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Hurricanes, Flood Risk and the Economic Adaptation of Businesses

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"Huracanes y Riesgo de Inundación: Cómo se Adaptan las Empresas"

Resumen

Este trabajo muestra que el aumento del riesgo de inundaciones produce un efecto muy negativo sobre la actividad económica en las zonas afectadas. Nuestro análisis se fundamenta en una base de datos administrativa que comprende todos los establecimientos comerciales de la ciudad de Nueva York en el momento en que se produjo el huracán Sandy. Nuestros datos también identifican con exactitud los edificios que sufrieron daños por las inundaciones provocadas por el huracán. Los datos demuestran que se produjo una reducción sostenida en el nivel de empleo y de ingresos en las empresas que resultaron afectadas, como también mayores tasas de salida. La continuidad de estos efectos se corresponde con el aumento del nivel de riesgo de inundación a partir del huracán. Estos resultados sugieren que las empresas se adaptan a esta nueva realidad y deciden trasladar su actividad hacia zonas más seguras. Este proceso de adaptación puede mitigar los costos provocados por el aumento del nivel del mar en la ciudad de Nueva York.

Palabras clave: Cambio climático, Elevación del nivel del mar, Adaptación económica, Huracán Sandy

"Hurricanes, Flood Risk and the Economic Adaptation of Businesses"

Abstract

This paper argues that increases in perceived flood risk entail a negative and persistent shock to local economic activity. Our analysis is based on a rich administrative dataset that contains all business establishments in New York City around the time of hurricane Sandy. Our data also identifies exactly which buildings suffered flooding-related damage due to the hurricane. We find evidence of a persistent reduction in the employment and wage income of establishments that suffered damage, along with higher exit rates. The persistence of the effects is consistent with an upward revision of flood-risk beliefs triggered by the hurricane. These findings suggest that businesses are adapting to the higher flood-risk environment by shifting operations toward safer areas. This adjustment process may mitigate the city-wide costs associated to sea-level rise.

Keywords: Climate change; Sea-level rise; Economic adaptation; Hurricane Sandy

Códigos JEL: E24, O13, Q54

1 Introduction

Sea levels have been rising over the last few decades and this trend is expected to continue in the foreseeable future (Stocker et al., 2013). As a result, large-scale flooding episodes will become more frequent. The associated economic costs and the volume of displaced population are expected to be large (Hinkel et al. (2014)). In the context of the United States, 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.

The economic costs are likely to be a function of how businesses adapt to the changes in the environment. 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 substantially lower (at about 0.2%) if companies and people gradually adapt to the changing environemnt. The authors also show that, absent these adjustments, the economic and welfare costs could be an order of magnitude larger.[1]

The main goal of our paper is to analyze empirically the economic effects of large-scale flooding episodes. Specifically, we focus on the effects of hurricane Sandy on the employment, wages and location decisions of New York's businesses. Hurricane Sandy hit New York on October 29, 2012, and caused $50 billion in damage (Abel et al. (2012)), much of it attributed to the effects of storm surge. Importantly, our dataset includes point-damage data from FEMA, which allows us to identify which structures suffered damage during the hurricane, and which businesses were located in those lots at the time.

Because companies and people can move, we expect the main effects of the storm to materialize as a reduction in the income generated at the affected locations. Lots that flooded during the storm may have experienced out-migration of businesses, either remaining vacant or taken over by possibly less

[1]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.

productive businesses. Alternatively, companies may have maintained those establishments but downsized them in favor of other establishments. Either way, the quantity and quality of employment (measured by the associated wage income) in the lots affected by the storm may have been negatively affected, entailing a negative income shock at the neighborhood level.[2]

More specifically, we provide estimates of the effects of hurricane Sandy on the employment and wage income of the lots that suffered damage during the storm. In addition, we also examine if 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, and allow for 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 suffered damage relative to non-damaged lots in the same flood zone. Our analysis also produces estimates separately by borough, to account for differences in industry composition and other dimensions.

Our paper is related to the growing literature analyzing the economic effects of hurricanes and large-scale flooding events, which we discuss in detail in the next section. Overwhelmingly, these studies find that these events disrupt economic activity, both at the individual level and in aggregate, and depress housing values. However, the vast majority of studies find that these effects vanish quickly. Our paper is also related to a flurry of recent studies that provide evidence showing that market participants' beliefs about flood risk in coastal areas are updated in response to new information regarding projected sea-level rise and other relevant information. These studies also show that these flood risk revisions have an impact on financial and real estate markets.

[2] A recent study by Balboni (2018) argues that, in the case of Vietnam, projected changes in flood risk affect the optimal location of public investments in new roads and other infrastructure require a shifting away from the current allocations, which favor flood-prone coastal areas.

The main contribution of our paper is the novel use of establishment-level data to estimate the effects of hurricane Sandy on employment and wage income. These data allow us to implement a very demanding empirical strategy based on the comparison of employment changes for businesses that suffered damage during the hurricane relative to undamaged businesses subject to the same risk of flooding. Our data also allow us to examine if the hurricane triggered relocation of businesses to safer areas, and the degree of persistence of these effects. Our approach emphasizes the importance of employing the establishment, or the parcel, as the unit of analysis.

Our data merges a confidential-version of the *Quarterly Census of Employment and Wages* (QCEW) containing the universe of establishments in New York City for years 2000-2017 with damage-point data from FEMA that identifies which structures (buildings) suffered damage during hurricane Sandy. The data show that there were over 200,000 establishments in New York City in year 2017. The data also show that, on average, there are two establishments per lot. However, while almost 70% of the lots contain only one establishment, other lots contain hundreds of establishments. Our data also shows that 2.6% of the lots (housing at least one business) are located on a FEMA special hazard flood area and 5.5% of the lots citywide suffered damage during hurricane Sandy.

Our analysis delivers several main findings. First, we estimate that employment fell by approximately 2-3 percent (in the 2013-2017 period) in lots that suffered damage during Sandy. However, the effects vary substantially across the city's boroughs. Employment in damaged lots fell by 5-7 percent in Brooklyn and Queens, and possibly more in the Bronx. In contrast, we do not find evidence of a drop in employment among affected lots in Manhattan. These effects are mirrored in terms of the wage income generated at the lot level, though of a larger magnitude, suggesting reductions in working hours or hourly wages, or out-migration of high-wage businesses. The differences between Manhattan and the other boroughs are probably due to differences

in building type, given that Manhattan's flood zone mainly contains large office buildings. Businesses located in those buildings were probably affected to a much lesser degree during the hurricane than businesses housed in lower elevation buildings.

Third, the reductions in employment and wage income we document are highly persistent, remaining practically unchanged between 2013 and 2017. Because most Sandy-related damage was repaired fairly rapidly, this pattern suggests 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 that were damaged by Sandy. Citywide, the probability of staying in the pre-Sandy location (parcel) was 1 percentage-point lower for firms located in parcels damaged by the storm. This is a large effect given that the average exit rates were around 4 percent.

A plausible interpretation for our findings is that businesses whose activity was disrupted by hurricane Sandy revised their beliefs about the flood risk associated with their specific location, consistent with recent studies of the housing market (Ortega and Taspinar (2018), Bernstein et al. (2019)). Responding to the increase in perceived risk, these businesses reacted by downsizing those establishments or moving to safer locations. Our analysis shows that these effects are persistent, suggesting that this change in beliefs has translated into a localized negative economic shock for New York's flood zone. From the viewpoint of the city as a whole, these adjustments may be rather positive. As noted by Desmet et al. (2018), the relocation of economic activity can help greatly mitigate the detrimental economic effects of sea-level rise.

The structure of the paper is as follows. section 2 presents a summary of the literature. section 3 introduces some useful notation, section 4 describes the data sources, section 5 discusses the empirical specification, section 6 presents descriptive statistics, section 7 discusses the main results, and sec-

tion 8 concludes. An Appendix contains additional information.

2 Literature

Our work is related to the empirical literature analyzing the economic effects of hurricanes, either on individual income or on aggregate outcomes, such as income or housing values.

A few studies have examined the effects on individual income, providing evidence of negative short-run effects that vanish in 3 or fewer years. Deryugina et al. (2014) build an individual panel using tax-records data to analyze the effects of hurricane Katrina on income. They find small and transitory negative effects. Within 3 years since the hurricane, individuals' income had recovered. Groen et al. (2015) also analyze the effects of hurricanes Katrina and Rita on individual earnings and find an initial drop that vanishes in less than two years. Importantly, we note that for many of these individuals, recovery entailed moving to other cities, such as Houston.

Other authors have analyzed the effects of hurricanes on employment at the city level, and found evidence of negative but short-lived effects. 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 labor market outcomes. They find reductions in county employment of 1 to 5% in the first quarter after the hurricane, increasing in the severity of the hurricane, relative to other counties that were not hit by the hurricane. At the same time they find *increases* in average earnings (of 1 to 4%). 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. These highly transitory effects are consistent with the observation that hurricanes are fairly common in Florida and, as a

result, unlikely to affect agents' beliefs. These findings are consistent with the conclusions of the study by Kocornik-Mina et al. (2015) regarding the the economic effects of flooding events using data for 1,800 cities worldwide for the period 2003-2008. In this study, which measures economic activity using night-lights data, the authors find that flooded cities typically recover rapidly, suggesting that businesses do not migrate to safer areas.

