Localized Commercial Effects from Natural Disasters: The Case of Hurricane Sandy and New York City

Rachel Meltzer
The New School

Ingrid Gould Ellen
New York University

Xiaodi Li
New York University

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Abstract

The density of urban areas makes them economically productive, but it also makes them particularly vulnerable in the face of natural disasters. In this paper, we consider the localized economic impacts of an extreme event, Hurricane Sandy, on a dense and diverse economy, New York City. We isolate establishments that are more dependent on local customers--retail establishments--and test whether or not they are more vulnerable to hurricane-induced flooding than other entities with geographically dispersed consumer bases. We exploit variation in micro-scale exposure to pre-storm risk and post-storm inundation to identify the impact of storm-induced flooding on establishment survival, employment and sales revenues. Results indicate that the neighborhood economic losses from Sandy were significant, persistent, and concentrated among retail businesses that tend to serve a more localized consumer base. After Sandy, retail establishments exposed to higher surge levels experienced higher rates of business closure and larger losses in jobs and sales revenues compared to retail establishments with no or little exposure to inundation. Furthermore, the losses among retail and non-retail establishments are persistent. Finally, declines in the number of retail establishments are concentrated among smaller and standalone establishments--some of the most vulnerable businesses in good times.

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1. Introduction

The density of urban areas makes them economically productive, but it also makes them particularly vulnerable in the face of natural disasters. In this paper, we consider the localized economic impacts of an extreme event, Hurricane Sandy, for a dense and diverse economy, New York City. We exploit the random variation in storm inundation across blocks in the city's pre-determined evacuation zone to identify the impact of storm-induced flooding on the number of commercial establishments, employment and sales revenues.

Previous studies have looked at the macroeconomic impacts from extreme events, such as national productivity or cross-regional migration (Boustan et al. 2017; Ono 2015; Xiao and Nilawar 2013; Leiter et al. 2009). However, the localized effects are less understood and can be highly uneven. Spatial variation in the potency of the natural disaster can contribute to wide variation in how urban neighborhoods within the same city experience such shocks. Further, some types of establishments are likely to be more vulnerable to hurricane-induced flooding than others.

We hypothesize that retail businesses that serve a more localized consumer base will be most vulnerable to flooding risk; businesses that do not rely on foot traffic and serve broader markets will be relatively less vulnerable. Our reasoning is that the risk for retail establishments is twofold: not only do they confront the physical damage from excessive flooding, but they also rely largely on the patronage of local customers who may be displaced by the storm and/or suffer reductions in income. Further, disruption in transportation networks and closure of nearby establishments may also reduce the number of visitors and workers in the neighborhood who might shop at local stores (Boarnet 1996).

Finally, smaller, independent retailers may face a heightened risk due to fewer resources and minimal or no insurance to cover damage and survive a temporary (or extended) hit.

We rely on a combination of several longitudinal, micro-datasets on establishments, employment, sales revenues and property characteristics in New York City, for intervals of time both before and after Hurricane Sandy. We overlay these data with spatial information on locally determined evacuation zones to capture pre-storm risk, as well as surge zones that show us exactly where, and to what height, the flood waters rose after the storm. We find that the commercial establishments in our sample are no more likely to locate in areas of the city deemed to be at greater flood risk, but the establishments that tend to locate in higher risk areas have somewhat different characteristics. In our preferred specification, we control for these differences by restricting the sample to only establishments located in the evacuation zone and rely on variation in water surge heights to identify the storm's impact.

Results indicate that the neighborhood economic losses from Sandy are significant and persistent. Consistent with theoretical expectations, losses are primarily concentrated among retail businesses that serve a more localized consumer base. While we find a net decrease in the number of both retail and non-retail establishments after Sandy, survival analyses suggest that these losses are driven by higher rates of business closures for retail establishments and lower rates of new business openings for non-retail establishments. Furthermore, any net losses in establishments are concentrated among smaller and standalone establishments. We also find that the storm led to reductions in employment.

For retail establishments, jobs declined by 25 percent after Sandy on blocks that experience three feet or more of inundation. There were no significant job losses, however, among non-retail businesses. Finally, businesses experienced declines in sales revenues after Sandy, which were, again, concentrated among retail entities in areas with higher levels of inundation. Economic losses among both retail and non-retail are persistent, indicating little sign of recovery to pre-Sandy levels as of 2016.

2. Global shocks and local commercial impacts

2.1 Background

While natural disasters, like hurricanes or earthquakes, typically cover large swaths of land area, their impacts are highly uneven. The intensity and nature of the impact is determined by both the force of the extreme event and an individual firm or person's predisposition to risk and harm, which vary across space. Therefore, looking at aggregate outcomes, especially across micro-geographies in large diverse cities, can obscure meaningful differences in localized post-disaster impacts.

To understand localized economic impacts, we compare outcomes across different types of businesses. Specifically, we focus on the degree to which businesses rely on local patronage or involves non-tradable goods and services (Meltzer and Capperis 2017; Waldfogel, 2008; Davis, 2006; Dinlersoz, 2004). Certain kinds of businesses, like restaurants, bars, and specialty stores, depend on street traffic (Jacobs 1961) and benefit from the concentrated clustering of other outward facing establishments that attract one-stop "comparison shopping" (Nelson 1958; Glaeser, Kolko, and Saiz 2001; Kolko and Neumark 2010, Jardim 2015, and Brandao et al. 2014). The clustering of establishments reduces the search costs for consumers. In addition, and more central to our analysis, proximity between the establishment and the consumer reduces travel costs. This feature is particularly important for goods and services that are frequently consumed and perishable, all of which require repeat visits within short periods of time (Hotelling 1929).

