. Hence, only 6% of the lots house more than five businesses. As shown in Table C1, the average lot in year 2019 had 42.5 employees and generated a wage income of $4.1 million on an annual basis, corresponding to an average wage of $95,492.

It is worth noting that there are important differences across boroughs in terms of lot size, measured by number of establishments. This is largely due to differences in building types. Based on Table 2, the median and mean establishments per parcel are 1 and 2.4 for the city as a whole. By borough, Manhattan has the highest median and mean values (2 and 5.0) while the corresponding values for all other boroughs are 1 and 1.6, respectively. The bottom panel of the table reports information restricting to the parcels located in the

15 The city as a whole has about 0.8 million lots, most of which are exclusively residential. Thus only about 1 in 10 lots (buildings) contains a business establishment.

Table 2. Establishments per lot by borough

Borough	NYC	MH	BX	BK	QN	SI
Whole borough						
Minimum	1	1	1	1	1	1
Median	1	2	1	1	1	1
Maximum	1024	1024	68	186	138	138
Count lots	86,993	20,793	8630	29,257	23,028	5285
Count establishments	210,636	104,182	14,762	45,626	38,312	7754
Mean estab/parcel	2.42	5.01	1.71	1.56	1.66	1.47
Flood zone						
Minimum	1	1	1	1	1	1
Median	1	1	1	1	1	1
Maximum	169	169	32	103	28	26
Count lots	2366	512	200	899	473	282
Count establishments	6607	2814	382	2046	982	383
Mean estab/parcel	2.79	5.50	1.91	2.28	2.08	1.36

Notes: Data for all years, 2000–2019. The counts and the mean establishments per lot are based on the average across the whole period. Top panel refers to all lots. Bottom panel only to lots located in the flood zone (defined as FEMA's Special Hazard Flood Area).

flood zone. The mean parcel size is slightly larger in the flood zone (2.8 versus 2.4 for the city as a whole) but the differences across boroughs in mean parcel size are largely unchanged. Hence, Manhattan's parcels are more than twice as large than in the other boroughs. To the extent that the establishments in those parcels are arranged vertically, the damage caused by Hurricane Sandy in the average establishment of an affected building in Manhattan is likely to be significantly smaller than in the corresponding establishment in other boroughs.

4. Specifications

Our main goal is to examine whether Hurricane Sandy has affected economic activity from the perspective of businesses. As discussed earlier, companies are highly mobile because many lease, as oppose to owning, the locations of their establishments. Hence, if a specific warehouse or commercial area becomes fundamentally less attractive, the companies operating in that space may choose to pay the cost to migrate to some other location. Hence, the long-term effects of an increase in flood risk will be manifested in the income-generating potential of the specific location (lots).

Naturally, some lots remain vacant in some quarters, for instance, due to seasonality effects. It is more appropriate to allow these idle lots to remain in the sample, rather than treat them as missing values. Furthermore, dropping lots that become vacant could introduce survival bias. Specifically, if severely flooded lots become vacant (i.e. zero employment) and disappear from the estimation sample, their weight will gradually diminish, thus understating the effects of the hurricane on the affected parcels. To address this problem, we create a *balanced* panel at the lot level. That is, the dataset contains an observation for each lot in each quarter during the whole sample period. As a result, the dataset roughly doubles in observations, from 6.4 to 13 million. The newly created cells are populated with zero values for employment and wage bill.

Let $y_{\ell,t}$ denote the outcome of lot ℓ in quarter t, typically the level of employment or wage income in the lot for that particular quarter. Clearly, our balanced panel will have a large number of zeros. As a result, it is unsuitable to work with log transformations of the dependent variable. We adopt a common alternative and use the inverse hyperbolic sine (*asinh*) transformation. Unlike logs, the *asinh* is well-defined at zero and has the same attractive features (Burbidge et al., 1988; MacKinnon and Magee, 1990).[16]

We will estimate difference-in-difference models for (the inverse hyperbolic sine of) employment and wage income using the following specifications:

$$y_{\ell,t} = \alpha_t + \alpha_\ell + \gamma_t FZ_\ell + \beta Post_t \times Flooded_\ell + \varepsilon_{\ell,t}, \tag{3}$$

where α_t is quarter-year dummies, α_ℓ is lot fixed effects and $\gamma_t FZ_\ell$ captures differential trends in and out of the flood zone.

Our main coefficient of interest, β, is associated with the interaction between a post-Sandy indicator ($Post_t$) and a dummy variable that indicates which lots were flooded during Hurricane Sandy ($Flooded_\ell$).[17] Intuitively, coefficient β is identified by changes in, say, employment around the time of Hurricane Sandy in flooded lots relative to the change for lots that did not flood, conditional on lot fixed effects and flood zone-specific trends. Importantly, the lot fixed effects absorb all time-invariant lot-level characteristics, such as location, elevation, building type and natural amenities. Standard errors are clustered at the block level, which allows for spatial correlation across locations within a block and is a more conservative choice.[18]

We will also estimate more flexible models that allow us to trace the evolution over time of the effect of Sandy on outcomes:

$$y_{\ell,t} = \alpha_t + \alpha_\ell + \gamma_t FZ_\ell + \beta_t Flooded_\ell + \varepsilon_{\ell,t}, \tag{4}$$

where the coefficient β_t is allowed to vary annually. Thus the estimated β_t will trace the within-parcel change in the dependent variable for the outcome of interest (in year t relative to before Sandy) in parcels that flooded, compared to the evolution for lots that did not flood during Sandy. These estimates will allow us to gauge the persistence of the effects over time (2012–2019), which is a point of contention in the literature estimating the effects of hurricanes and other natural disasters on housing values.

Another important consideration is that FEMA's storm surge data identify the lots which experienced storm surge during Sandy, but not the specific businesses in the lot that were affected. Clearly, for single-business lots, there is no distinction, and these account for

16 More specifically, the inverse hyperbolic sine transformation is given by: $asinh(x) = \ln(x + \sqrt{x^2+1})$ for any $x \in \mathbb{R}$. Note that $ihs(0) = 0$. Except for very small values of x, the inverse sine is approximately equal to $\ln(2x) = \ln(2) + \ln(x)$, thus it can be interpreted in exactly the same way as the log transformation. For robustness, we will also provide estimates for models where the dependent variable is the log of the corresponding variable, rather than the inverse hyperbolic sine. Naturally, in these cases, the sample size will fall importantly because all the artificially created cells to create a balanced panel will be dropped.

17 Indicator $Post_t$ takes a value of one for quarters 2013Q1 and onward.

18 An alternative specification is a pure within-lot model where we substitute the $Post_t \times Flooded_\ell$ interaction term by a time-varying $Flooded_{\ell,t}$ variable taking value of one for lots that flooded during Sandy in the post-Sandy years, and zero otherwise. The key difference with our difference-in-difference approach is that the pure within estimator captures only contemporaneous effects. In contrast, our estimator captures the permanent effect and allows us to analyze its evolution over time. In theory, our specification could also include lot linear time trends but because of the very high number of lots (over 160,000) we are concerned about the feasibility and performance of the estimation of such a model.