Thus, the general message is that hurricanes and large-scale flooding events disrupt economic activity, but these effects are not persistent. This finding is echoed in the large literature analyzing the effects of hurricanes on housing values. Most studies find that flooding events (typically in connection to hurricanes) have negative effects on 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). In a similar vein, Gallagher (2014) studies flood-insurance take-up rates after flooding events. He finds strong evidence of an immediate increase in the fraction of homeowners covered by flood insurance in communities affected by flooding, though the effect vanishes after a few years.

It is important to note, however, that there are numerous instances of natural disasters or other large shocks with highly persistent effects. Ambrus et al. (2016) analyze the effects of a cholera outbreak in London in the 19th century on housing values. Similar to us, their data identifies exactly the houses where cholera-related deaths occurred. They find evidence of a large and very persistent reduction in the value of these properties. They argue that the cholera episode triggered selective out-migration, which permanently lowered socio-economic 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 housing values linked to the exact area burned. They document large *increases* in property values following the fire and argue that this was due to the (well used) opportunity to redevelop the zone, breaking away past inertia.

In both of these studies, the authors suggest that the theoretical underpinnings for the persistent shift in outcomes is multiple equilibria. The (cholera and fire) shocks triggered a shift from one equilibrium to another, without affecting the fundamentals of the economy. It is important to note though that the empirical relevance of explanations based on shocks to a system with multiple equilibria is in dispute. Two influential studies explicitly analyze the occurrence of this type of equilibrium shift in the context of the Allied bombing of Japanese cities during World War II and fail to find support for it. The bombings only had temporary effects on the population size (Davis and Weinstein (2002)) and industry composition of the affected cities (Davis and Weinstein (2008)).

A flurry of recent empirical studies argue that there has been an increase in perceived flood risk in coastal areas in the United States and elsewhere, which is responsible for a persistent reduction in housing values. Ortega and Taspinar (2018) analyze the effects of hurricane Sandy on the New York housing market, using a parcel-level dataset with administrative data on all housing sales in the city. Their estimates provide robust evidence of a persistent, negative impact on the price trajectories of houses that were affected by Sandy, ranging from 6% to 20%, with larger price reductions for properties that were more severely damaged. The authors argue that rare events, like hurricane Sandy, provide useful information on tail flood risk and entail persistent effects on housing values. Using Zillow data for thousands of counties in the United States, Bernstein et al. (2019) show that coastal properties exposed to projected increases in seal-level rise sell at a 7% discount. They argue that their results are more consistent with an explanation based on long-run flood risk, suggesting a gradual updating of beliefs. Thus, also in this case, new information is changing the fundamentals of the economy, resulting in a change in outcomes that does not depend on the existence of multiple equilibria.[3] Last, Bakkensen and Barrage (2017) provide

[3]Other studies that focus on financial data confirm that investors' beliefs about climate

new data documenting that residents of coastal homes perceive lower flood risk and display higher valuation for coastal amenities. Their analysis also shows that accounting for belief heterogeneity is important: it substantially increases the projected home price declines due to sea level rise and increases market volatility.

3 Setup

It is helpful to introduce a bit of notation. Consider the set of companies in the city, with each company indexed by i: $I = \{1, 2, ..., I\}$. In practice each company is identified by its employer identification number (EIN). Consider also the set of locations, indexed by ℓ: $L = \{1, 2, ..., L\}$. In practice, each location corresponds to a parcel (tax lot). Each company needs at least one location, but a location can host several companies. We will refer to a pair (i, ℓ) as an *establishment*.

Let us define the matching function between companies and locations by $M : I \times L \longmapsto \{0, 1\}$, where $M(i, \ell) = 1$ means that company i is established at location ℓ. We denote the pre-Sandy and post-Sandy matching functions by M_0 and M_1, respectively.

3.1 Business relocation

In our dataset, observations are defined at the level of company (i), location (ℓ) and quarter (t). For each observation, we have data on employment and the wage bill at the establishment level, which can be used to compute the average wage per worker.

Consider for now two periods, corresponding to before ($t = 0$) and after hurricane Sandy ($t = 1$). We can identify the set of movers (and stayers) around the time of the hurricane using the following procedure:

change appear to be incorporated into financial markets (Schlenker and Taylor (2019)).

1. For each company i, we define the set of *initial locations* as $\{\ell : M_0(i, \ell) = 1\}$. We denote a particular element of this set as $\ell_{i,0}$.

2. Likewise, we define company i's set of *final locations* as $\{\ell : M_1(i, \ell) = 1\}$, and an element of this set as $\ell_{i,1}$.

3. For a given company i, the intersection of the sets of initial and final locations contains the *staying* establishments. For single-location companies, we can refer to *stayer* companies as those for which $\ell_{i,1} = \ell_{i,0}$, and *movers* when $\ell_{i,1} \neq \ell_{i,0}$.

In practice, we will take the quarter immediately prior to hurricane Sandy (2012Q3) as period 0. We will then define a company as a *stayer* if it changes location at any point in time after hurricane Sandy (2012Q4-2017Q4).[4]

These definitions will be helpful in subsection 7.3 to examine whether companies exited locations that suffered damage during hurricane Sandy, presumably moving to safer locations (or closing down altogether).

3.2 Location-specific outcomes: downsizing

Clearly, if hurricane Sandy triggered businesses to move out of their original locations, there may have been a reduction in the quantity or the quality of the employment in those parcels. Those vacancies may have been filled up by smaller (in terms of employment) or less productive businesses (paying lower wages). However, even if there was no exit, companies may have downsized, either reducing employment or diverting investment to their establishments in other locations. Importantly, these effects take place at the location (parcel) level, rather than at the level of companies. And, because of the geographic clustering of the parcels affected by the hurricane, these changes would amount to a negative income shock at the neighborhood level.

[4]In the case of multi-establishment companies (i.e. one EIN that operates in multiple BBLs), we define stayers and movers in terms of establishments (pairs EIN-BBL).

To test the downsizing hypothesis it is helpful to create location-specific measures of employment and wages. Specifically, we define the employment and wage bills at location (parcel) 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 co-exist at the same location. Hence, location aggregates may pool employees from companies belonging to different industries. A more precise measure of the economic effect of the storm on a parcel is the wage bill, which measures the wage income generated by the businesses located in that parcel. Because, typically, workers live close to their workplace, a reduction in the wage income paid out by an establishment generates a highly localized negative shock.

4 Data sources

To build our dataset we merge data from two sources: the Bureau of Labor Statistics' *Quarterly Census of Employment and Wages (QCEW)*, and FEMA's 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 the tax lot number of the corresponding parcel. Second, we spatially joined the coordinates in the damage-point dataset to the footprints of all structures in the city, along with the corresponding tax lot number. Last, we merged the two datasets by tax lot number.[5] Next, we

[5]The success rates in the first and second steps were 95% and 98%, respectively. The footprints data was obtained from the NYC PLUTO dataset. More details are provided

provide more details on each of the sources along with summary statistics.

4.1 Establishment data

Our establishment data is based on the QCEW, which provides a quarterly count of establishments, employment and wages reported by employers and covering more than 95% of jobs in the United States. The data is based on workers covered by federal and state unemployment insurance programs.[6] We requested a confidential version of these data from the New York State Department of Labor containing the exact location (address) and employer identification number for all establishments in New York City. The dataset contains quarterly information on average employment and wage bill over the quarter, along with the sector of activity (industry code), for the period 2000Q1 through 2017Q4.

In our dataset, companies are uniquely identified by their Federal Employer Identification Number (EIN). Each company can have multiple *establishments*, defined as a company-parcel combination. Restricting to establishments with positive employment and wage bill, our data for 2017 contain 212,045 establishments for New York City with an average employment of 18.0 workers and an annual wage bill of $1.6 million, which results in an average annual salary of $89,874 (as shown in Appendix Table 1).[7] The data also

in the Appendix.

[6]More details on the QCEW can be found at `https://www.bls.gov/cew/cewover.htm`.