In sum, the vulnerability of what we collectively refer to as retail establishments is twofold: in addition to losses from any physical damage to their location or inventory (which any other commercial establishment could similarly experience), they also face interruptions from a depleted consumer base that is either displaced from the area or suffers economic losses of their own. Furthermore, many of these retailers rely on the agglomerative benefits of nearby commercial establishments; therefore, the contraction or death of one establishment can have a ripple effect on the other establishments in the cluster.

In contrast, commercial activity that draws consumers from long distances or does not rely on face-to-face interactions is less vulnerable to disruptions in consumption-based agglomerative economies. Non-retail enterprises should be less locationally bound by their consumers, although they may enjoy production side benefits, such as input sharing or knowledge spillovers, from locating close to other businesses (Marshall 1890; Duranton and Puga 2004).

2.2 Empirical literature

Much of the research on the economic impacts from natural disasters takes a macroeconomic perspective, focusing more on outcomes related to economic growth and welfare (Kliesen 1994; Skidmore and Toya 2002; Zissimopoulos and Karoly 2010;

Kellenberg and Mobarak 2011; Bakkensen and Barrage 2017; Boustan et al. 2017). The research on business-related outcomes using micro-geographies meanwhile tends to be case studies or small-sample analyses (for example, Alesch and Holly 2002; LeSage et al. 2011; Asgary et al. 2012; Sydnor et al. 2017).

The literature covers a range of disaster types, including tornadoes, hurricanes, flooding, and earthquakes. The studies looking at micro-geographies yield a few common findings: (i) businesses are as vulnerable to indirect damages, such as lifeline utility outages and supplier disruptions, as they are to direct physical damages (Tierney 1997a and 1997b, Alesch and Holly 2002, Wasileski et al. 2011, Corey and Dietch 2011) and (ii) the extent of physical damage, preparedness and post-disaster governmental aid do not consistently predict business loss, resilience or recovery (Kroll et al. 1990, Dahlhamer and Tierney 1998, Webb et al. 2000, Chang and Falit-Baiamonte 2002; Runyan 2006; Haynes et al. 2011; De Mel et al. 2012; Davlasheridze and Geylani 2017).

LeSage et. al. (2011) consider the variation in post-disaster outcomes over time and space, and find that immediate effects often differ from longer term impacts. In the short term, severity of the disaster (flood depth) reduces the probability of businesses reopening post-disaster; ownership structure (specifically, sole proprietorship) and local household income increased the probability. Based on post-disaster observations only, the authors find that all of these effects diminish over time. This is consistent with findings from Baade et al.'s study (2007) of the impacts of Hurricane Andrew on taxable sales in south Florida: they report an immediate drop in the taxable sales for affected areas (relative to unaffected areas), but a recovery to pre-storm levels within 18 months. Studies testing the “creative destruction” hypothesis produce mixed results. Analyses using macroeconomic data tend to find positive correlations between natural disasters and economic growth (for example, Skidmore and Toya 2002 and Leiter et al. 2009); however Tanaka (2015) uses plant-level data and finds evidence of severe negative economic outcomes after the Kobe earthquake.

The research to date convincingly shows that the characteristics of the businesses matter, supporting the notion of differential recovery (Cutter et. al. 2000 and 2003, Smith and Wenger 2007, Cutter and Finch 2008, Finch et. al. 2010, Van Zandt et. al. 2012). Communities and individuals, that is, possess different characteristics that make them more or less vulnerable to negative disaster impacts. A number of studies find that larger businesses, and those that were performing relatively better prior to the disaster, cope better in post-disaster circumstances (Tierney 1997b, Dahlhamer and Tierney 1998, Wasileski et al. 2011; Basker and Miranda 2017). It is understood that larger businesses do more to prepare leading up to the disaster, most likely due to resource availability (administrative and financial) (Webb et al. 2000; Basker and Miranda 2017). Indeed, some commercial enterprises can actually benefit from disasters since they end up providing goods and services to aid the recovery process or benefit from serving a captive market (Dahlhamer and Tierney 1998).

A few cross-sectional studies based on small or systematically-selected sample surveys suggest that business recovery also depends on the vulnerabilities and assets of the surrounding community (findings from Corey and Dietch (2011) also support this idea).

For example, Xiao and Van Zandt (2012) find that the return of businesses to a community is dependent on the return of residents (and vice versa) and Chang and Falt-Baiamonte (2002) deduce from interviews that the disrepair of the surrounding commercial district matters for the degree of a business's loss. In addition, wholesale and retail businesses are more likely to close after disasters, because they are more affected by the local economy, intense competition, and levels of consumer confidence (Wasileski, Rodríguez, and Diaz 2011; Webb et. al. 2000). These studies, however, rely on only post-disaster observations and therefore omit many of the businesses that may have closed due to disaster-induced damages.

The current analysis contributes to the literature in several ways. First, we rely on longitudinal data and can observe commercial activity for a diverse and large sample of micro-geographies and over an extended period before and after the disaster. Second, we track multiple measures of commercial activity. Third, we isolate impact estimates using fine-grained spatial controls and narrowing the counterfactual to include other commercial establishments similarly at risk prior to the storm.[1] Finally, we test for, and observe, different responses for different types of businesses and in a untested context (New York City).