Table 3. Summary statistics: balanced panel

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	13,216,240	2009.5	5.76	2000	2019
Employment	13,216,240	19.48	390.94	0	154,532
Wage bill ($M)	13,216,240	1.50	38.92	0	24414.58
Wage per worker	6,375,241	33745.93	70737.71	0	4.60e+07
Flood zone (*FZ*)	13,216,240	0.0259	0.1588	0	1
Flooded	13,216,240	0.0591	0.2359	0	1
Flooded1	13,216,240	0.0535	0.2251	0	1
Flooded2	13,216,240	0.0056	0.0746	0	1
Damaged	13,216,240	0.0548	0.2275	0	1
Damaged1	13,216,240	0.0503	0.2186	0	1
Damaged2	13,216,240	0.0044	0.0665	0	1

Notes: Balanced panel at the lot level, containing 165,000 unique lots. Thus, there is one quarterly observation for each lot. In the newly expanded cells, employment and wage income are zero. The wage bill has been annualized and its units are millions of current dollars. Wage per worker is computed by dividing the annualized wage bill in a lot over the number of employees in the lot. Notation *asinh* stands for the inverse hyperbolic sine transformation of the corresponding variable. *FZ* is an indicator for whether the lot belongs to FEMA's SFHA. *Flooded* is an indicator identifying lots that were flooded during Hurricane Sandy. Indicators *Flooded*1 and *Flooded*2 identify lots that were flooded but suffered below median flooding (depth of 5.5 feet) and above median flooding, respectively. Similarly, *Damaged* is an indicator identifying lots that were damaged during Hurricane Sandy. Indicator *Damaged*1 takes a value of 1 for lots that suffered relatively low levels of damage (damage levels *Affected* or *Minor*). Similarly, *Damaged*2 identifies the lots that suffered relatively high levels of damage (damage levels *Major* or *Destroyed*).

over two-thirds of the sample. However, in multiestablishment lots, not all establishments may have been affected to the same degree. Given that building types differ across boroughs, we will also provide estimates of our models separately for each borough. The expectation is that the effect of flooding on a lot's employment or wage bill will be lower in boroughs where a large share of the affected lots are high rises, as is the case in downtown Manhattan.

5. Summary statistics and validity identification

Our balanced panel contains 165,203 business lots, totaling 13.2 million lot-quarter observations. Among these, 52% of the observations have zero employment and wage bill. As a result, the average employment per lot is 19.5 workers (Table 3), roughly half of what we observe in the unbalanced panel (Table C1).

Similarly, the average annual wage bill is $1.5 million and the average (nominal) wage per worker is $33,745.[19] The table also shows that around 2.6% of the observations correspond to lots located in the flood zone and 5.9% and 5.5% of the observations correspond to lots that were flooded or damaged during Sandy, respectively. Thus many parcels located outside the FEMA flood zone were affected by the storm.

Next, we provide a comparison of the average outcomes (employment and wage income) across boroughs and by flooded status in the quarter immediately prior to Sandy

19 Note that employment includes part-time as well as full-time workers. Naturally, average wage per worker is only defined in lot-quarter cells with positive employment.

Table 4. Pre-Sandy trends (2009Q3–2012Q3)

Dep. Var.	1 Emp	2 Wage bill	3 Wb/Emp	4 Δln Emp	5 Δln Wb	6 Δln Wb/Emp
Flooded	−2.16	−232.14	2.51***	−0.01	−0.02	−0.01
	(4.87)	(355.08)	(0.65)	(0.01)	(0.02)	(0.01)
FZ	37.22***	3452.68***	5.06***	0.05**	0.06**	0.02
	(8.54)	(880.42)	(0.90)	(0.02)	(0.03)	(0.01)
MH	93.50***	8124.57***	41.47***	0.09***	0.14***	0.05***
	(3.72)	(421.30)	(1.36)	(0.01)	(0.01)	(0.00)
BX	24.01***	1019.68***	28.19***	0.04***	0.05***	0.01**
	(2.16)	(138.02)	(0.25)	(0.01)	(0.01)	(0.01)
BK	23.31***	965.24***	27.89***	0.09***	0.12***	0.04***
	(5.60)	(284.05)	(0.20)	(0.00)	(0.01)	(0.00)
QN	17.48***	700.29***	29.86***	0.06***	0.09***	0.03***
	(0.79)	(49.51)	(0.23)	(0.00)	(0.01)	(0.00)
SI	14.77***	497.19***	31.64***	0.03***	0.04***	0.01
	(1.62)	(106.16)	(0.51)	(0.01)	(0.01)	(0.01)
Observations	83,144	83,144	83,144	66,095	65,932	65,932
R^2	0.01	0.01	0.10	0.01	0.02	0.01

Notes: Wb is short for Wage bill. Only data for 2009Q3 and 2012Q3. No intercept included in these regressions. In columns 1–3, the sample includes all lot-year observations with positive employment. In columns 4–6, we restrict to positive employment in both years. The wage bill and average wage per worker are in thousands of current dollars. Heteroskedasticity-robust standard errors.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(2012Q3). Specifically, Table 4 provides estimates of simple models for each of the outcomes of interest, where the right-hand side contains indicators for flooded status (*Flooded*), flood zone location (*FZ*) and borough.[20] Column 1 shows that business lots in Manhattan have an average employment of 93.5 workers. In comparison, mean employment per lot is noticeably lower in the other boroughs. Additionally, lots located on the FEMA flood zone are also larger in terms of employment than those outside the flood zone within the same borough. More importantly, we do not observe statistically significant level differences in mean employment between lots that flooded during Sandy and lots that did not (conditional on borough and flood zone location). The same pattern is observed in column 2, which refers to the wage income generated by the lot. Column 3 reports the mean average annual wage per worker, which is also substantially higher in Manhattan ($41,470) and in the flood zone. In this case, we do observe significantly higher average wages for lots that flooded during Sandy (by $2510).

Next, we turn to the most relevant part of the table, where we assess the pre-Sandy trends in outcomes. Our main findings are based on difference-in-difference estimates and, thus, causal interpretation requires assuming that treatment units (those flooded by Sandy) would have followed the same trends as control units in the absence of the storm. Columns 4–6 in Table 4 report the *within-lot* change in the log of the corresponding

20 These models do not include intercept so that each coefficient coincides with the corresponding mean. The estimates are based on the balanced panel and contain over 82,000 lots in 2012Q3.

outcome during pre-Sandy period 2009Q3–2012Q3. These estimates reveal noticeable differences in mean growth rates across boroughs and by flood zone location. However, we do not observe any significant differences in pre-Sandy growth between lots that flooded during Sandy and those that did not, after conditioning on borough and flood zone location. Hence, these estimates provide support for the *parallel trends* assumption in models that account for cross-borough differences and differential flood zone trends. We will provide additional support for this assumption on the basis of our event-study estimates (Section 6.4).

6. DiD estimates at the lot level

We now turn to the estimation of the effects of Hurricane Sandy on the lots that flooded during the storm, which hit New York City on 29 October 2012. We begin by providing difference-in-difference estimates (as in Equation 3) of the effects on the various outcomes. We also analyze the robustness of the estimates by using a more comprehensive measure of damage, test for spillover effects from neighboring properties, and characterize the evolution of the effects over time (as in Equation 4). Throughout, we provide estimates disaggregated by borough and discuss the reasons for the disparity in the estimated effects.

6.1. Employment

Table 5 focuses on employment effects. The dependent variable in the top panel of Table 5 is the inverse hyperbolic sine of employment in the lot. The first two columns provide estimates based on the whole sample (of 13.2 million lot-quarter observations). Employment in lots that flooded during Sandy grew significantly less, by about 4%, than in comparable lots that did not flood. In column 2, we differentiate by the severity of flooding, measured by depth of the storm surge. The estimates suggest larger reductions in employment for the lots that experienced more severe flooding. Specifically, above median (5.5 feet) flooding is associated with a roughly 8% drop in employment, compared to a 4% drop for flooded lots with below-median depth. Columns 3–7 disaggregate the analysis by borough. The reason to do this is that the severity of flooding, as well as building types and industry composition vary considerably across boroughs. The estimates suggest that flooded lots in Manhattan and Staten Island did not experience systematic changes in employment after the storm, relative to non-flooded lots. In contrast, flooded lots in the Bronx, Brooklyn and Queens did suffer substantial reductions in employment (of about 8%).