[7]All workers included, regardless of number of hours worked. Our data matches well the official BLS data. According to the BLS, in 2017 there were 270,106 establishments in New York city with a total employment of 4.25 million. Average employment per establishment in that year was 15.7 employees and the annual wage per worker was $89,831. In comparison, when we use all the establishments that were successfully geo-located, our data contains 243,511 establishments, with an average of 15.7 workers per establishment and an average annual wage of $89,973 per worker. The lower count of establishments in our data is largely due to the fact that we report the average number of establishments across the four quarters in each year, whereas the BLS may be reporting the overall number that were active at any point during the year. As noted earlier, we were unable to geo-locate a small fraction of establishments, which also reduces our count. However, our data

indicates an upward trend in the number of establishments, from 166,182 in year 2000 to 212,045 in year 2017, and a fairly stable level of employment per establishment, averaging 17.4 employees. It is helpful to examine the aggregate trends graphically. Figure 1 and Figure 2 plot the annual average employment and wage income (in millions of current dollars) citywide. Clearly, these variables are highly pro-cyclical: employment and the wage bill fell between 2000 and 2003 and again between 2008 and 2010, in line with the NBER recessions. Figure 3 shows that the annual wage income per worker increased between 2003 and 2008, fell in 2009 and then resumed its upward trend (in nominal terms). Over the 18-year period in our data, the average annual wage per worker has risen from $58,581 to $89,874, an 8.52% nominal average annual increase.

4.2 Damage-point data

Our second data source is FEMA's damage-point estimates for hurricane Sandy. These data contain information on the 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. In our analysis we restrict to structures within the New York City boundaries. The data show that over 13 percent of the buildings in the city's inundation area suffered major damage. Staten Island and Queens were the boroughs that were hit the hardest, followed by Brooklyn. Many fewer buildings were damaged in the Bronx and Manhattan.

We also created indicator variables to identify locations on the flood zone, as defined by FEMA's 100-year flood zone (Special Flood Hazard Areas). 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

matches very accurately the average establishment size in terms of employment and the average wage per worker.

amenity value, the flood zone is an important part of the city for residential and commercial purposes. In fact, over the last two decades, the number of businesses has risen at a faster pace in the flood zone than in the rest of the city, as illustrated in Figure 4. To accommodate this pattern, our econometric specifications will include differential trends for businesses located in the flood zone.

4.3 Data by parcel

Our main unit of analysis is the parcel (tax lot). We construct the parcel-level outcomes by adding the employment and wage bill across all companies located in the same parcel at each point in time. The resulting dataset has 6.2 million parcel-quarter observations for the period 2000Q1-2017Q4. In the average year in our sample there are almost 188,000 establishments housed in approximately 78,000 unique parcels.[8] The data show that most parcels house just one business (68%), 15% contain 2 businesses, 6% contain 3 businesses, and 5% contain 4 or 5 businesses. Hence, only 6% of the lots house more than 5 businesses.

It is worth noting that there are important differences across boroughs in parcel size, measured by number of establishments, reflecting 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 5.1). In contrast, the median number of establishments per parcel is 1 for all other boroughs and their mean value is around 1.6. The bottom panel of the table reports information restricting to the parcels located in the flood zone (SFHA). As shown in the Table, 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

[8]The city as a whole has about 0.8 million parcels, most of which are exclusively residential.

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 the other boroughs.

Next, we turn to summarize the data on employment and wage income at the parcel level. As shown in Table 3, the average lot in year 2017 had 41.3 employees and generated a wage income of $3.7 million on an annual basis, corresponding to an average wage of $89,502. Between 2000 and 2017, the average annual growth of wage income per worker was 8.5% in nominal terms.

It is also interesting to compare the employment size of the lots located in the flood zone to those elsewhere in the city. The 2017 data show that flood zone lots are much larger in terms of employment, with 76.2 workers versus 36.5 workers per lot elsewhere in the city. Additionally, average wage per worker is also higher in the flood zone. In year 2017, annual wages were $108,477 versus $88,416, respectively (about a 20% difference). These level differences may be due to the fact that the flood zone contains the financial district in lower Manhattan. In those locations we find many large office buildings with high-paying jobs and high business density. Excluding Manhattan reduces the size gap but does not wipe it out completely: 38.5 workers per lot, compared to 20.1 outside the flood zone. Similarly, differences in average wage per worker are also reduced to about 10%.[9] As we discuss next, our econometric specification will account for these differences by including parcel-level fixed effects and will also allow for differential trends in the flood zone.

[9]Excluding Manhattan, in year 2017 average wage per worker was $53,869 in flood zone parcels and $48,611 in parcels elsewhere in the city.

5 Specifications

Our main goal is to examine whether hurricane Sandy has affected economic activity from the perspective of local 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 of migrating 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 locations (parcels).

To investigate this question, we choose parcels (tax lots) to be the unit of analysis. Thus, we aggregate the outcomes of all companies sharing the same location (parcel). That is, for each lot and quarter, we compute the total number of employees and the wage bill of the lot. Using these data, we analyze if the lots affected by Sandy experienced a deviation in trend employment and wage income relative to unaffected lots facing the same flood risk.

It is possible that some business parcels remain vacant in some quarters. These lots should be viewed as being idle during that period. In other words, they generate zero income until re-occupied. As a result, it is not appropriate to treat these parcel-quarter observations as missing. To remediate this problem we create a balanced panel at the parcel level. More specifically, we characterize the complete list of business parcels over our whole period of analysis and expand it to create a complete array of cells covering all parcels in all periods. Among these, the new cells are assigned zero values for employment and wage income.

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 (IHS), transforma-

tion. Unlike the logarithmic transformation, the IHS is well-defined at zero and has the same attractive features (Burbidge et al. (1988), MacKinnon and Magee (1990)). In addition, the point estimates can be interpreted exactly in the same way as the log transformation.[10]

We will estimate difference-in-difference models for (the inverse hyperbolic sine of) employment and wage income in specifications that include lot fixed-effects:

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

where α_t are quarter-year dummies, α_ℓ are 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 to the interaction between a post-Sandy indicator ($Post_t$) and a dummy variable that indicates which lots suffered damage during hurricane Sandy (Dam_ℓ).[11] Intuitively, coefficient β is identified on the basis of the within-parcel change in the value of, say, employment around the time of hurricane Sandy in damaged parcels relative to the change for parcels with the same flood-zone status that did not suffer any damage.

Standard errors are clustered at the block level, which allows for spatial correlation across locations within a block and is a more conservative choice. It is important to highlight that the specification contains lot fixed-effects, which absorb all time-invariant lot-level characteristics that affect the income-generating potential of the lot, such as location, elevation, building type and the relevant socio-demographic characteristics of the neighborhood.

[10] More specifically, the inverse hyperbolic sine transformation of variable y is given by: $ihs(x) = asinh(x) = \ln(x + \sqrt{x^2+1})$. 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.

[11] Indicator $Post_t$ takes a value of one for quarters 2013Q1 and onward.

We will also estimate more flexible (event-study) models like

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

where the coefficient β_t is allowed to vary over time. More specifically, we allow β_t to vary annually in the post-Sandy years (2013-2017). Thus the estimates will trace the within-parcel change in the dependent variable in year $t \geq 2013$ for the outcome of interest in damaged parcels, relative to the pre-Sandy value, compared to the evolution of the outcome in parcels with the same flood-zone status that were not damaged by the storm. Naturally, we expect these coefficients to take negative or zero values. What is less clear is whether the estimated effect will vanish quickly or remain persistent.

As discussed earlier, our preferred unit of observation are parcels, rather than establishments. The latter is defined as a company-location pair. Consequently, if a given location (parcel) becomes undesirable and the company migrates to another location, the establishment will cease to exist. Because flood risk is a feature tied to the specific parcel, measuring it and estimating its effects requires focusing on parcels. Typically, a vacant parcel will eventually be re-occupied (possibly at a lower rental rate) but, obviously, the income generated at that location will depend on the businesses inhabiting the parcel at each point in time.

Our preferred estimates will be based on a balanced parcel-level panel. That is, we will expand our dataset to create a cell for every parcel in each quarter during the sample period. For our purposes, a balanced panel is preferred because estimates based on an unbalanced panel may suffer from selection (survival) bias. Specifically, if the parcels that suffered the most damage during hurricane Sandy remain vacant with a higher probability than other parcels, they may disappear from the data and this would lead us to underestimate the effects of the hurricane on the economic activity of the affected parcels. Our balanced panel roughly doubles the number of parcel-quarter observations, from 6.2 to 11.9 million. The newly created

cells are populated with zero values for employment and the wage bill.[12] For comparison purposes, we will also report estimates based on the unbalanced panel.

Another important consideration is that damage-point data identifies only which parcels suffered damage during the storm. Clearly, for single-business parcels, this also identifies which establishments suffered damages. However, in multi-establishment parcels, not all establishments may have been affected to the same degree.

6 Summary statistics

Our balanced panel dataset contains 165,203 business parcels, totaling 11.9 million parcel-quarter observations.[13] As displayed in Table 4 , average employment per parcel is 19.2 workers, roughly half of what we observed in the unbalanced panel due to the increased presence of zeros. Similarly, the annual wage bill is $1.44 million.[14] Around 2.6% of the observations correspond to lots located in Special Flood Hazard Areas (SFHA), the 100-year floodplain defined according to FEMA flood maps, and 5.5% of the observations correspond to lots that suffered damage during hurricane Sandy. Thus many parcels located outside the flood zone suffered damage during the storm, and this may have been rather unexpected.[15]

The key treatment in our analysis consists in having been damaged during the hurricane. It is thus interesting to compare the size and growth (in terms of employment) of parcels that were damaged by Sandy and those that were

[12]Recall that our dependent variables are inverse hyperbolic sine transformations of employment and the wage bill, which are well defined at zero.