[1] There are newer studies focusing on the impacts of Hurricane Sandy in New York City, primarily on residential prices. Barr, Cohen, and Kim (2017) find that houses, apartments, and commercial properties prices have the most volatility in older, denser, and central urban neighborhoods. Ortega and Taspinar (2017) find that prices fell after Hurricane Sandy, and did not fully recover over time. This was true for properties directly damaged and properties flooded, but not physically damaged (although the former incurred bigger losses).

3. Data and analytical strategy

In October of 2012 the eastern seaboard of the United States was hit by Hurricane Sandy, one of the strongest storms it had seen in recent history, and New York City was hit particularly hard. The storm surge reached almost nine percent of all residential units in the city, and nearly four percent of all households registered with the Federal Emergency Management Agency (FEMA) for post-disaster assistance (Furman Center, 2013). Data on the impact of the hurricane on businesses are scarce, but media reports indicate that many businesses struggled with their operations for months following the storm (Birch, 2013, Eha, 2013). Hurricane Sandy is estimated to be the fourth-costliest hurricane on record in the U.S., after Hurricane Katrina in 2005, Hurricane Harvey in 2017, and Hurricane Maria in 2017.[2]

The sheer scale of New York City provides a sizable and diverse sample of businesses and neighborhoods to study. Further, New York City neighborhoods experienced widely divergent levels of flooding and damage. For example, FEMA estimates that the surge covered 39.6% of Lower Manhattan, but even within this area, the Bowling Green neighborhood saw 58.1% of its land surface flooded while the Church Street neighborhood experienced a flooding rate of only 19.6%.

3.1 Data

We compile a rich micro-dataset that captures flooding risk and exposure and a range of economic outcomes for businesses at the neighborhood level. We first obtain maps with information on the boundaries of local evacuation zones (defined by New York City

[2] See the NOAA website for details: https://www.coast.noaa.gov/states/fast-facts/hurricane-costs.html

officials) in effect at the time of Hurricane Sandy together with information on the water surge heights in the flood zones. The evacuation zones are used to proxy for the pre-storm vulnerability of businesses, as well as access to information about pre-storm evacuation warnings.[3] The surge maps, on the other hand, capture the storm's actual impact (from water inundation). The evacuation zone maps were obtained from the New York City Mayor's Office of Recovery and Resiliency and can be seen in Figure 1. We obtain the surge zones maps from the FEMA Modeling Task Force (MOTF), which uses statistical modeling and on-the-ground surge sensors and field observations to regularly update flood impacts. They use high-water marks and surge sensor data to interpolate water surface elevation after the storm.[4] MOTF reports surge levels at a very micro level (one- or three-square meter), but since they are based on interpolated values, we collapse the raster-level surge heights to block-level averages. We classify a city block with surge height above zero as part of the surge zone, but surge heights within the zone vary widely. Figure 2 displays a map of surge levels across the city.

Second, we obtain information on establishments from the InfoUSA historical business database, a longitudinal panel of establishments constructed by Infogroup.[5] Infogroup identifies establishments using yellow pages, phone books, and newspapers, and

[3] In anticipation of Hurricane Sandy in 2012, New York City officials issued mandatory evacuation orders for evacuation zone A; zones B and C were not told to evacuate. In our empirical analysis, we treat only zone "A" as the evacuation zone.

[4] Surge levels for the boroughs of Manhattan, Brooklyn, Queens and Staten Island are based on 1-meter digital elevation model (DEM) resolution and for the Bronx, 3-meter resolution. Information on the FEMA MOTF is available here: http://www.arcgis.com/home/item.html?id=307dd522499d4a44a33d7296a5da5ea0.

[5] See http://resource.referenceusa.com/available-databases/ for details.

incorporates phone verification for the entire database (Lavin, 2000).[6] We use data from 2008 through 2016. Unlike publicly available government data on establishments, the InfoUSA dataset provides full street addresses for each establishment, and it is more likely to capture self-employed establishments and small chain establishments than public records.[7] The dataset reports industry at the 6-digit North American Industry Classification System (NAICS) level to allow for a fine-grained distinction across establishment types.[8] The dataset also reports on the number of employees at each establishment and distinguishes between chains and standalone businesses. Most importantly for this analysis, we can track both the closure of businesses and their movement into and out of very precise locations, i.e. single city borough-blocks, using a unique ID that stays with the establishment over time. Our sample for the establishment count analysis includes 187,758 block-year observations, covering 20,862 borough-blocks.[9]

[6] Every business in the database is contacted at least once each year, and large companies are called several times throughout the year. The operator asks the respondent to confirm the number of employees, address, and type of business. The response rate is high, because InfoUSA asks only basic information. Keeping track of defunct businesses has been a part of InfoUSA's database maintenance, and InfoUSA counts answering machine or voice mail reply as a successful verification (Lavin, 2000). Information for businesses that benefit most from the advertisement from the database is expected to be more reliable (Hoehner and Schootman, 2010). We compared InfoUSA establishments with those available through the public County Business Patterns (CBP) data, and while the absolute counts are slightly different the coverage is similarly steady over time.