In the bottom panel of the table, the dependent variable is the log of employment. Because observations with zero values are dropped from the estimation sample, the number of observations falls to 6.37 million. Nonetheless, we obtain very similar results, both quantitatively and qualitatively. Namely, employment fell by about 3% in flooded lots in the citywide sample, largely reflecting the effects found in the Bronx, Brooklyn and Queens subsamples.

6.2. Wage income and average wage

Analyzing the effects of Sandy on businesses' wage income (measured by the wage bill in the lot) provides a combined measure of the effects on the quantity and quality of

Table 5. Effect of flooding on employment: DiD estimates

	1 NYC	2 NYC	3 MH	4 BX	5 BK	6 QN	7 SI
asinh(*Emp*)							
Post × *Sur*	−0.04***		−0.01	−0.05	−0.08***	−0.08***	0.06
	(0.01)		(0.04)	(0.14)	(0.02)	(0.03)	(0.04)
Post × *Sur*1		−0.04***					
		(0.01)					
Post × *Sur*2		−0.08*					
		(0.04)					
Obs ('000)	13,216	13,216	2336	1232	4777	3897	974
ln(*Emp*)							
Post × *Sur*	−0.03**		−0.03	−0.07	−0.04**	−0.07**	0.03
	(0.01)		(0.04)	(0.08)	(0.02)	(0.03)	(0.04)
Post × *Sur*1		−0.03**					
		(0.01)					
Post × *Sur*2		−0.06					
		(0.04)					
Obs ('000)	6375	6375	1578	637	2121	1662	373
Lots	165,203	165,203	29,195	15,399	59,714	48,714	12,181
% Flooded	5.91	5.91	4.27	1.36	8.77	3.84	9.87
% Damaged	6.26	6.26	4.44	1.87	9.09	4.10	10.98
FZ trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel
Cluster SE	Block	Block	Block	Block	Block	Block	Block

Notes: The dependent variable in top panel is the inverse hyperbolic sine of employment in the lot (BBL) and in the bottom panel it is the log, which is undefined at zero. In both cases, we are pooling all businesses located in the same lot. The panel dataset is balanced (i.e. all lots appear in each quarter). About half of the lot-quarter observations have zero employment and wage bill. *Post* is an indicator for quarters 2013Q1 and onward. *FZ* is an indicator for the lot being located in a special flood hazard area (according to the 2007 FEMA flood map for New York). *Flooded* is an indicator for having flooded during Hurricane Sandy. Indicators *Flooded*1 and *Flooded* 2 partition flooded lots into above and below median (5.5 feet) storm surge depth.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

employment. In addition, the wage bill is closely related to the overall income created by a business.[21]

Table 6 (top panel) presents the estimates. As before, the dependent variable in the top panel is the *asinh* of wage income in the lot (in millions of dollars). Echoing the findings for employment, columns 1–2 provide evidence of a negative effect on the wage income of lots that flooded during Sandy, with a larger effect on the lots that suffered more severe flooding. Across the borough subsamples (columns 3–7), we obtain mostly negative point estimates, but we can only reject the zero null hypothesis for the Brooklyn subsample.[22]

The previous results show that lots that flooded during Hurricane Sandy have suffered a loss in employment and wage income, plausibly caused by the storm. Next, we investigate

21 For instance, if we assume that factor prices are given by their marginal products and production functions are Cobb–Douglas, company sales and its wage bill are proportional.

22 Although not shown for the sake of brevity, we have also estimated the models using the standard log transformation of the dependent variable and the results are qualitatively similar. For the NYC sample, the estimated effect of Sandy flooding on wage income implies a reduction of 6 log points. Unlike the standard log transformation, the *asinh* is unit-dependent.

Table 6. Effect of flooding on wage bill (top) and wage per worker (bottom)

	1 NYC	2 NYC	3 MH	4 BX	5 BK	6 QN	7 SI
asinh(*WB*)							
Post × *Flooded*	−0.01***		−0.02	−0.02	−0.01**	0.01	−0.01
	(0.005))		(0.025)	(0.061)	(0.005)	(0.011)	(0.013)
Post × *Flooded*1		−0.01**					
		(0.005)					
Post × *Flooded*2		−0.06***					
		(0.014)					
Obs ('000)	13,216	13,216	2336	1232	4777	3897	974
asinh(*w*)							
Post × *Flooded*	−0.02***		−0.02	0.04	−0.04***	0.01	−0.01
	(0.008)		(0.024)	(0.036)	(0.012)	(0.017)	(0.025)
Post × *Flooded*1		−0.022***					
		(0.009)					
Post × *Flooded*2		−0.018					
		(0.022)					
Obs ('000)	6372	6372	1578	637	2121	1662	373
Lots	165,203	165,203	29,195	15,399	59,714	48,714	12,181
% Flooded	5.91	5.91	4.27	1.36	8.77	3.84	9.87
% Damaged	6.26	6.26	4.44	1.87	9.09	4.10	10.98
FZ trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel
Cluster SE	Block	Block	Block	Block	Block	Block	Block

Notes: The dependent variable in top panel is the inverse hyperbolic sine of the wage bill in the lot (BBL) and in the bottom panel it is the same transformation but applied to the average wage per worker. In both cases, we are pooling all businesses located in the same lot. The panel dataset is balanced (i.e. all lots appear in each quarter). About half of the lot-quarter observations have zero employment and wage bill. *Post* is an indicator for quarters 2013Q1 and onward. *FZ* is an indicator for the lot being located in a special flood hazard area (according to the 2007 FEMA flood map for New York). Indicators *Flooded*1 and *Flooded*2 partition flooded lots into above and below median (5.5 feet) storm surge depth.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

the effects on the average wage per worker at the lot level, which is only defined for lot-quarter observations with positive employment.[23] The estimates are collected in the bottom panel of Table 6. As seen in column 1, average wages per worker appear to have fallen by about 2% in the lots that flooded during Sandy, with the effect reaching 4% in the Brooklyn subsample.[24]

23 Annualizing the quarterly data, the average wage per worker in our data increased from $58,234 in year 2000 to $80,079 in year 2008. After a slight drop in years 2009 through 2013, it reached $95,492 in 2019. In interpreting these figures, it is important to keep in mind that both full-time and part-time workers are included in the calculations.

24 In the log specification, we estimate a 2 log-point reduction on average wages per worker (NYC sample). As expected, this reduction is consistent with the estimated effects on the wage bill and employment in the logarithmic specifications. In the logs specifications, the estimated negative 6 log-point change in the wage bill minus the negative 4 log-point change in employment imply a negative 2 log-point change in the wage per worker.

It is important to note that these reductions in wages at the lot level can be due to a variety of reasons. They could be a reflection of a change in the composition of the businesses located in the lot, with higher-wage businesses departing the lot and being replaced by lower-wage businesses, or some (but not all) commercial spaces in the lot remaining vacant for some period of time. Alternatively, these estimates could also reflect a reduction in hourly wages or in working hours affecting all businesses in the lot. The analysis in the later sections will shed some light on the mechanisms.

6.3. Additional difference-in-difference estimates

Here we depart from our canonical specification along several dimensions.

6.3.1. The effects of damage

Next, we use the more comprehensive measure that also incorporates damage assessed through aerial imagery, which allows to take into account wind-related damage in addition to flooding. The estimates are collected in Table C2. The general pattern of results is very similar to what we obtained in the case of flooding: damaged lots experienced lower growth in employment (by about 2%), with reductions of 5–7% for damaged lots in Brooklyn and Queens.