[13]Among these, 52% of the observations have zero employment and wage bill.

[14]The wage bill in the data are quarterly. Hence, the annual figure is reached by multiplying $360,007 times 4.

[15]The city has its own definitions of flood risk, known as *Hurricane Evacuation Zones* (HEZ). About 3.7% of the observations correspond to lots located in the highest risk zone (HEZ A).

not. As seen in Table 5, out of the 90,872 lots with business activity in New York City in year 2012 (second quarter), about 5.48% were damaged by the hurricane. In terms of employment size, damaged lots were clearly larger (57.5 versus 34.8 employees). This was also true for each borough in the city.[16]

Next, we assess whether differential pre-treatment trends existed between damaged and non-damaged parcels. The bottom panel of the table reports the change in the log of employment over the 3-year period prior to hurricane Sandy (2009Q2-2012Q2). For the city as a whole, lots that were damaged by Sandy (in 2012Q4) were growing slightly faster (in terms of employment) than undamaged lots: approximately 8.21% versus 6.97%. At the borough level, the pre-Sandy employment growth rates of damaged and undamaged lots were very similar in Brooklyn (7.79% vs. 8.36%) and Queens (5.39% vs. 5.99%). Only in Manhattan and the Bronx do we observe larger differences between the two sets of business lots. In the former, Sandy-damaged business lots were growing 5.4 percentage points faster than non-damaged lots, whereas in the Bronx damaged lots were growing 3.9 percentage points more slowly than non-damaged ones. These data suggest that a causal interpretation of our difference-in-difference estimates will be more plausible for the boroughs of Brooklyn and Queens.

7 Main Results

We now turn to the estimation of the effects of hurricane Sandy on the business activity taking place in lots that suffered damage during the storm (October 29, 2012). We analyze three outcomes: employment, wage income,

[16] If we restrict to comparisons by damage status across lots within the flood zone, business lots are larger (in terms of employment) only in Manhattan but not in the other boroughs. The FEMA damage-point estimates data do not contain any damaged (commercial) structures/buildings in Staten Island, even though many residential buildings suffered damages.

and company relocations.

7.1 Employment and Wage income

Our main results are based on a balanced panel but we also conduct sensitivity analysis by providing estimates using the original, unbalanced dataset. To account for the large number of zero lot-quarter observations, we transform our dependent variables (employment and wage income) using the inverse hyperbolic sine transformation.

7.1.1 Balanced panel

The top panel in Table 6 collects the results on employment. Column 1-3 present estimates for the city as a whole and we include increasingly more geographically detailed fixed-effects, at the borough (column 1), block (column 2) and parcel (column 3) levels. Confirming previous results, the estimates in column 1 show that lot employment is higher in the flood zone (by 25 log points) and among lots that were damaged during Sandy (by an additional 5 log points). More importantly, the estimates show a 2 log-point reduction in employment in the lots that suffered damage during hurricane Sandy. The latter estimate remains unchanged when we add block fixed-effects (column 2) or parcel fixed-effects, although standard errors (clustered by block) increase.

The previous estimates mask heterogeneous effects across boroughs, as can be seen in columns 4-7. While businesses located in damaged buildings in Manhattan (column 4) did not suffer any employment loss after the storm, and may have even experienced a small increase, in the other boroughs, employment fell strongly in the parcels that suffered damage during the storm. Specifically, the employment losses experienced by damaged lots in the outer boroughs were: 18 log points in the Bronx, 7 log points in Brooklyn, and 5 log points in Queens. As discussed earlier (Table 5), the estimates for

Manhattan and the Bronx need to be interpreted cautiously because of indications of differential pre-treatment trends in these boroughs. In contrast, the estimates for Brooklyn and Queens are more likely to capture a causal effect.

The effects on wage income are reported in the bottom panel of Table 6. Not surprisingly, the pattern is similar to that of employment, but the effects are larger than for employment. The estimates for the city as a whole (columns 1-3) suggest an 8-log-point reduction in wage income. The larger point estimate suggests that damage during the hurricane may have also had an intensive margin effect, reducing working hours, and possibly lowering hourly wages. As before, we obtain more precise estimates for Brooklyn and Queens. The estimates in columns 6 and 7 imply wage income losses of approximately 30 log points for the business lots that suffered damage during the hurricane.

In our view, the fact that damaged parcels in Manhattan may have suffered smaller economic disruption than damaged parcels elsewhere in the city can be explained by differences in building size and type. As documented earlier (Table 2), the average parcel in Manhattan contains about twice as many establishments as the average parcel elsewhere in the city. Very often the multi-establishment parcels correspond to high rises and the more elevated establishments may have suffered less disruption during the hurricane than ground-level businesses.[17]

Another factor that may contribute to the heterogeneous effects associated to storm damage across boroughs may be differences in industry composition across the flood zone in the different boroughs. Relative to the other boroughs, Manhattan's flood zone is highly specialized in Finance and Professional services (Figure 5), whereas the flood zone in Brooklyn specializes

[17]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.

in the Health industry, and Queens' on Construction and Retail (Figure 6).[18] The county-level analysis of the effects of hurricanes in Florida by Belasen and Polachek (2008) suggests that manufacturing businesses are more negatively affected than businesses in construction or services. This observation is only partially consistent with our findings, suggesting that building type may also play an important role.

7.1.2 Unbalanced panel

The results above are based on the balanced dataset (with 11.9 million observations), which required generating a great deal of zero-valued cells. Next, we check if the results are influenced by this feature of the data. Specifically, we estimate our models on the original dataset (with 6.2 million observations). As can be seen in Table 7, the pattern of the estimates is the same as before, though the estimated effects on wage income are quantitatively smaller. The estimates based on the unbalanced panel suggest a citywide 3 percent drop in employment for the damaged lots. The effects are larger and more statistically significant for Brooklyn and Queens, with 4 and 7 log point reductions associated to Sandy-damage, respectively. The bottom panel presents the estimates for the effects on the wage income generated by the businesses. According to these estimates, the wage bill fell by about 9 percent for the damaged lots citywide (column 3), with larger drops in Brooklyn (of about 13 percent) and Queens (with about 23 percent). We also observe similar coefficients for the Manhattan and Bronx subsamples, but we cannot reject the null hypothesis of no effects.

[18] We classified all businesses by their 1-digit industry: (1) Finance, (2) Manufacturing, (3) Wholesale, (4) Construction, (5) Health, (6) Professional services,(7) Other services, and (8) Retail. We then computed the employment shares by industry in the city's flood zone. Then we computed the difference between each borough's flood-zone industry composition of employment and that of the flood zone for the city as a whole. Appendix Figure C.1 reports the industry composition of employment in the flood zones of Staten Island, which resembles that of Queens, and the Bronx, which specializes in the wholesale industry.

The unbalanced panel estimates deliver slightly higher estimated effects (in absolute value) associated to hurricane damage for the city as a whole, but smaller effects in Brooklyn and Queens. The smaller effects for these boroughs, compared to the balanced panel estimates, are consistent with the possibility of survival bias. That is, the worst damaged commercial parcels may have remained vacant for longer or, in extreme cases, they may have disappeared permanently. If this is the case, we would expect to underestimate the effects of storm damage when using the unbalanced panel. An additional factor that may also account for the differences across the estimated effects at the borough level between the balanced and unbalanced panels is that the number of business parcels has risen more in some boroughs than in others in the post-Sandy period due to rezoning. The observations corresponding to the boroughs that have expanded more rapidly may have gained weight over time in the balanced panel.

Summing up, the estimates based on the unbalanced panel suggest employment losses of around 5 percent for damaged parcels in Brooklyn and Queens, with slightly lower effects for damaged businesses elsewhere in the city. As before, the employment loss appears to underestimate the total effect because we find reductions in wage income ranging between 13 and 23 log points in Brooklyn and Queens, respectively, and smaller effects in the rest of the city.

7.2 Dynamic effects

Let us now trace the evolution of the effects of hurricane Sandy over time. To do so we consider more flexible models that allow for year-specific effects (event studies) and return to the balanced panel. The results for employment are presented in Table 8 (top panel). Column 1 shows a roughly 3% drop in employment in the year after Sandy in the lots that suffered damage, which gradually tapered off over a 5-year period. This pattern, which is also observed for the wage bill (bottom panel), suggests that the effects of the

storm were temporary.