[7] See "exclusions and undercoverage" for County Business Patterns (CBP): https://www.census.gov/programs-surveys/cbp/technical-documentation/methodology.html#par_textimage_36648475

[8] NAICS is a classification system for U.S. businesses, which identifies the industry for the establishment's primary activities. NAICS are self-declared by the business and exist "for the purpose of collecting, analyzing, and publishing statistical data related to the U.S. economy" (https://www.sba.gov/contracting/getting-started-contractor/determine-your-naics-code).

[9] For all analyses, borough-blocks in Sub-borough Areas (SBAs) without any inundation or evacuation blocks are dropped.

Third, we obtain employment information from the LEHD Origin-Destination Employment Statistics (LODES) dataset, which is publicly available from the Census Bureau. The LODES dataset includes annual employment counts by 2-digit NAICS code for every census block in New York City dating from 2008 to 2015.[10] The LODES data is derived from state unemployment insurance records, which means that the employment counts, while reliable, are likely undercounts of actual employment on the ground (i.e. they do not capture the jobs for which unemployment insurance is not reported, usually those at non-employer firms that are operated by the owner or those reporting little or no compensation).[11] We use the variable that records jobs based on the location of employment. Our sample for the employment analyses includes 160,776 block-year observations, covering 24,929 census blocks.

Fourth, we use reported quarterly taxable sale revenues for all NYC commercial filers from the city's Department of Finance (NYC DOF).[12] Due to statutory restrictions on data sharing, we could not access filer-level information. Instead, NYC DOF aggregated the data in order to ensure the confidentiality of the tax filers according to the following protocol: (i) the blocks in the city were divided into four sub-groups: blocks outside both

[10] We can access LODES data back to 2002. We replicate the analyses with this longer time frame and the results are substantively the same. We restrict the time frame to 2008-2015 to be consistent with the other outcomes.

[11] The compensation threshold for reporting unemployment insurance varies depending on the type of entity (available at https://labor.ny.gov/ui/employerinfo/registering-for-unemployment-insurance.shtm).

[12] The following items and services are exempt from sales tax: Unprepared and packaged food products, dietary foods, certain beverages, and health supplements sold by food markets; diapers; drugs and medicines for people; medical equipment and supplies for home use; newspapers, magazines, and other periodicals; prosthetic aids and devices, hearing aids, and eyeglasses; laundry and dry cleaning services; shoe repair services; some items used to make or repair clothing and footwear; veterinary medical services. However, returns for clothing and footwear under $110 eligible for exemption are included in the sales even though they have zero sales tax.

the evacuation zone and surge zones; blocks in the evacuation area but not the surge area; blocks in a surge area but not in the evacuation zone; and blocks in both the evacuation and surge zones; (ii) filers were then grouped first according to their ZIP Code, then according to their location in one of these four designated zones[13] and finally whether or not they belong to the retail industry, a classification defined in the following section. In the resulting ZIP-zone level data set, each observation contains summary data for a set of at least ten commercial filers for each quarter-year spanning 2008 to 2016. The dataset includes, for each group-quarter, the number of filers (on average there are 351 filers per ZIP-zone per quarter), as well as means and standard deviations of sales revenues. The sales mean is $65,407, and the standard deviation is $125,440.[14] In total, our sample for the sales analyses covers 307 ZIP-zones, comprised of 10,644 Zip-zone-Year-Quarter observations.

Finally, we obtain building characteristics, like age, height, size, and number of residential and commercial units from the New York City Department of City Planning's Primary Land Use Tax Lot Output (PLUTO) dataset. These variables are useful for understanding the physical structures in which establishments operate in the city and to control for land-

[13] These ZIP-zone aggregations were the smallest groupings we could achieve without violating DOF's aggregation minimum of 10 observations per quarter-year. ZIP-zones with fewer than 10 filers were dropped these constituted about 20% of the sample; in some cases ZIP-zones could be constructed, but not broken out by industrial classification. We also replicate the analyses using aggregations within bigger geographies (Sub-borough areas, or SBAs), such that we end up with a higher number of SBA-zone observations. The results from regressions using this unit of analysis are substantively to the ZIP-zone ones presented in the paper.

[14] Outliers in sales revenues were omitted before constructing the summary statistics. Filers with sales revenues in the top 5 percent for Manhattan and the top 1 percent for the other boroughs were dropped from the sample.

use zoning that could affect the clustering of certain types of businesses.[15] We have this information for every year from 2002 through 2016.

3.2 Identifying Commercial Economic Activity

We examine outcomes for all types of businesses but also conduct all of our analyses separately for retail and non-retail sectors given that we want to test for differential responses between retail and other neighborhood-based businesses on the one hand and broad-based (non-retail) businesses on the other. See Table 1 for a list of NAICS codes included in broad classification (our definition of retail is consistent with other studies (Meltzer and Capperis, 2017; Bingham and Zhang, 1997; Stanback, 1981)). In addition to the establishments classified as retail by NAICS (44-45), we include food services and other personal services that tend to rely on neighborhood-based markets.[16]

Our dependent variables capture three aspects of commercial economic performance. First, we examine net changes in the number of establishments and individual establishment closure using InfoUSA data. We calculate a simple count of establishments, in total and for retail and non-retail sectors separately, for each borough-block and each year in the

[15] We cannot access information on whether or not establishments possessed flood or business interruption insurance. However, prior research (Asgary et al. 2012, Yoshida and Deyle 2005) and a more current assessment of the insurance market (Dixon et al. 2013, conversations with the New York City Mayor's Office of Recovery and Resiliency) both indicate that small businesses have minimal access to insurance. We do not expect that insurance is widespread enough to affect the validity of our results.