6.3.2. Neighborhood spillovers

Here we attempt to disentangle the own effects of flooding from those that spill over due to neighboring lots having flooded.[25] Specifically, we compute the average number of flooded lots in each block and incorporate this new term, *BlockFlooded*, in the specification.[26]Table C3 presents the estimates for employment. Compared to the estimates reported in Table 5, column 1 suggests that own flooding and the neighbors' flooded status may both have contributed to the reduction in employment, although the standard errors are now more than twice as large as before. The lack of precision stems from the fact that $Flooded_\ell$ and $BlockFlooded_\ell$ are highly correlated. Cross sectionally, the correlation coefficient between these two variables is 0.90. As a result, disentangling the neighbors' spillover from the own effect is a daunting task.

6.3.3. Various control groups

We believe that identification of the subtle effects of flooding on business outcomes (or other outcomes such as housing values) in a credible manner that takes into account the high degree of heterogeneity across lots requires very large samples. This intuition guided our choice of sample (i.e. the whole city) and specification (flood zone trends to make the lots inside and outside the flood zone as comparable as possible). Alternatively, one could

25 There is a growing literature that studies local spatial spillover effects. The focus is on multiplier effects due to local interactions (Glaeser et al. 2001; Dougal et al. 2015). As far as we are concerned, the literature studying spillover effects from natural disasters tends to focus on propagations through the supply chain (Barrot and Sauvagnat, 2016; Boehm et al., 2019) rather than on the spatial spillover effects that concern us here.

26 Our averages are lot-specific because they leave out lot ℓ in the computation of the block average for that specific lot. This way we avoid introducing a mechanical correlation between a lots flooded status and its block average.

restrict the sample to a subset of more similar lots, such as those in the flood zone. As robustness, we consider two variations on this alternative approach. The first one considers a large flood zone, defined by New York City's Hurricane Evacuation Zone ABC, which contains approximately 30% of the lots in the whole city. The second flood zone is narrower and is defined by FEMA's Special Hazard Flood Zone, which contains less than 3% of the city's lots.

Table C4 reports the estimates for our preferred employment model across three scenarios: (i) the full sample with flood zone trends (top panel), (ii) the large flood zone sample (middle panel) and (iii) the narrow flood zone sample (bottom panel). The sample sizes vary greatly across the three variations. The sample in the top panel contains 13.2 million lot-quarter observations whereas the middle and bottom panels have 3.9 million and 0.3 million observations, respectively. Second, the three variations produce negative effects on employment for the full sample. According to the top and middle panels, flooding led to approximately 4% reductions in employment. The point estimate in the bottom panel is twice as large (in absolute value) but estimated with very low precision. Last, both for the Brooklyn and Queens subsamples, the estimates in the three panels suggest negative effects of flooding. However, the significance of the estimates falls monotonically. In the top panel, we are able to reject the zero null hypothesis at a significance level of 1%. In the middle panel, we are only able to reject this hypothesis at a 10% significance level, and in the bottom panel, we cannot reject the zero null at conventional significance levels. In sum, our finding of a negative effect on employment (based on the full NYC sample and a model with flood zone trends) is robust to restricting the estimation sample to the flood zone, as long as we employ a definition of flood zone that is not too restrictive.

6.4. Dynamics and persistence

Next, we investigate the evolution of the employment effect of Hurricane Sandy over time, estimating more flexible models. We begin with a version of Equation (4) that allows for year-specific effects in the post-Sandy years. Analogous to the standard DiD estimates, each coefficient β_t (associated with the interaction between year t and the *Flooded* dummy) is identified by the change between the average pre-Sandy period and year $t \geq 2013$, relative to the same change for the business lots that did not flood. In addition, Table 7 also presents coefficients γ_t associated with the interaction between year dummies and the flood zone location indicator.

We begin by focusing on the post-Sandy evolution of employment for *nonflooded* lots in the flood zone. The estimates in columns 1 and 2 suggest *increases* in employment for nonflooded lots in the flood zone, regardless of the transformation applied to the dependent variable (log or *asinh*). This positive trend stands in stark contrast to the negative evolution of employment for lots flooded by Sandy. As seen in the bottom set of estimates for the full NYC sample (columns 1 and 2), flooding during Sandy led to a reduction in employment of about 4–5% between 2013 and 2016. Columns 3–7 show that these estimates mainly reflect negative employment effects of flooding in the subsamples for Brooklyn and Queens. Column 5 shows that the employment losses for the flooded lots in Brooklyn amounted to around 6% in year 2013 and 7% in 2019. In the case of flooded lots in Queens, the employment losses were much larger in 2013, at roughly 13%, gradually converging toward values similar to those for flooded lots in Brooklyn, at 9% in

Table 7. Dynamic effects of flooding on employment: event study

	1 NYC	2 NYC	3 MH	4 BX	5 BK	6 QN	7 SI
Dep. Var.	ln	*asinh*	*asinh*	*asinh*	*asinh*	*asinh*	*asinh*
FZ × 2013	0.03	0.02	−0.01	0.11	0.02	0.07	−0.06
	(0.02)	(0.02)	(0.07)	(0.08)	(0.03)	(0.05)	(0.05)
FZ × 2014	0.04**	0.03	0.04	0.13	0.05	0.07	−0.05
	(0.02)	(0.02)	(0.07)	(0.09)	(0.04)	(0.05)	(0.05)
FZ × 2015	0.05**	0.06**	0.18**	−0.01	0.09**	0.07	−0.10*
	(0.02)	(0.03)	(0.07)	(0.10)	(0.04)	(0.06)	(0.06)
FZ × 2016	0.05*	0.06**	0.19**	−0.06	0.11**	0.09	−0.13**
	(0.02)	(0.03)	(0.08)	(0.11)	(0.04)	(0.06)	(0.06)
FZ × 2017	0.06**	0.06**	0.19**	−0.18*	0.12***	0.10*	−0.12**
	(0.02)	(0.03)	(0.08)	(0.11)	(0.04)	(0.06)	(0.06)
FZ × 2018	0.07***	0.07**	0.24***	−0.17	0.11**	0.10	−0.09
	(0.03)	(0.03)	(0.08)	(0.11)	(0.04)	(0.07)	(0.06)
FZ × 2019	0.06**	0.07**	0.25***	−0.14	0.10**	0.10	−0.10*
	(0.03)	(0.03)	(0.08)	(0.11)	(0.04)	(0.07)	(0.06)
Flooded × 2013	−0.05***	−0.04***	0.03	−0.16	−0.06***	−0.13***	0.03
	(0.01)	(0.01)	(0.04)	(0.11)	(0.01)	(0.03)	(0.04)
Flooded × 2014	−0.05***	−0.04***	0.02	−0.19	−0.07***	−0.08***	0.04
	(0.01)	(0.01)	(0.04)	(0.14)	(0.01)	(0.03)	(0.04)
Flooded × 2015	−0.04***	−0.05***	−0.03	−0.08	−0.09***	−0.05	0.03
	(0.02)	(0.01)	(0.05)	(0.16)	(0.02)	(0.03)	(0.04)
Flooded × 2016	−0.04**	−0.04***	−0.02	−0.06	−0.09***	−0.06*	0.05
	(0.02)	(0.01)	(0.05)	(0.17)	(0.02)	(0.03)	(0.05)
Flooded × 2017	−0.02	−0.03*	−0.03	0.04	−0.08***	−0.06*	0.07
	(0.02)	(0.02)	(0.05)	(0.17)	(0.02)	(0.04)	(0.05)
Flooded × 2018	−0.02	−0.03*	−0.03	0.04	−0.07***	−0.08**	0.08*
	(0.02)	(0.02)	(0.05)	(0.16)	(0.02)	(0.04)	(0.05)
Flooded × 2019	−0.01	−0.03*	−0.04	0.06	−0.07***	−0.09**	0.09**
	(0.02)	(0.02)	(0.06)	(0.16)	(0.02)	(0.04)	(0.05)
Observations	6,371,673	13,216,240	2,335,600	1,231,920	4,777,120	3,897,120	974,480
FE	BBL	BBL	BBL	BBL	BBL	BBL	BBL
Cluster SE	Block	Block	Block	Block	Block	Block	Block

Notes: The data pool all businesses located in the same lot. The panel dataset is balanced (i.e. all lots appear in each quarter) and, as a result, there are many lot-quarter observations have zero employment. The dependent variable in column 1 is the log of employment. In the other columns, it is the *asinh* of employment in the lot (BBL), which is well defined at zero. *Flooded* is an indicator for having flooded during Hurricane Sandy, and it is interacted with year dummies. Similarly, the *FZ* indicator is also interacted with year dummies. This indicator takes a value of one for lots located in a SFHA (according to the 2007 FEMA flood map for New York).
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

2019. Thus, for both of these boroughs, the employment losses associated with flooding during Sandy appear to be highly persistent.