However, a closer look reveals that the previous pattern is due to a compositional effect. Specifically, columns 2-5 of Table 8 present estimates by borough. Once again, we find evidence that the effects of the storm on business activity differed between Manhattan and the rest of the city. Employment (and wage income) seemed to surge in damaged buildings in Manhattan in the year after the storm, gradually tapering off. However, we do not put much stock on this finding given that these estimates are not statistically significant. In sharp contrast, we find large and highly persistent reductions in employment in damaged lots in the other boroughs. The estimates corresponding to Brooklyn and Queens suggest reductions in employment (top panel) and wage income of about 6 and 30 log points, respectively. Importantly, these effects are as large 5 years after the storm as they were on impact. The point estimates corresponding to the Bronx are larger in magnitude, but not statistically significant. However, we documented slower employment growth in the (later-to-be) damaged lots in this borough, suggesting that the estimates for the Bronx may exaggerate the reductions in employment and wage income.

In sum, the dynamic analysis of the effects of hurricane Sandy provides evidence of highly persistent negative effects on employment and, with larger intensity, on wage income.

7.3 Relocation

Our main estimates are based on a balanced panel. As a result, parcels that remain vacant stay in the sample and display zero employment and wage bill. Hence, the estimated reductions in the employment and wage income of parcels that suffered hurricane damage may reflect two different types of adjustment. On the one hand, some businesses located in the affected parcels may have downsized their operations, reducing employment and working hours. However, other companies may have decided to close

their establishments in parcels damaged by the storm, moving to less risky locations.

The goal of this section is to focus on the relocation effects, which requires switching our unit of analysis from the parcel to the *establishment*, defined as a company-lot combination. We now examine whether exit rates increased for establishments located in parcels affected by hurricane Sandy, relative to establishment exit rates in unaffected parcels.

More specifically, we conduct the following exercise. First, we identify the establishments that appear at least in one quarter in our dataset. Next, we extend the dataset so that every establishment appears in the dataset in each quarter, and fill in the newly created company-quarter cells with zeros for employment. Third, we focus on the quarter preceding hurricane Sandy (2012Q3) and keep record of the exact location (parcel) of each company at that time. Last, we drop all periods prior to 2012Q3 and create a dummy variable $Stay_{i,\ell,t}$ that takes a value of 1 when company i is found at the same parcel ℓ in period $t > 2012Q3$ as in 2012Q3. Thus, observations with $Stay_{i,\ell,t} = 0$ identify exit, which may indicate migration to a different location or that the firm shut down the establishment (i.e. exited that location). Clearly, exit instances happen regularly for reasons unrelated to hurricane Sandy. Our approach will estimate the excess exit activity displayed by the lots that were affected by Sandy.

The model we estimate is as follows.[19] The dependent variable indicates whether company i remains at pre-Sandy location ℓ in period t. The factors governing this choice are modeled as

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

where we include company fixed-effects, flood-zone specific trends and the interaction between the post-Sandy indicator and damage status. Thus,

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

coefficient β identifies the within-firm change in the probability to remain (stay) in the pre-Sandy parcel for companies located in parcels damaged by the hurricane, relative to unaffected companies with the same flood-zone status.

Table 9 presents the results. The estimates reveal negative effects on the probability to remain in the pre-Sandy parcel associated to hurricane damage. In other words, damage during Sandy is approximately associated to a 1 percentage-point increase in the probability of *exit* citywide, as well as in Manhattan, Brooklyn and Queens. Despite the small coefficients, these effects are not small. The mean exit rate in any given quarter is 4%. Hence, a 1 percentage-point increase amounts to a 25% increase in the exit rate.

In sum, this new finding implies that, to some extent, our earlier finding of negative effects of storm damage on the employment and wage bill of damaged parcels (Table 6) is likely driven by relocation of firms towards less risky locations.

8 Conclusions

As sea levels rise the frequency of large-scale flooding events in coastal areas is rising as well. These events disrupt economic activity and some business owners may choose to relocate their establishments to less risky locations. However, there may be frictions that slow down the updating of beliefs toward flood risk and delay relocation decisions.

Our findings suggest that companies that experienced first-hand the effects of hurricane Sandy have overcome these frictions. Our analysis shows that some of these companies have reacted by shutting down establishments in locations affected by the storm. Furthermore, we find that both the level of employment and the wage income generated in these locations has fallen. Because damage from the storm was heavily clustered, these results point toward a highly localized negative and persistent income shock.

Our findings have implications for the value of the commercial lots that were affected by hurricane Sandy. The sale value of a commercial lot is determined by the present value of the income it can generate, appropriately discounted. Our analysis has shown that there has been a persistent reduction in the wage income generated by the lots affected by hurricane Sandy, which probably reflects the overall income-generating potential of these locations. As a result, their value is likely to have diminished. Assuming that the reduction in (wage) income of the lots affected by Sandy turns out to be permanent, the estimated 20 percent reduction in the wage income generated in these lots could lead to a reduction in their value of the same magnitude. This wealth shock would then reinforce the negative income shock caused by hurricane Sandy in the affected neighborhoods.

In closing, our analysis suggests that businesses are adapting to climate change, in line with the conclusions of Bleakley and Hong (2017) regarding adaptation in the agricultural sector. Our findings suggest that companies may be shifting their activities away from flood-prone areas, reducing the size of their establishments located in high flood risk areas or moving away altogether. Our results also suggest that first-hand experience of catastrophic events may be needed to overcome informational frictions and update flood risk beliefs. While business migration entails a negative economic shock for the affected areas, the overall effect may be positive. As argued by Desmet et al. (2018), migration of companies and people is an important dynamic adjustment to sea-level rise that will greatly mitigate the associated economic costs.

References

Abel, Jaison R., Jason Bram, Richard Deitz, and James Orr, "What are the costs of Superstorm Sandy?," *Federal Reserve Bank of New York*, 2012.

Ambrus, Attila, Erica Field, and Robert Gonzalez, "Loss in the Time of Cholera: Long-run Impact of a Disease Epidemic on the Urban Landscape," Mimeo Duke University May 2016.

Atreya, Ajita, Susana Ferreira, and Warren Kriesel, "Forgetting the Flood? An Analysis of the Flood Risk Discount over Time," *Land Economics*, 2013, *89* (4).

Bakkensen, Laura A. and Lint Barrage, "Flood Risk Belief Heterogeneity and Coastal Home Price Dynamics: Going Under Water?," Working Paper 23854, National Bureau of Economic Research September 2017.

Balboni, Claire, "In Harm's Way? Infrastructure Investments and the Persistence of Coastal Cities," Technical Report, LSE Mimeo 2018.

Belasen, Ariel R. and Solomon W. Polachek, "How Hurricanes Affect Wages and Employment in Local Labor Markets," *The American Economic Review*, 2008, *98* (2), 49–53.

Bernstein, Asaf, Matthew Gustafson, and Ryan Lewis, "Disaster on the Horizon: The Price Effect of Sea Level Rise," Forthcoming, Journal of Financial Economics 2019.

Bin, Okmyung and Craig Landry, "Changes in implicit flood risk premiums: Empirical evidence from the housing market," *Journal of Environmental Economics and Management*, 2013, *65* (3), 361–376.

_ and Stephen Polasky, "Effects of Flood Hazards on Property Values: Evidence Before and After Hurricane Floyd," *Land Economics*, 2004, *80* (4).

_ , Jamie Brown Kruse, and Craig Landry, "Flood Hazards, Insurance Rates, and Amenities: Evidence From the Coastal Housing Market," *Journal of Risk & Insurance*, 2008, *75* (1), 63–82.

Bleakley, Hoyt and Sok Chul Hong, "Adapting to the Weather: Lessons from U.S. History," *The Journal of Economic History*, September 2017, *77* (03), 756–795.

Burbidge, John B., Lonnie Magee, and A. Leslie Robb, "Alternative Transformations to Handle Extreme Values of the Dependent Variable," *Journal of the American Statistical Association*, 1988, *83* (401), 123–127.

Davis, Donald R. and David E. Weinstein, "Bones, Bombs, and Break Points: The Geography of Economic Activity," *American Economic Review*, December 2002, *92* (5), 1269–1289.

_ **and** _ , "A Search For Multiple Equilibria In Urban Industrial Structure," *Journal of Regional Science*, 2008, *48* (1), 29–65.

Deryugina, Tatyana, Laura Kawano, and Steven Levitt, "The Economic Impact of Hurricane Katrina on Its Victims: Evidence from Individual Tax Returns," Technical Report 2014.

Desmet, Klaus, Robert E. Kopp, Scott A. Kulp, Dvid Krisztian Nagy, Michael Oppenheimer, Esteban Rossi-Hansberg, and Benjamin H. Strauss, "Evaluating the Economic Cost of Coastal Flooding," NBER Working Papers 24918, National Bureau of Economic Research, Inc August 2018.

Gallagher, Justin, "Learning about an Infrequent Event: Evidence from Flood Insurance Take-Up in the United States," *American Economic Journal: Applied Economics*, July 2014, *6* (3), 206–33.

Groen, Jeffrey A., Mark J. Kutzbach, and Anne E. Polivka, "Storms and Jobs: The Effect of Hurricanes on Individuals Employment and Earnings over the Long Term," Working Papers 15-21r, Center for Economic Studies, U.S. Census Bureau January 2015.