[16] We estimate impacts for three outcomes, each of which comes from a different source. Therefore, the precision in the NAICS classification varies across the sources. The InfoUSA data provides the most flexibility in defining retail such that we can include the full range of retail-oriented establishments, including some from the "Other Personal Services" NAICS category (81). The LODES data provides classifications only at the 2-digit level, such that we cannot include 5-digit NAICS categories from NAICS 81. The DOF data provides the least flexibility due to cell size requirements. In order to maximize the number of observations in the DOF analysis, we group the retail categories with other service-based establishments, like Health and Social Services. We are not concerned that these discrepancies drive differences in the estimations, as 84 percent of zip-zone observations in the DOF sample have fewer than 10 health and social service filers.

sample. We consider closure as the most severe outcome after the storm, or as the establishment's response along the extensive margin. Second, we track employment using LODES data. We construct a count of the number of jobs on each census block by year for "retail" and "non-retail" establishments. Third, we consider sales revenues, using NYC DOF data. We observe the total reported revenues for commercial filers by "retail" and "non-retail" classifications for each ZIP-zone and quarter-year.[17] Together, changes in these last two metrics (employment and sales) indicate how the establishment adjusts its operations to stay open in the face of an extreme event, or their response along the intensive margin.

We also explore the heterogeneity of effects across retail establishments. For example, smaller establishments may be more vulnerable to a natural disaster shock. Typically operating off of tight margins (in good times), they do not have the financial cushion of other, larger establishments. When hit by power outages, flooding and other storm damage, they are less likely to have access to the capital needed to continue to pay fixed costs and to make any needed repairs. As a result, they may be more likely to cut back on staff to save on expenses or even to shut down entirely. If an establishment employs few people in the first place, it has fewer places to cut back in the face of unexpected losses. In addition, independent businesses may be more vulnerable, compared to multi-establishment chains, since the latter are likely to have establishments in unaffected areas with continuing operations that help cushion the economic blow for the flooded location (LeSage et al. 2011).

[17] We can also observe the mean reported sales, but we present results only for the total sales. The results are substantively the same when we use mean sales instead of total sales.

We use several variables from the InfoUSA database to proxy for the size and organizational structure of an establishment. Building off of the existing literature, we use the number of employees to measure the size of the establishment (Tierney 1997b, Dahlhamer and Tierney 1998, Wasileski et al. 2011). We also divide retail establishments into chains or standalone categories, based on the reported status code.[18]

3.3 Addressing selection bias

The biggest threat to our estimates is selection bias, from two different sources. First, the establishments that choose to locate in riskier areas of the city may be systematically different from other establishments. For example, less capitalized businesses could sort into flood-prone areas if the rents are lower there, or, alternatively, businesses of a particular industry (i.e. manufacturing) that are more or less resilient due to immobile and expensive infrastructure could cluster in flood-prone areas if that is also where land use is zoned to support their activities.

To assess the severity of this threat, we compare differences in the characteristics of establishments located in vulnerable locations, i.e. evacuation zones, prior to the storm. We consider characteristics of both the establishment, as well as the structures where they are located. Figure 3 shows that most establishments are located outside of the flood-prone areas of the city (as identified by evacuation zone).[19] Figures 4a through 4c show that the

[18] We classify "Headquarter", "Branch", and "Subsidiary" establishments as chains, and "Single" establishments as standalones.

[19] This is also true for employment: over 90 percent of jobs are located outside of the evacuation zone A pre-Sandy.

businesses located inside and outside the zones have similar distributions with respect to size, age, and organizational structure (i.e. chain versus standalone establishment configuration). Although it is not displayed, average commercial property prices per square foot (as a proxy for the cost of renting a space) are also very similar outside and inside the evacuation zone.

Figures 5a through 5d, however, reveal some differences in sector and property characteristics between businesses inside and outside of evacuation zones. First, the share of establishments characterized as retail (drawing solely from NAICS codes 44-45) is almost five percentage points lower in the evacuation zone. Similarly, restaurants are slightly less likely to be located in the higher risk areas; there are no other meaningful differences across sub-types of the firms (and if anything, they represent a marginally smaller share of businesses in the evacuation zone). Second, establishments in the evacuation zone are more likely to be located in industrial buildings than their counterparts outside the zone. Third, we see that commercial establishments inside the zone are located in somewhat older structures than those outside the zone, though the overwhelming majority of both sets of establishments were built before 1990, when new resilience standards were put into place. Finally, establishments in evacuation zones are slightly more likely than those outside to be located in 1- and 2-story buildings, increasing their exposure to flood-induced damage.

The second source of selection bias relates to the establishments' varied preparation for the storm. Specifically, closer to the onset of Sandy, the city actively issued warnings and evacuation plans for areas at highest risk. It is possible that firms located in the evacuation zone differentially prepared for the storm's landfall compared to those located outside the zone, such as moving inventory to avoid flooding and reinforcing windows and levee-type structures. It is this selection issue that we are most concerned with, since we do not have information on the establishments' activities leading up to the storm.

In order to address both selection concerns, we restrict the sample to establishments located on blocks in the pre-determined evacuation zone, and therefore subject to evacuation warnings. We assume that, in all areas of the evacuation zone, establishments perceived relatively similar risk levels and that any difference in preparedness was randomly distributed (controlling for other location-specific and establishment-specific characteristics). About nine percent of gross non-residential square footage (five percent of gross square footage) and five percent of all establishments were located in the evacuation zone in the year preceding Sandy.