It is puzzling that we do not find employment effects on the flooded lots located in the borough of Staten Island. After all, damage was more widespread in this borough than in the rest of the city. As seen at the bottom of Table 5, slightly less than 6% of the lots in the city (with business activity) flooded during Sandy. However, this rate reached almost 11% in Staten Island. Table 7 (column 7) provides an explanation for this puzzle: the

estimates show substantial employment loss in the period 2013–2019 for *nonflooded* lots in Staten Island's flood zone. These losses were around 5% in years 2013–2014 and closer to 10% in year 2019. Thus, Staten Island's whole flood zone appears to have experienced a generalized loss in employment, which turned out to be more muted for the lots flooded by Sandy, perhaps because of differences in industry composition or building type.

In order to provide a better assessment of the pre-Sandy trends in lots that would eventually flood during Sandy and those that would not, we now estimate a second variation of the model in Equation (4) in a sample starting almost 5 years prior to the storm. In this case, we allow coefficients β_t and γ_t to vary over time prior to Sandy, as typical in event studies. Figure 6 plots the estimates of the interaction terms between year dummies and the flooded indicator (β_t) and Table C5 contains the corresponding estimates. For the full city sample, we do not reject the no-difference assumption between treatment and control groups (conditional on lot fixed effects and flood zone trends), lending additional support to the parallel trends assumption required for identification of causal effects in the difference-in-difference estimation. Second, starting from the Sandy year (2012), we find a drop in employment in the flooded lots relative to nonflooded lots, which partially fizzles out from 2016 onward in the full city sample. The pattern is similar for the Brooklyn sample, but the employment losses are larger and more persistent than for the full city sample.

6.5. Heterogeneous effects across boroughs

Our previous analysis has uncovered heterogeneous effects of flooding across the five city boroughs: flooded lots in Brooklyn and Queens exhibit large and persistent employment losses, whereas this does not seem to be the case in the other boroughs. This section discusses some possible explanations: borough differences in the severity of flooding, in industry composition and in building types.

6.5.1. Severity of flooding

As shown at the bottom of Table 5, the extent of flooding varied widely across boroughs. Citywide, 5.9% of the lots in NYC were flooded by Sandy. But flooding affected only small shares of the lots containing businesses in the Bronx (1.4%), Queens (3.9%) and Manhattan (4.3%). In contrast, flooding rates among business lots in Brooklyn and Staten Island were 8.8% and 9.9%, respectively. Widespread flooding may help explain the more detrimental effects of flooding in Brooklyn, but is at odds with our estimates for Staten Island.

6.5.2. Building type and lot size

Damaged parcels in Manhattan may have suffered smaller economic disruption than damaged parcels elsewhere in the city because this borough's flood zone is home to a high concentration of financial and business service companies, mostly housed in modern high rises. These buildings contain many establishments and flooding is unlikely to affect much those businesses located in floors above the ground level. In contrast, in other boroughs, most buildings contain very few establishments and these are typically located on the ground floor and thus more vulnerable to flooding.[27]

The differences in building type map into differences in the number of establishments in the lot. As documented earlier (Table 2), Manhattan's lots contain significantly more

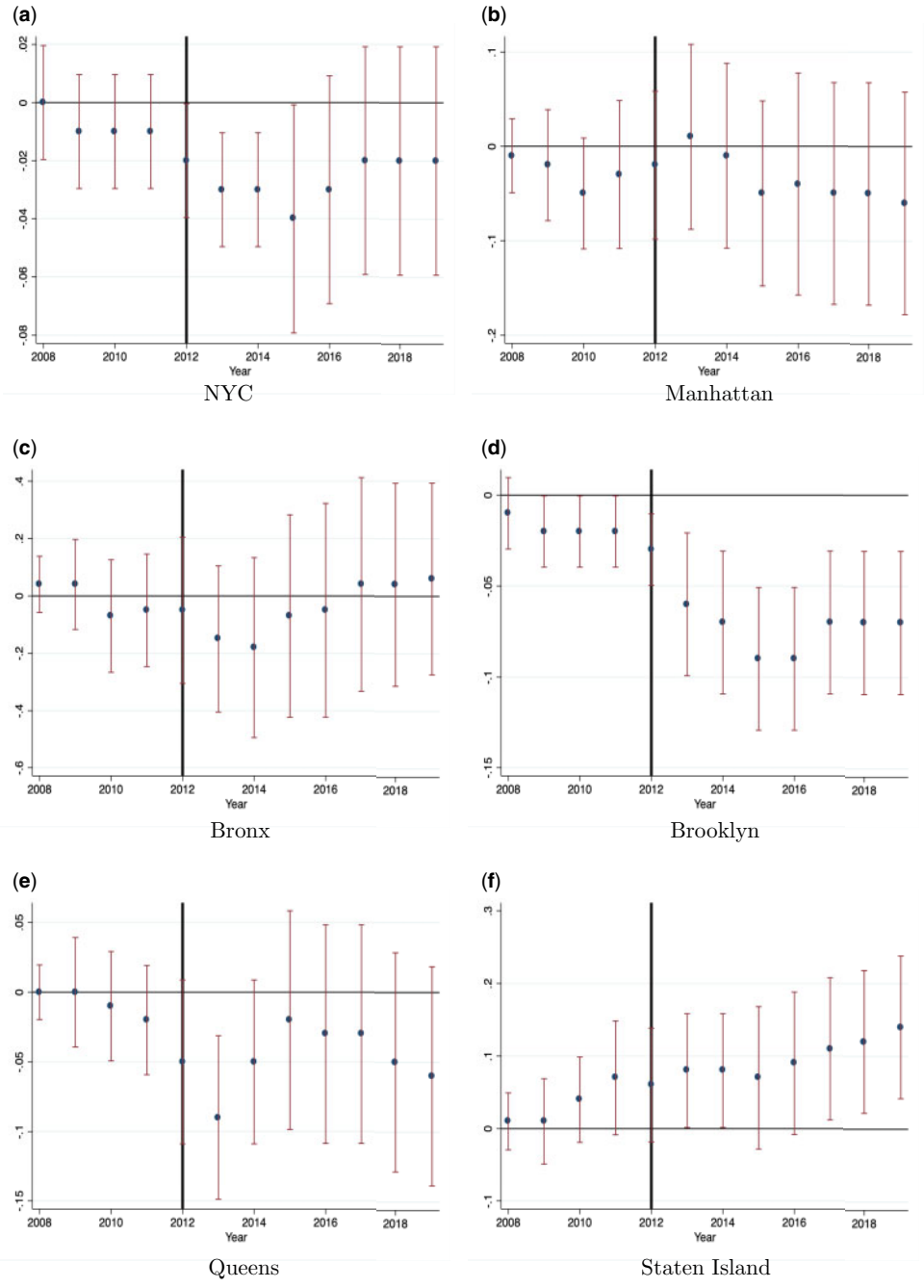

Figure 6. Employment event study. (**a**) NYC, (**b**) Manhattan, (**c**) Bronx, (**d**) Brooklyn, (**e**) Queens, (**f**) Staten Island.