Harrison, David M., Greg T. Smersh, and Jr Arthur L. Schwartz, "Environmental Determinants of Housing Prices: The Impact of Flood Zone Status," *Journal of Real Estate Research*, 2001, *21* (1/2), 3–20.

Hinkel, Jochen, Daniel Lincke, Athanasios T Vafeidis, Mahé Perrette, Robert James Nicholls, Richard S J Tol, Ben Marzeion, Xavier Fettweis, Cezar Ionescu, and Anders Levermann, "Coastal flood damage and adaptation costs under 21st century sea-level rise," *Proceedings of the National Academy of Sciences of the United States of America*, 03 2014, *111* (9), 3292–3297.

Hornbeck, Richard and Daniel Keniston, "Creative Destruction: Barriers to Urban Growth and the Great Boston Fire of 1872," *American Economic Review*, June 2017, *107* (6), 1365–1398.

Kocornik-Mina, Adriana, Thomas K.J. McDermott, Guy Michaels, and Ferdinand Rauch, "Flooded Cities," CEP Discussion Papers dp1398, Centre for Economic Performance, LSE December 2015.

Liu, Crocker, Stuart S. Rosenthal, and William C. Strange, "The Vertical City: Rent Gradients, Spatial Structure, and Agglomeration Economies," *Journal of Urban Economics*, 05 2018, *106*.

MacKinnon, James G and Lonnie Magee, "Transforming the Dependent Variable in Regression Models," *International Economic Review*, May 1990, *31* (2), 315–339.

Neumann, James, Kerry Emanuel, Sai Ravela, Lindsay Ludwig, Paul Kirshen, Kirk Bosma, and Jeremy Martinich, "Joint effects of storm surge and sea-level rise on US Coasts: new economic estimates of impacts, adaptation, and benefits of mitigation policy," *Climatic Change*, March 2015, *129* (1), 337–349.

Ortega, Francesc and Suleyman Taspinar, "Rising sea levels and sinking property values: Hurricane Sandy and New York's housing market," *Journal of Urban Economics*, 2018, *106* (C), 81–100.

Schlenker, Wolfram and Charles A Taylor, "Market Expectations About Climate Change," NBER Working Papers 25554, National Bureau of Economic Research, Inc February 2019.

Stocker, Thomas F, Dahe Qin, Gian-Kasper Plattner, M Tignor, Simon K Allen, Judith Boschung, Alexander Nauels, Yu Xia, Vincent Bex, and Pauline M Midgley, "Climate Change 2013: The Physical Science Basis," Technical Report 2013. 1535 pp.

Zhang, Lei, "Flood hazards impact on neighborhood house prices: A spatial quantile regression analysis," *Regional Science and Urban Economics*, 2016, *60*, 12 – 19.

Table 1: Summary statistics establishments panel

Year	Establishments	Employment	Wage bill ($Mn annual)	Wage income per worker ($ annual)
2000	166,182	17.4	1.0	58,581
2001	168,147	17.4	1.0	60,019
2002	165,823	17.4	1.0	59,328
2003	166,854	17.2	1.0	59,270
2004	168,783	17.3	1.1	63,718
2005	172,998	17.4	1.2	67,914
2006	176,763	17.3	1.3	73,083
2007	181,807	17.5	1.4	80,049
2008	184,353	17.6	1.4	80,679
2009	183,517	17.1	1.3	74,366
2010	186,819	17.0	1.3	78,491
2011	190,879	17.0	1.4	79,622
2012	194,375	17.1	1.4	80,375
2013	198,244	17.2	1.4	80,046
2014	203,726	17.3	1.5	84,566
2015	209,653	17.6	1.5	85,419
2016	210,945	17.7	1.5	85,773
2017	212,045	18.0	1.6	89,874
Average	185,662	17.4	1.3	74,510

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.

Table 2: Establishments per parcel by borough

Borough	All (NYC)	MH	BX	BK	QN	SI
Whole Borough						
Minimum	1	1	1	1	1	1
Median	1	2	1	1	1	1
Maximum	1032	1032	63	183	134	155
Count parcels	86,119	20,773	8,572	28,793	22,743	5,237
Count establishments	210,907	105,726	14,736	44,814	37,877	7,754
Mean parcels/estab	2.45	5.09	1.72	1.56	1.67	1.48
Flood zone						
Minimum	1	1	1	1	1	1
Median	1	1	1	1	1	1
Maximum	169	169	33	107	28	26
Count parcels	2,343	508	199	887	469	279
Count establishments	6,558	2818	378	2012	972	379
Mean parcels/estab	2.80	5.55	1.90	2.27	2.07	1.36

Notes: Data for all years, 2000-2017. The counts and the mean establishments per parcel are based on the average across the whole period. Top panel refers to all parcels. Bottom panel only to parcels located in the flood zone (defined as FEMA's Special Hazard Flood Area).

Table 3: Summary statistics parcels panel

Year	Lots	Employment	Wage bill ($Mn annual)	Wage income per worker ($ annual)
2000	69,010	41.1	2.4	58,423
2001	70,066	41.0	2.4	59,713
2002	69,966	40.6	2.4	59,000
2003	70,828	39.8	2.3	58,907
2004	71,658	40.0	2.5	63,365
2005	73,129	40.4	2.7	67,522
2006	74,563	40.4	2.9	72,624
2007	76,403	40.9	3.3	79,467
2008	77,509	41.0	3.3	80,146
2009	78,086	39.5	2.9	73,843
2010	79,508	39.3	3.1	78,044
2011	81,184	39.3	3.1	79,194
2012	82,639	39.6	3.2	79,957
2013	84,383	39.8	3.2	79,574
2014	86,230	40.4	3.4	84,109
2015	89,120	40.8	3.5	85,003
2016	90,177	41.0	3.5	85,375
2017	91,216	41.3	3.7	89,502
Average	78,648	40.3	3.0	74,098

Notes: Unbalanced dataset at the parcel level, that is, we pool the employment and wage bill of all businesses located in the same parcel (BBL). Only parcel-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. Per worker wage income is computed by dividing the wage bill (column 4) by employment (column 3).

Table 4: Summary statistics. Balanced panel.

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	11,894,616	2008.5	5.188	2000	2017
Employment	11,894,616	19.208	404.403	0	154532
ihs Emp	11,894,616	1.192	1.603	0	12.641
Wage bill	11,894,616	360007.1	9597944	0	6.10e+09
ihs Wage bill	11,894,616	5.348	5.703	0	23.225
Flood Zone (SHFA)	11,894,616	.026	.159	0	1
Damaged	11,894,616	.055	.228	0	1

Notes: Balanced panel at the lot level, containing 165,000 lots. Thus, there is one quarterly observation for each lot. In the newly expanded cells employment and wage income are zero. *ihs* stands for the inverse hyperbolic sine transformation of the corresponding variable. SHFA is an indicator for whether the lot belongs to FEMA's Special Hazard Area. *Damaged* (*Dam*) is an indicator identifying lots that were damaged during hurricane Sandy.

Table 5: Damaged vs. Non-damaged. Pre-Sandy levels and trends.

	NYC	MH	BX	BK	QN	SI
Number lots	90872	21212	8854	31150	24191	5465
Pct. Damaged lots	5.48	4.33	2.08	9.11	4.27	0
2012Q2						
Employment						
Non-damaged	34.76	86.6	21.9	20.7	15.9	15.1
Damaged	57.48	147.2	76.9	37.9	28.1	NA
2012Q2 - 2009Q2						
100 × DLnEmp						
Non-damaged	6.97	8.26	3.99	8.36	5.99	3.32
Damaged	8.21	13.63	1.13	7.79	5.39	NA

Notes: Summary statistics balanced panel. Top panel reports mean values for the quarter before Sandy (2012Q2). Bottom panel reports the change in the log (multiplied by 100) between 2012Q2 and 3 years earlier (2009Q2) for the lots that were in the dataset in both periods, which can be interpreted as approximately the percent change in employment.

Table 6: Effects on Employment and Wage Income.

	1 NYC	2 NYC	3 NYC	4 MH	5 BX	6 BK	7 QN
ihs(Emp)							
FZ	0.25***	0.09					
	[0.014]	[0.056]					
Dam	0.05***	0.18***					
	[0.003]	[0.039]					
$Post \times Dam$	-0.02***	-0.02	-0.02	0.02	-0.18*	-0.07***	-0.05*
	[0.005]	[0.012]	[0.012]	[0.041]	[0.102]	[0.015]	[0.028]
ihs(Wbill)							
FZ	0.55***	0.07					
	[0.045]	[0.167]					
Dam	0.05***	0.51***					
	[0.009]	[0.117]					
$Post \times Dam$	-0.08***	-0.08	-0.08	0.11	-0.43	-0.28***	-0.31***
	[0.018]	[0.050]	[0.050]	[0.138]	[0.323]	[0.066]	[0.110]
Obs.	11,894,616	11,894,616	11,894,616	2,102,040	1,108,728	4,299,408	3,507,408
FZ trends	yes	yes	yes	yes	yes	yes	yes
FE	borough	block	parcel	parcel	parcel	parcel	parcel
Cluster s.e.	robust	block	block	Block	Block	Block	Block

Notes: The dependent variable in top panel is the inverse hyperbolic sine of employment in the lot (BBL). In the bottom panel the dependent variable is the same transformation but applied to the wage bill in the lot. 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). *Dam* is an indicator for having suffered damage during hurricane Sandy, regardless of location in a specific hurricane evacuation zone. *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$

Table 7: Effects on Employment and Wage income. Unbalanced panel.