We take advantage of the fact that the impacts of the storm were uneven within the evacuation zone. Some areas of the evacuation zone were hit hard by the storm surge, while others experienced little or no flooding. In our crudest specification, we consider a city borough-block/census block flooded if any part of it was inundated; we then refine the definition to distinguish between those with high and low surge levels (discussed below).[20]

[20] We replicate the analyses using information on observed damage, as reported by FEMA. The observed damage and surge heights by block are consistent. 97% of high-surge blocks have damaged buildings; 91% of low-surge blocks have damaged buildings; and only 3% of non-surge blocks have damaged buildings. In terms of severity, 55% of high-surge blocks have destroyed/major damaged buildings, and only 15% of low-surge blocks have destroyed/major damaged buildings. We prefer the identification strategy based on surge heights as it is arguably more exogenous than the subjectively determined damage classifications provided

To capture the impact from flood exposure, we divide city blocks in the evacuation zone into two categories: (i) blocks inside evacuation zone that did not experience any flooding (*Evacuation_only*), and (ii) blocks in evacuation zone that experienced flooding (*Evacuation_surge)*. Based on our classification, about 94 percent of the establishments in the evacuation zone were affected by some level of flooding. Figure 6 shows how blocks are allocated with respect to evacuation designation and flooding, and within one sample Sub-Borough Area (SBA), a collection of census tracts with aggregate population of at least 100,000. The dotted blocks are in the *Evacuation_only* zone, the black blocks in the *Evacuation_surge* zone, the grey blocks in the *Surge_only* zone, and the hollow blocks are outside of both (*None*).

This within-evacuation zone analysis constitutes our cleanest estimation of the hurricane impact, since, under our assumptions stated above, all of the establishments in the evacuation zone had access to the same notification of risk prior to the storm, but only a subset were actually "treated" (i.e. flooded) by the storm. In addition, restricting to only evacuation zone blocks mitigates against selection bias due to firm sorting across low- and high-risk areas. Nonetheless, we still control for establishment-level and location-specific factors that vary within the evacuation zone. We make the reasonable assumption that any unobservable factors driving differential exposure to storm surge are correlated with the observables that we can control for.[21]

by FEMA (which can also be endogenously determined by mitigation efforts by the property owner or business).

[21] It is unlikely that establishments systematically selected locations based on information on storm and flooding vulnerability, as prior to Sandy there was little awareness around severe flood-risk. This is based on conversations with emergency management officials. Indeed, it was Sandy that triggered an update of the evacuation zones and the flood maps months later (Huffington Post 2013).

To further refine our identification of the storm's effect, we differentiate between blocks that had higher and lower surge heights (still within the larger evacuation zone). Those blocks with three or more feet of flooding are designated "high surge" and those with less than three feet are "low surge" (those without any flooding are still "no surge").[22] We expect that any effects from the storm should be concentrated or more intense for the "high surge" observations.

3.4 Estimation

We estimate a series of regression models in which the dependent variable is one of the three outcomes we discussed above (number of establishments by year; number of jobs by year; and total sales revenue by quarter-year) observed at geography *i* and time *t*.

3.4.1 Establishments and jobs

For the establishment and jobs models the unit of analysis is the block;[23] for the sales models the unit of analysis is the ZIP-zone, described above. The regression model for establishment and job outcomes takes the following form:[24]

$$Outcome_{it} = \lambda Sandy_t + \beta\, High_i * Sandy_t + \gamma\, Low_i * Sandy_t + \delta N_i + \theta D_{b,t} + e_{it} \qquad (1)$$

[22] Conceptually, three feet makes sense since at that water height inventory and spaces would be damaged to the point of drastic business interruption. Three feet falls at about the 60th percentile of surge heights, across all blocks in the city that experience some degree of flooding. See Appendix A for a distribution of the surge heights across blocks that experienced any level of flooding.

[23] More precisely, establishment counts are observed at the city block and jobs are observed at the census block; the two are very similar spatially.

[24] We also run log-linear models and the results are substantially the same.

Here, *Sandy* takes on the value of 1 starting in 2013.[25] *High* and *Low* capture the intensity of the surge. *High* takes on the value of 1 if block *i* saw more than 3 feet of water surge (averaged across all of the commercial properties on the block), and 0 otherwise. Similarly, *Low* takes on the value of 1 if block *i* saw some flooding but less than three feet of water surge. The omitted category captures those blocks without any inundation. We are most interested in β and γ, which capture the post-Sandy impacts (specifically, the net change in establishments or jobs), and we expect that β will have a larger magnitude than γ. We include N_i, a block fixed effect (either the boro-block or census block), and $D_{b,t}$, a vector of SBA-year dummies to control for broader neighborhood changes over time. We also estimate models where the post-Sandy impact varies across time, by interacting the *High* and *Low* dummies with year-specific indicators. In all cases, our preferred specification is one in which the sample is restricted to only observations in the evacuation zone.