Notes: The figures here plot the estimates collected in Table C5. The dependent variable is the asinh transformation of employment at the lot level estimated on the corresponding sample. The right-hand side contains parcel (lot) fixed effects and flood zone-specific year dummies. Standard errors are clustered at the block level. The estimation sample contains all quarters between 2008 (first quarter) and 2019 (fourth quarter).

establishments than the lots in the other boroughs. To investigate heterogeneity on the basis of building type, we define a sample of *small lots* (containing lots with one to three establishments) and a sample with *large lots* (containing more than three establishments).[28] As shown in Table C6, the small-lot sample is roughly 8 times larger than the large-lot sample. In addition, the estimated effect of flooding in the citywide sample (column 1) appears to be larger in the small-lot sample (roughly a 5% reduction) than in the large-lot sample (approximately a 2% reduction). This is consistent with the hypothesis that flooding causes a much larger disruption in the activity of establishments in smaller lots. The borough samples (columns 2–6) tend to confirm this finding.

6.5.3. *Industry composition*

Differences in industry composition could also help explain the heterogeneous effects of flooding across boroughs. The county-level analysis of the effects of hurricanes in Florida by Belasen and Polachek (2008) (and also the analysis by Groen et al., 2020) suggest that manufacturing businesses are more negatively affected than businesses in construction or services, which could even benefit because of their role in reconstruction.

Relative to the other boroughs, Manhattan's flood zone is highly specialized in finance and professional services (Figure 7, top panel), whereas the flood zone in Brooklyn (middle panel) specializes in the health industry, and that of the Bronx in wholesale (bottom panel). In turn, the flood zones of Queens and Staten Island specialize in construction and retail.[29]

To investigate this issue, we partition all establishments by industry, and then aggregate employment and wage income at the lot level. We then re-estimate a slight variation of our models separately for each industry. The specification now only examines the effect of the incidence of flooding *in the block* where each lot is located. That is, we do not include the indicator for whether the specific lot flooded. The reason is twofold. First, as we saw earlier, the block-level flooding average is highly correlated with the flooding indicator at the lot level. Second, our previous results show that own flooding has a negative effect on employment and, conceivably, flooding in neighboring lots may have a *positive* effect on the employment of lots in some industries, such as construction.

The estimates are collected in Table 8, sorted by the size of the estimated effect. The sign of the effects of block-level flooding varies across industries, that is, we identify both winners and losers. Second, flooding is associated with *increases* in employment in lots with businesses involved in the reconstruction phase, such as construction and professional services and, to a lesser extent, retail. Among businesses in these industries, employment grew between 2% and 5%. In contrast, we find negative employment effects of flooding in wholesale, other services and finance. Because Manhattan's flood zone is specialized in professional services and finance, the effects of flooding on employment in this borough

27 Liu et al. (2018) provide evidence of productivity differences across establishments on the basis of elevation within a building, with higher establishments typically having higher productivity.

28 The number of establishments in a given lot may vary over time. Our definition of lot size is based on the median number of establishments in each lot (across all quarters).

29 We classified establishments using one-digit NAICS industry codes. Specifically, we considered eight industries: Finance, Manufacturing, Wholesale, Construction, Health, Professional services, Other services and Retail. We then computed the employment shares by industry in the city's flood zone, and the difference between each borough's flood-zone industry composition (of employment) and that of the flood zone for the city as a whole.

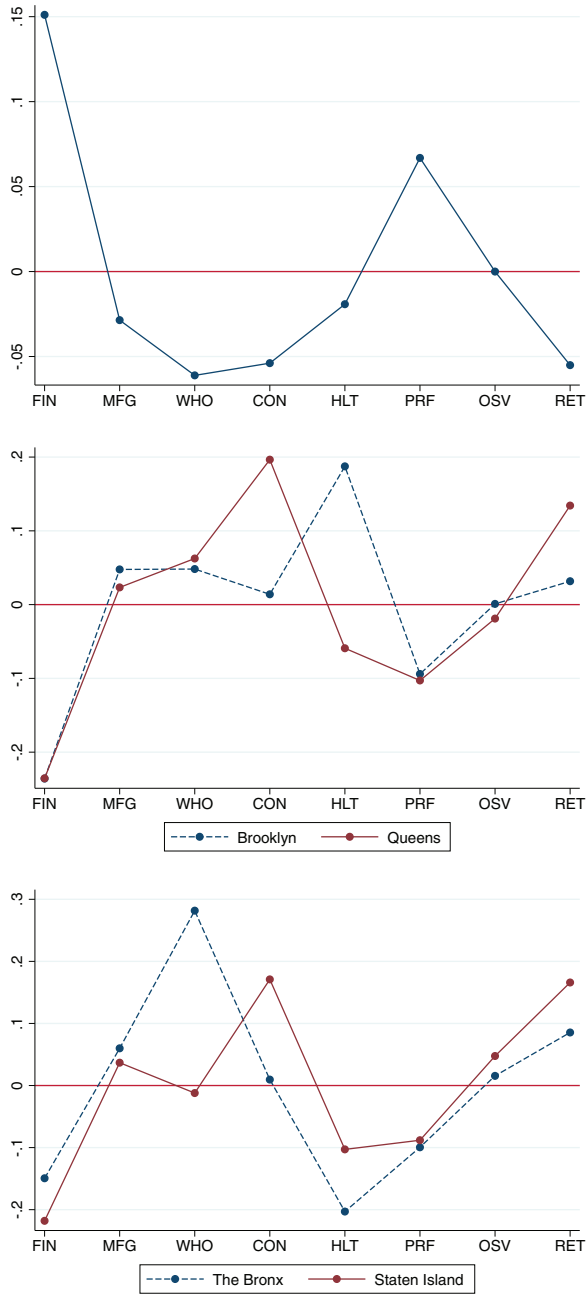

Figure 7. Industry shares (in employment) in each borough's flood zone, relative to the city's flood zone. Manhattan versus NYC (top), Brooklyn and Queens (middle) and the Bronx and Staten Island (bottom).

Notes: Data for years 2009–2012 pooled. Only establishments in the city's flood zone are used in the construction of these figures. Industry distribution for each borough is normalized using NYC industry shares by employment. The industry labels (in the horizontal axis) are Finance, Manufacturing, Wholesale, Construction, Health, Professional Services, Other Services and Retail. These industries are based on one-digit NAICS codes.

Table 8. Employment effects by industry

asinh(Emp)	1 Constru	2 Prof. Sv.	3 Retail	4 Health	5 Mnf	6 Wholesa	7 Other Sv.	8 Fina
All lots								
Post × *BlkFlood*	0.05***	0.02***	0.02***	0.01	0.01	−0.02***	−0.08***	−0.10***
	(0.006)	(0.005)	(0.006)	(0.008)	(0.013)	(0.007)	(0.005)	(0.013)
Obs. ('000)	2250	2164	3234	1927	831	1588	3185	786
Small lots								
Post × *BlkFlood*	0.08***	0.02***	0.01	−0.00	0.07***	0.04***	−0.10***	−0.20***
	(0.012)	(0.005)	(0.009)	(0.010)	(0.023)	(0.013)	(0.009)	(0.023)
Obs. ('000)	585	2164	1443	793	240	485	1326	293
FZ trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel
Cluster SE	Block	Block	Block	Block	Block	Block	Block	Block

Notes: The top panel contains all business lots and the bottom panel restricts to those with fewer than 25 workers in the quarter prior to Hurricane Sandy. The industries are Construction, Professional Services, Retail, Health, Manufacturing, Wholesale, Other Services and Finance. The data are based on the balanced panel restricted to parcels (BBLs) with median number of establishments (over whole sample period) between 0.95 and 3.05 and pools employment for all establishments located in the same lot. The dependent variable is the hyperbolic sine of employment, which is well defined at zero. *BlkFlood* is the average flooded lots (at the block level) during Hurricane Sandy.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

partially offset each other. The table also reports the estimates on the subsample of businesses located in small lots (defined as having fewer than 25 employees in the quarter prior to Sandy), which are qualitatively similar to those for the full sample.