	1 NYC	2 NYC	3 NYC	4 MH	5 BX	6 BK	7 QN
ihs(Emp)							
FZ	0.44***	0.25***					
	[0.020]	[0.074]					
Dam	0.11***	0.13***					
	[0.004]	[0.045]					
$Post \times Dam$	-0.02***	-0.03*	-0.03*	-0.03	-0.12	-0.04**	-0.07**
	[0.007]	[0.016]	[0.014]	[0.039]	[0.081]	[0.020]	[0.031]
ihs(Wbill)							
FZ	0.66***	0.37***					
	[0.037]	[0.121]					
Dam	0.15***	0.18**					
	[0.009]	[0.073]					
$Post \times Dam$	-0.05***	-0.06*	-0.09***	-0.09	-0.11	-0.13***	-0.23***
	[0.016]	[0.037]	[0.034]	[0.088]	[0.154]	[0.048]	[0.075]
Observations	6,200,555	6,200,460	6,197,458	1,495,447	616,920	2,071,886	1,636,425
FZ trends	yes	yes	yes	yes	yes	yes	yes
FE	borough	block	parcel	parcel	parcel	parcel	parcel
Clustering s.e.	robust	block	Block	Block	Block	Block	Block

Notes: The dependent variable in top panel is the inverse hyperbolic sine of employment in the lot (BBL). In the bottom panel the dependent variable is the same transformation but applied to the wage bill in the lot. In both cases we are pooling all businesses located in the same lot. The panel dataset is not perfectly balanced and about 8% of 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). *Dam* is an indicator for having suffered damage during hurricane Sandy, regardless of location in a specific hurricane evacuation zone. A column for Staten Island is missing from the table because the data does not contain any damaged structures pertaining to that borough. *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$

Table 8: Dynamic effects on Employment.

	1 NYC	2 MH	3 BX	4 BK	5 QN
$ihs(Emp)$					
Dam 2013	-0.03***	0.05	-0.20**	-0.06***	-0.06***
	[0.011]	[0.04]	[0.09]	[0.01]	[0.01]
Dam 2014	-0.02**	0.03	-0.18*	-0.07***	-0.07***
	[0.012]	[0.04]	[0.10]	[0.02]	[0.02]
Dam 2015	-0.02	0.00	-0.14	-0.08***	-0.08***
	[0.014]	[0.04]	[0.12]	[0.02]	[0.02]
Dam 2016	-0.01	0.02	-0.19	-0.08***	-0.08***
	[0.015]	[0.05]	[0.12]	[0.02]	[0.02]
Dam 2017	-0.01	0.01	-0.17	-0.06***	-0.06***
	[0.016]	[0.05]	[0.12]	[0.02]	[0.02]
$ihs(Wbill)$					
Dam 2013	-0.10**	0.23	-0.43	-0.22***	-0.45***
	[0.05]	[0.15]	[0.30]	[0.06]	[0.10]
Dam 2014	-0.09*	0.21	-0.45	-0.27***	-0.29***
	[0.05]	[0.14]	[0.33]	[0.07]	[0.11]
Dam 2015	-0.10*	0.01	-0.39	-0.34***	-0.21*
	[0.06]	[0.15]	[0.35]	[0.08]	[0.13]
Dam 2016	-0.07	0.06	-0.41	-0.32***	-0.28**
	[0.06]	[0.17]	[0.39]	[0.08]	[0.13]
Dam 2017	-0.05	0.02	-0.44	-0.28***	-0.33**
	[0.06]	[0.17]	[0.40]	[0.08]	[0.14]
Observations	11,894,616	2,102,040	1,108,728	4,299,408	3,507,408
FZ trends	yes	yes	yes	yes	yes
Fixed-effects	parcel	parcel	parcel	parcel	parcel
Cluster s.e	block	block	block	block	block

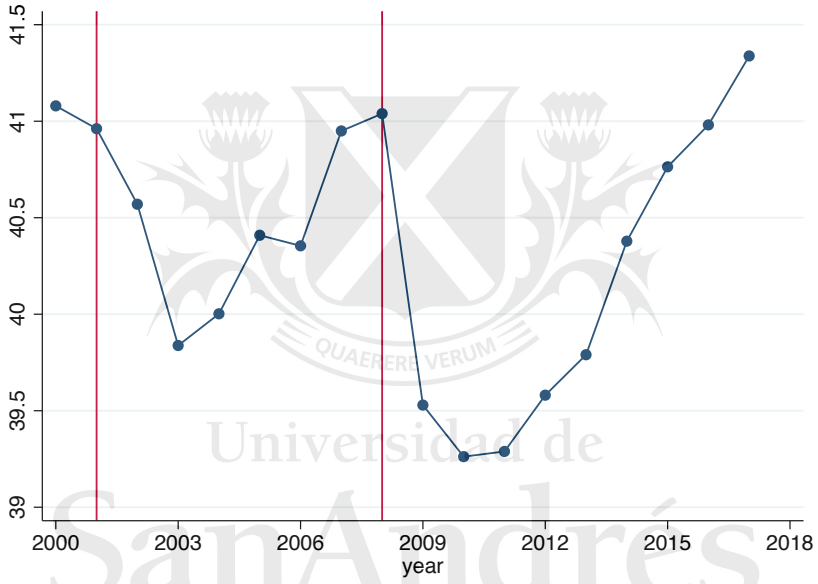
Notes: The dependent variable in top panel is the inverse hyperbolic sine of employment in the lot (BBL). The outcome in the bottom panel is the same transformation but applied to the wage income generated by the lot. We pool all businesses located in the same lot. The panel dataset is balanced (i.e. all lots appear in each quarter). Many lot-quarter observations have zero employment. *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). *Dam* is an indicator for having suffered damage during hurricane Sandy, regardless of location in a specific hurricane evacuation zone. *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$

Table 9: Probability that a establishment stays in the same location as prior to Sandy

	1	2	3	4	5
Stay	NYC	MH	BX	BK	QN
$Post \times Dam$	-0.01*	-0.02*	-0.002	-0.01	-0.01
	[0.006]	[0.014]	[0.019]	[0.007]	[0.010]
Observations	4,260,696	2,072,444	297,770	946,066	789,140
R-squared	0.663	0.667	0.660	0.661	0.638
Fixed-effects	company	company	company	company	company
FZ trends	yes	yes	yes	yes	yes
cluster s.e.	block	block	block	block	block

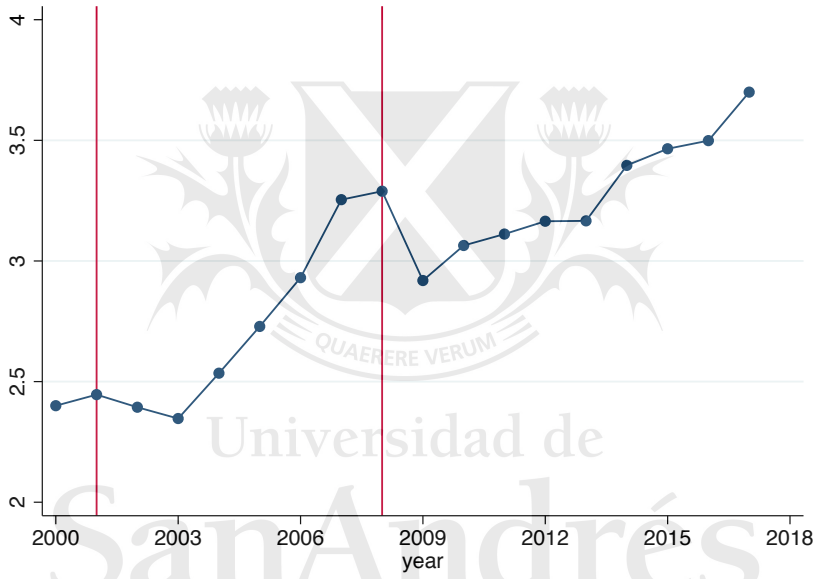
Notes: The dependent variable, $Stay_{it}$, takes a value of one if company i is at the same location (parcel) in quarter $t \geq 2012Q4$ as in the last quarter prior to Sandy ($2012Q3$). Companies are uniquely identified by their Employer Identification Number (EIN). The estimation sample here is 2012Q3-2017Q4. 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). *Dam* is an indicator for having suffered damage during hurricane Sandy. Standard errors are clustered at the block level. *** $p < 0.01$, **$p < 0.05$, * $p < 0.1$

Figure 1: Average employment per lot.