Because we can follow establishments' locations and operations over time, we can also estimate an establishment-level model to test for any changes in the probability of closure after Sandy. We identify closure when the establishment ceases to exist in the InfoUSA data or when we observe a move to a different location within New York City. We test whether the time until closure shortens after Hurricane Sandy in the blocks seeing high surge levels, using a Cox model with non-proportional hazards to estimate the likelihood that an establishment closes between time *t* and Δt, given that it is operational at time *t* (also known as the hazard rate $h_i(t)$). We compare the hazard rate in high-, low- and no-

[25] Hurricane Sandy hit New York City on October 29th, 2012. Since we have quarterly data for sales revenues, we set 2012 Q3 (September 1 through November 30) and after as post-Sandy in those analyses.

surge areas using a difference-in-differences strategy (Clotfelter et al. 2008), where $1/h_i(t)$ is the expected duration until the event, or closure, occurs.[26]

$$h_{i,j}(t) = h_0(t)\exp(\lambda Sandy_t + \beta High_j + \gamma Low_j + \eta High_i * Sandy_t + \zeta Low_i * Sandy_t + \delta Chain_i + \theta Employee_{it-1} + \alpha Cluster_{jt-1} + \iota Open_i) \quad (2)$$

$h_{i,j}(t)$ is the hazard rate for an establishment i in boro-block j, and $h_0(t)$ is the baseline hazard function - the hazard function for establishment *i* when all the covariates are set to zero. *High* takes on the value of 1 if the establishment is located on a block with more than 3 feet of surge; *Low* is 1 if the establishment is on a block with a lower surge. Chain is a dummy that takes on the value of 1 if the establishment is part of a multi-establishment chain, $Employee_{it-1}$ captures the number of employees at establishment *i* at time *t-1*, $Cluster_{jt-1}$ is the number of retail/non-retail establishments in block *j* at time *t-1*, and $Open_i$ controls for when the establishment opened.[27] The *Cluster* covariate controls for any effect of being located in a cluster with other businesses the *Open* variable differentiates between establishments that newly enter the sample after the start of the study period (and controls for higher probabilities of closure among younger establishments). Finally, we stratify the model, to allow for different hazard rates across zip codes and census tracts (separately).

[26] The partial likelihood of the Cox model is a flexible estimation option, for it allows for an unspecified form for the underlying survivor function as well as time-varying explanatory variables.

[27] Additional specifications, not shown here, control for building characteristics of where the establishments are located; including these controls does not change the results presented here.

3.4.2 Sales revenues

Since sales revenues are only available at an aggregate unit of analysis (Zip-zone), the regressions take on a slightly different form:

$$log(Sales_{jq}) = \lambda Sandy_q + \beta High_i * Sandy_t + \gamma Low_i * Sandy_t + + \delta N_j + \theta \boldsymbol{D}_{b,q} + e_{jq} \quad (3)$$

Our dependent variable is the log of total sales, in order to facilitate the comparison between retail and non-retail sub-samples (the volume of sales for non-retail filers is disproportionately higher than retail ones). The indicators, *Sandy*, *High*, and *Low* are defined the same as in equation (1). $\boldsymbol{D}_{b,q}$ is a vector of borough-quarter dummies to control for macro changes over time and N_j is a zip-zone fixed effect. Zip-zone fixed effects are included in our preferred specification so that we can estimate changes in sales over time within a single zone (i.e. evacuation and surge) and across surge intensities. Since the sales data do not allow us to isolate the blocks in the evacuation zone, as we do for the other outcomes, the fixed effects allow us to approximate a similar identification strategy. All of the regressions are weighted by the number of tax filers in the ZIP-zone. We also replicate all of the regressions for retail and non-retail sub-samples to test for different post-Sandy responses across the two types of businesses.

4. Findings

The paragraphs below summarize findings for each of our outcomes. In each case, we first present findings for the full sample and stratify the observations by retail and non-retail classifications, and then present findings for only blocks in the evacuation zone, our preferred specification. While we discuss in more detail the trends over time for the three outcomes in a later section, we note that we observe parallel trends leading up to Sandy, across low and high surge areas, for all samples.

4.1 What are the short-term effects from Hurricane Sandy on establishments?

4.1.1 The number of establishments

Table 2 reports the estimates for equation (1) for the number of establishments using the full sample. The first column shows that Hurricane Sandy is actually associated with an *increase* in the number of establishments per block citywide, likely capturing the general growth in commercial activity over this time period. When we introduce *High Surge* and *Low Surge* controls, we find that a small portion of the establishment growth is driven by blocks that experienced modest inundation, but that there is no significant growth on *High Surge* blocks. The final four columns of Table 2 show results when we stratify the sample by retail and non-retail classifications. For retail sample, the coefficient on High Surge interaction remains insignificant, while the coefficient on the *Low Surge* interaction term retains its positive sign; the coefficients for both interactions terms for non-retail establishments remain insignificant. In all, these results contradict priors (i.e. that Hurricane Sandy would decrease the number of retail establishments on inundated blocks), but the Sandy coefficient could be capturing other contemporaneous changes that affected the type of businesses that tended to locate in high-risk areas of the city.

Thus, we refine the estimation by restricting the sample to blocks in the evacuation zone--these results are displayed in Table 3. The coefficients for the interaction terms now show negative signs across the board, which is more consistent with expectations and suggests that our previous estimates were likely affected by the heterogeneity of establishments located on high-risk blocks more generally. Without regard to the type of businesses, blocks in *High* surge areas (i.e. more than 3 feet of water) experienced a net loss of about 1.3 establishments per block following Sandy. When we stratify the sample by type of business, we observe a net loss among both retail and non-retail establishments, relative to areas that did not experience any flooding; the magnitude of the loss is about three times larger for the non-retail establishments, but the baseline number of non-retail establishments is also significantly higher. The coefficients translate to a 12 percent loss for retail establishments and a 9 percent loss for non-retail ones. While the coefficient on *Low*Sandy* is not statistically significant in any model, the difference between the coefficients on *High*Sandy* and *Low*Sandy* is only statistically significant for the retail sample.