6.5.4. Summing up

In light of the previous discussions, it is not surprising that flooded lots in Manhattan do not exhibit negative effects of flooding. Manhattan's flood zone has a high prevalence of modern high rises, which insulates businesses from persistent adverse effects of flooding, and its industry composition contains both sectors that participate in reconstruction and sectors that were negatively affected by flooding. In comparison, Brooklyn's flood zone is characterized by more vulnerable building structures and a high rate of flooding, which may have exacerbated the negative effects of flooding for each affected lot through a multiplier effect. The effects of flooding for Queens and the Bronx can also be interpreted through a combination of these factors.

What remains unexplained on the basis of the previous factors is the lack of negative employment effects for flooded lots in Staten Island. This borough experienced more widespread flooding than the other boroughs, vulnerable building types are prevalent, and its industry composition is not markedly different from that of Brooklyn and Queens. As we discussed earlier (column 7 in Table 7), the solution to the puzzle may lie in generalized downward trend in this borough's flood zone. Direct experience of flooding during Sandy does not seem to have revealed any additional information to businesses located in Staten Island.

7. Establishment exit and relocation

Our finding of a negative effect of flooding on the employment (and wage income) of lots that flooded during Sandy is consistent with several scenarios. Affected businesses may have closed those establishments and relocated to safer areas. However, our finding could also be explained by affected establishments deciding to downsize, without necessarily closing. This section investigates which of these two mechanisms has been at play.

7.1. Exit

The goal here is to analyze whether establishments that flooded during Sandy exhibit larger exit rates than expected. To investigate this question, we first identify the establishments that appear at least in one-quarter of our dataset and create a balanced panel at the establishment level. We focus on each company's location (lot) in the quarter when Hurricane Sandy hit (2012Q3) and create a dummy variable $Stay_{i,\ell,t}$ that takes a value of 1 when company i is found at the same lot ℓ in period $t > 2012Q3$ as in 2012Q3. Thus, observations with $Stay_{i,\ell,t} = 0$ identify firm i's exit from location ℓ. Clearly, exit events happen regularly for reasons unrelated to Hurricane Sandy. Our approach will estimate the *excess* exit activity displayed by the lots flooded by Sandy.

The model we estimate is as follows:

$$Stay_{i,\ell,t} = \alpha_i + \gamma_t FZ_\ell + \beta Post_t \times Flooded_\ell + \varepsilon_{i,\ell,t}, \tag{5}$$

where we include company fixed effects (α_i), flood zone-specific trends (γ_t) and the interaction between the post-Sandy indicator and flooded status. Thus, coefficient β identifies the change in the probability to remain in the pre-Sandy location for companies in lots that flooded during the hurricane, relative to unaffected companies (conditional on lot fixed effects and flood zone trends).[30]

The dataset contains 5.8 million establishment-quarter observations corresponding to the sample period 2012Q3 through 2019Q4. Table 9 presents the estimation results. First, we note that the estimate based on the citywide sample (column 1) suggests that the probability to remain in the pre-Sandy lot fell by 1 percentage point in lots that suffered flooding during the storm. Note also that same-sign estimates are found for the other boroughs (column 2–6), providing a consistent pattern but lacking precision to make strong claims.

Despite the seemingly small point estimate, the estimated increase in exit rates associated with flooding can account for a sizable part of the reduction in employment in the lots that flooded during Hurricane Sandy.[31] By virtue of the 4% reduction in employment in the lots that flooded during Sandy (Table 5), the increase in establishment exit rates accounts for up to one-fourth of the reduction. To the extent that some of the vacancies may have been filled with newcomers, the increase in (gross) exit rates will account for a smaller share of the (net) effect.

30 Difference-in-difference estimation is feasible because period 0 is included (i.e. $Post_{2012Q3} = 0$ and $Post_t = 1$ for $t \geq 2012Q4$).

31 Given that the median number of establishments per lot is 1 in New York's flood zone (Table 2), our estimated reduction in the probability to stay in the lot implies a 1 percentage point reduction in the employment of the average lot flooded during the storm, assuming that the lot remains vacant.

Table 9. Probability that an establishment stays in the pre-Sandy location

Stay	1 NYC	2 MH	3 BX	4 BK	5 QN	6 SI
All companies						
Post × *Flooded*	−0.01*	−0.02*	−0.05	−0.002	−0.004	−0.02
	(0.006)	(0.013)	(0.038)	(0.008)	(0.012)	(0.020)
Obs.	5,809,830	2,825,850	406,050	1,290,090	1,076,100	211,740
Single establishment						
Post × *Flooded*	−0.01	−0.01	−0.04	−0.00	0.00	−0.01
	(0.007)	(0.014)	(0.041)	(0.008)	(0.013)	(0.024)
Obs.	5,290,110	2,554,680	356,790	1,200,630	991,770	186,240
Multiple establishments						
Post × *Flooded*	0.01	−0.01	−0.13*	0.03	−0.05	−0.07
	(0.016)	(0.031)	(0.078)	(0.024)	(0.035)	(0.055)
Obs.	519,720	271,170	49,260	89,460	84,330	25,500
FE	EIN	EIN	EIN	EIN	EIN	EIN
Cluster SE	Block	Block	Block	Block	Block	Block
FZ trends	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable, $Stay_{it}$, takes a value of one if company i is at the same location (parcel) in quarter $t \geq 2012Q4$ as in the last quarter prior to Sandy ($2012Q3$). Companies are uniquely identified by their EIN. The estimation sample here is 2012Q3–2019Q4. The panel dataset is balanced, that is, all establishments appear in each quarter. *Post* is an indicator for quarters 2012Q4 and onward. *FZ* is an indicator taking a value of one for parcels located in the flood zone (SFHA). *Flooded* is an indicator for having been flooded during Hurricane Sandy. The top panel contains all establishments. The second panel contains only those establishments belonging to single-establishment companies in NYC. The third panel contains only establishments belonging to companies with two or more establishments in NYC. Standard errors are clustered at the block level.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Potentially, large and small companies, defined as having one or more than one establishments, could respond differently to the flooding shock. The estimates for single-establishment companies (middle panel of Table 9) are similar to those including all establishments, although the precision of the estimates is now a bit lower.[32] Unfortunately, the much smaller sample of establishments belonging to multiestablishment companies (bottom panel) is too noisy to draw conclusions.

7.2. Relocation

The analysis so far has shown evidence supporting that experiencing flooding during Hurricane Sandy increased the probability to exit the affected lot. Next, we focus on businesses that did relocate and examine whether flooded businesses were more likely to relocate within the same neighborhood or move to another one.

Our starting point is the set of establishments that were open (i.e. had positive employment) in the quarter when Sandy hit the city (2012Q3) but closed sometime after (2013–2019). Obviously, post-Sandy closings might have been related to Hurricane Sandy or to a

32 Single-establishment companies account for 93% of the establishments in New York City.

myriad of other factors. To the extent that these other factors affected similarly flooded and nonflooded establishments, the comparison between the two groups will isolate the effects of flooding during Sandy.