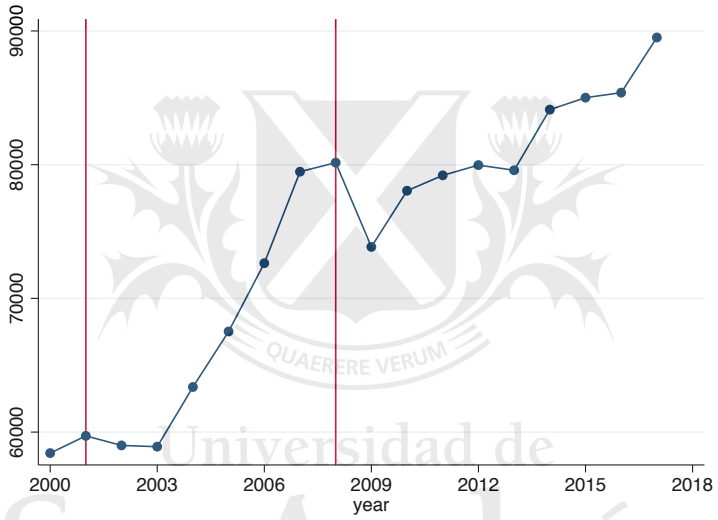
Notes: Annual average quarterly employment. We restrict to lots with positive employment and wage bill in the corresponding year. Vertical lines for NBER recession years 2001 and 2008.

Figure 2: Annual wage income per lot.



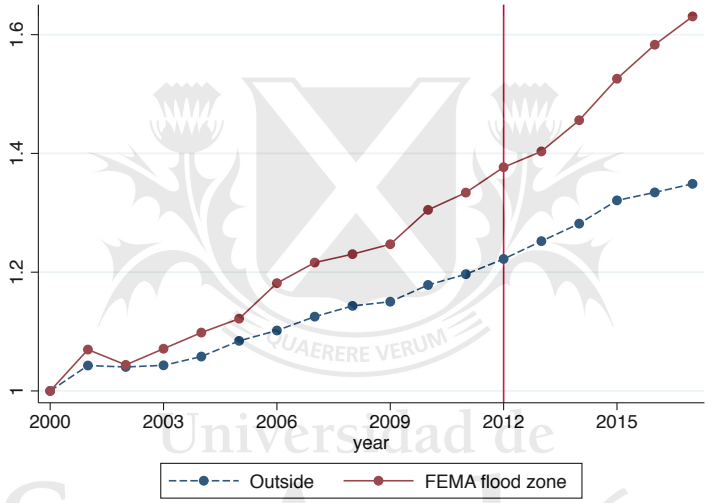
Notes: The figure reports the average annual wage bill. We restrict to lots with positive employment and wage bill in the corresponding year. Vertical lines for NBER recession years 2001 and 2008.

Figure 3: Annual wage income per worker.



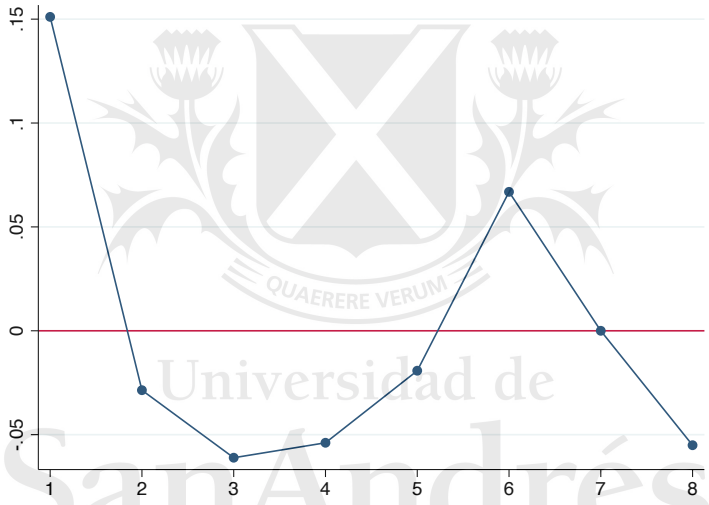
Notes: Average of the ratio between the quarterly wage bill and quarterly employment by lot. We restrict to lots with positive employment and wage bill in the corresponding year and compute the average year by year. Annualized by multiplying the quarterly wage income by four. Vertical lines for NBER recession years 2001 and 2008.

Figure 4: Trends in count of businesses.



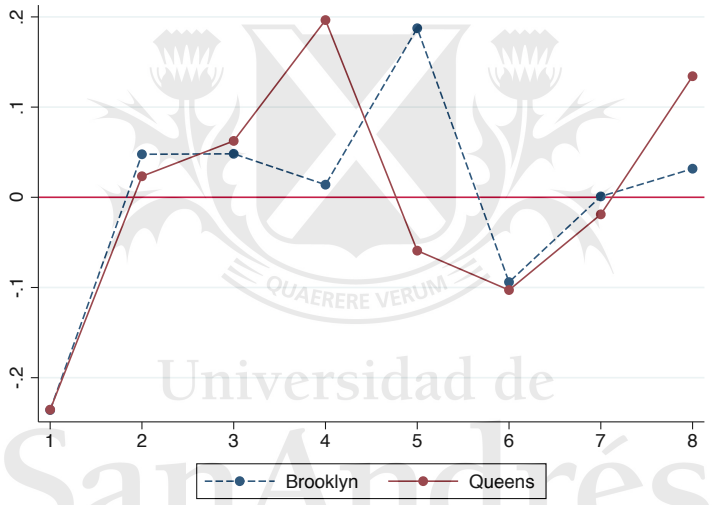
Notes: We computed the count of businesses (by EIN) in each year in the flood zone (33,633 in year 2017) and outside (948,406 in year 2017). Then we normalize each series by the year 2000 value (20,626 and 703,175, respectively). Our definition of flood zone is based on FEMA's Special Hazard Flood Areas (2007 map).

Figure 5: Industry shares (by employment) in the flood zone. Manhattan versus NYC. Pooled years 2009-2012



Notes: Data for years 2009-2012. Industry distribution for each borough is normalized using NYC industry shares by employment.

Figure 6: Industry shares (by employment) in the flood zone. Brooklyn and Queens versus NYC. Pooled years 2009-2012



Notes: Data for years 2009-2012. Industry distribution for each borough is normalized using NYC industry shares by employment.

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 Inverse hyperbolic sine transformation: marginal effects

Consider the following relationship for the inverse hyperbolic sine of variable y:

$$f(y) \quad = \quad asinh(y) = \alpha + \beta x. \tag{6}$$

By inverting the function, we obtain

$$y = f^{-1}(f(y)) \quad = \quad \sinh(\alpha + \beta x). \tag{7}$$

Ultimately, we are interested in the marginal effect of x on y. By the chain rule,

$$\frac{\partial y}{\partial x} \quad = \quad \beta \cosh(\alpha + \beta x), \tag{8}$$

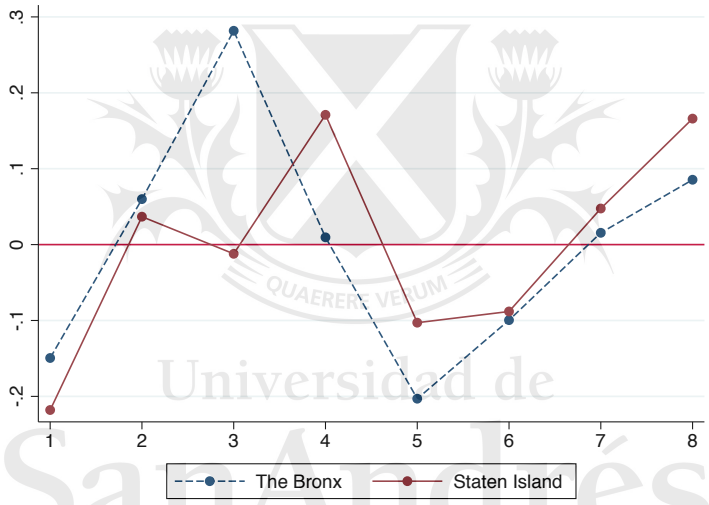
where $cosh(x) = \frac{e^x + e^{-x}}{2}$.[20] Hence, the marginal effect at the sample mean can be computed as:

$$\frac{\partial y}{\partial x} \quad = \quad \beta cosh(\alpha + \beta \overline{x}). \tag{9}$$

C Tables and Figures

[20] For the basics of hyperbolic functions and their derivatives, see `https://www.math24.net/derivatives-hyperbolic-functions`.

Figure C.1: Industry shares (by employment) in the flood zone. The Bronx and Staten Island relative to the rest of the city. Pooled years 2009-2012



Notes: Data for years 2009-2012. Industry distribution for each borough is normalized using NYC industry shares by employment.