As shown in the first row of Table C7, over the period 2013–2019, there were almost 107,000 closings of establishments that did *not* flood during Sandy (column 1). These establishments belonged to roughly 42,000 companies. In turn, these companies opened about 40,000 new establishments.[33] Our main interest lies in the location of these new establishments. The data show that 46.3% of the openings took place in other neighborhoods (defined by zip code).

Now we turn to column 2 in Table C7, which refers to the openings of establishments by the 2687 companies *affected* by flooding during Sandy. Out of the more than 10,000 establishment openings by these companies since Sandy, a striking 84.8% took place in other neighborhoods. Thus, suffering flooding appears to have increased the probability of leaving the neighborhood by about 38.5 percentage points (84.8–46.3%). In sum, we find evidence of companies exiting from the lots that suffered flooding during Sandy, with an important proportion of them choosing to open new establishments in other neighborhoods.

8. Conclusions

As sea levels rise, the frequency of large-scale flooding events in coastal areas is rising as well. Our analysis of the effects of Hurricane Sandy on New York City's businesses has provided evidence of negative effects on employment and wages for the locations that flooded. The evidence suggests that these effects are fairly persistent in some parts of the city, suggesting that companies that experienced first-hand the effects of the storm have modified their production plans to adapt to the new information.

Our results also provide evidence of an increase in closings of establishments that flooded during the storm and an increase in the chance that the affected companies chose to open their new establishments in different neighborhoods. Furthermore, because damage from the storm was heavily clustered, our results point toward a highly localized negative income shock in the affected neighborhoods. This interpretation is consistent with the findings in Boustan et al. (2017) showing that large-scale natural disasters trigger out-migration (of people). Our findings also have implications for the value of the commercial lots that were affected by Hurricane Sandy. The price of a commercial lot is determined by the present value of the income it can generate, appropriately discounted. Thus, persistent reductions in the wage income generated in a lot (and in its overall income-generating potential) are expected to lower its sale price.

In closing, our analysis suggests that businesses are adapting to climate change, in line with the conclusions of Dell et al. (2009) (based on the dynamics of the economic effects of higher temperatures) and Bleakley and Hong (2017) (regarding adaptation in the agricultural sector). Our findings suggest that companies may be gradually shifting their activities away from flood-prone areas, reducing the size of their establishments located in those locations or moving away altogether. While this entails a negative income shock for those neighborhoods, there may be a silver lining regarding the citywide effects. As

33 Defined as company–lot pairs that had positive employment for the first time in some quarter after Sandy (2012Q3).

argued by Desmet et al. (2018), geographical relocation of companies and people is an important dynamic adjustment to sea-level rise that can greatly mitigate the associated welfare costs. The physical reorganization of firms may be rather sticky, due to sunk organizational costs, but large natural events (such as Hurricane Sandy) may change risk beliefs enough to trigger such adjustments.

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Appendix

A. Details on merging datasets

In order to merge the QCEW and the damage-point datasets, we followed several steps.

1. Obtaining the tax lot (parcel) number for all establishments in the QCEW data. We used New York City's *Geosupport* application, which provides a crosswalk between addresses and tax lot numbers (commonly known as BBL for borough, block and lot) for each structure in New York City. The success rate was roughly 95%. When we examined the unmatched addresses, we realized that they either referred to cross streets (e.g. Fifth avenue and 34th street), to landmarks (e.g. JFK Airport), or had typos, which prevented assigning a tax lot number.

2. Assigning a tax lot number to the structures in the FEMA damage-point data. We used New York City's *PLUTO* polygon data to spatially join the latitude–longitude points in the damage-point dataset to the footprints of all structures in the city, along with the corresponding tax lot number.

3. Starting from the QCEW dataset, we merged the damage-point datasets by tax lot number. The success rate was over 98% for each of the 17 years in our data. Mostly, the unmatched observations corresponded to condos in the QCEW dataset. For instance, this would be the case if an accountant runs her business off of her residence, and she lives in a condominium. The tax lot numbers for condos have been recoded in PLUTO and cannot be matched to other datasets.

B. FEMA damage indicators

The FEMA (MOTF unit) classified all properties affected by Hurricane Sandy according to the damaged they suffered in the following way:

1. Affected lot: aerial imagery shows superficial damage to solid structures (e.g. loss of tiles or roof shingles), or flooding is observed but remains below 2 feet.

2. Minor Damage: aerial imagery shows exterior damage to solid structures (e.g. missing roof segments), or observed flooding with depth between 2 and 5 feet.

3. Major Damage: aerial imagery shows some solid structures are destroyed due to wind and most sustain exterior and interior damage (roofs missing, interior walls exposed). Also in this category, if storm surge produced extensive structural damage or partial collapse of exterior bearing walls. Also in this category if observed flooding with depth over 5 feet.

4. Destroyed: aerial imagery showing destruction of most solid structures or the structure has been completely washed away by the storm surge.

C. Tables

Table C1. Summary statistics lots

Year	Lots	Employment	Wage bill ($Mn annual)	Avg. wage per worker ($ annual)
2000	69,008	41.1	2.4	58,234
2001	70,065	40.9	2.4	59,604
2002	69,965	40.5	2.4	58,924
2003	70,827	39.8	2.3	58,825
2004	71,657	40.0	2.5	63,270
2005	73,128	40.4	2.7	67,403
2006	74,563	40.3	2.9	72,566
2007	76,402	40.9	3.3	79,408
2008	77,509	41.0	3.3	80,079
2009	78,086	39.5	2.9	73,788
2010	79,508	39.3	3.1	77,986
2011	81,184	39.3	3.1	79,193
2012	82,639	39.6	3.2	79,955
2013	84,384	39.8	3.2	79,572
2014	86,230	40.4	3.4	84,106
2015	89,120	40.8	3.5	85,000
2016	90,177	41.0	3.5	85,375
2017	91,216	41.3	3.7	89,502
2018	88,697	41.4	3.8	92,894
2019	85,221	42.5	4.1	95,492
Average	79,479	40.5	3.1	76,059

Notes: Unbalanced dataset at the lot level, that is, we pool the employment and wage bill of all businesses located in the same lot (parcel). Only lot-quarter observations with positive employment and a positive wage bill included. Employment refers to the average employment across the four quarters in the corresponding year. The wage bill (and wage per worker) have been annualized. Average wage per worker is computed by dividing the wage bill (column 4) by employment (column 3).

Table C2. Effect of damage on employment

	1	2	3	4	5	6	7
NYC	NYC	NYC	MH	BX	BK	QN	SI
asinh(*Emp*)							
Post × *Dam*	−0.02		0.02	−0.17*	−0.07***	−0.05*	0.01
	(0.013)		(0.042)	(0.103)	(0.015)	(0.029)	(0.032)
Post × *Dam*1		−0.02					
		(0.013)					
Post × *Dam*2		0.04					
		(0.046)					
Obs. ('000)	13,216	13,216	2336	1232	4777	3897	877
FZ trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel	Parcel
Cluster SE	Block	Block	Block	Block	Block	Block	Block

Notes: In all regression models, the dependent variable is the inverse hyperbolic sine transformation of employment (pooling all businesses located in the same lot). The panel dataset is balanced (i.e. all lots appear in each quarter). *Post* is an indicator for quarters 2013Q1 and onward. *FZ* is an indicator for the lot being located in a special flood hazard area (according to the 2007 FEMA flood map for New York). *Damage* is an indicator for having suffered damage during Hurricane Sandy, partitioned into *Damage*1 (lot Affected or Minor damage) and *Damage*2 (Major damage or Destroyed lot). ***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.