The InfoUSA data provides enough industry detail that we can break out our "retail" category to confirm that the results are indeed driven by the neighborhood-based businesses, like grocery stores and drug stores (see the full list in Appendix B). These results are displayed in Table 4. They show that while all the *High*Sandy* coefficients are negative for all of the retail sub-categories, the estimate is only statistically significant for neighborhood-based retailers. Unfortunately, the other outcomes are not reported with enough detail to distinguish across types of retail and therefore we cannot disaggregate the retail classification in the same way; to keep the categories consistent we maintain the larger "retail" classification for the remaining analyses.

4.1.2 Survival analyses

A net loss could be a product of two processes: a decline in the number of new establishments opening on the block and an increase in establishment closures. In order to identify the likelihood of closure (as opposed to fewer openings) we estimate hazard models to estimate the difference in time until closure between pre- and post-Sandy periods.[28] We run these for retail and non-retail samples separately and display the results in Table 5.[29]

Two key findings emerge from these regressions. First, there is no significant difference in the odds of closure across *High*, *Low*, and no surge areas for non-retail establishments. This suggests that any significant net loss for non-retail establishments at the block level is largely driven by a decrease in new business opening after Sandy. By contrast, the odds of closure are significantly higher for retail establishments located in both *High* and *Low* surge areas (compared to area without any surge).[30] When we stratify by census tract the relative magnitude of the coefficients persists, but the significance goes away. It's unclear whether we have enough variation within census tracts over time to estimate the odds of closure. Using the coefficients from the zip-stratified models, retail establishments are between 15 and 43 percent more likely to close when exposed to any level of inundation, depending on the level of geographic control in the model. This suggests that the net loss for retail establishments observed in the block-level analysis is at least in part due to higher

[28] Schoenfeld residual tests reject non-proportionality among all of the covariates, except the open year dummies.

[29] Since the data is left-censored (i.e. we cannot observe when all establishment form) we also run models excluding all establishments that we cannot observe enter the dataset prior to 2009. The results are consistent with those presented, albeit less precise due to the smaller sample.

[30] The coefficients on *High*Sandy* and *Low*Sandy* are not significantly different.

rates of closure after the storm. We do not find that the rate of closure after Sandy varies with the establishment's size, chain status or concentration of nearby retail clusters (these results are not displayed).

4.1.3 Testing for heterogeneous effects

Thanks to the detailed nature of our establishment data, we can test for heterogeneous effects across the retail establishments that exhibit the most significant post-Sandy response. For comparison, we also display results for non-retail establishments.

We first consider establishment size. We use the number of employees to proxy for establishment size and set up discrete size categories based on the distribution of establishments in New York City. Over 95 percent of establishments have fewer than 50 employees.[31] The stratified regressions are displayed in Table 6; we show only results for the evacuation sample. As expected, for both retail and non-retail sectors, losses are concentrated among the smallest establishments. And the losses are especially profound for the very smallest establishments--those with fewer than 20 employees. Specifically, blocks with *High* surges lost, on average, 0.4 retail establishments with fewer than 20 employees, after Sandy compared to blocks without any surge. These effects are not driven by composition, since about 91 percent of both retail and non-retail establishments have fewer than 20 employees.

[31] The U.S. Census' definition of "small business" is an entity with fewer than 100 employees. In our sample, 99 percent of the establishments have fewer than 100 employees and therefore we used a breakdown, i.e. 1-19, 20-50, 50+, that reflects the diversity of the establishments in our sample.

As for differences in impacts across chain and standalone establishments, our results again conform with theoretical expectations. Table 7 shows that the coefficient on *High*Sandy* is highly significant and negative for both retail and non-retail sectors for stand-alone establishments; but we see no effects for chain businesses.

4.2 Jobs

Table 8 shows employment results for the full sample, while Table 9 shows results for the restricted sample of blocks in the evacuation zone. A similar pattern emerges as that observed with the establishment analyses. First, we find that employment generally increased in the quarters after Hurricane Sandy. When controlling for surge intensity (column 2), the post-Sandy effect is insignificant. However, when the sample is stratified by retail and non-retail classifications, the coefficient on *High*Sandy* is significant and negative only for the retail sub-sample. This effect intensifies when we restrict the sample to only blocks in the evacuation zone (see Table 9). In our preferred specification, blocks with *High Surge* designation lose on average about 10 retail jobs per year after Sandy, compared to blocks without any water surge.[32] This represents a 25 percent net loss for the typical block with non-zero employment prior to Sandy. Unlike establishments, we see no significant net loss for non-retail establishments. Blocks with low surge levels are not significantly harmed either.

[32] The *High*Sandy* and *Low*Sandy* coefficients are significantly different at the 5 percent level for the retail sample.

4.3 Sales revenues

Finally, we present the findings for the third outcome of interest, sales revenues. As was the case with establishments and jobs, the first column of Table 10 shows that sales revenues go up after Sandy, indicating an upward trend over this time period for the city overall. When controlling for surge intensities, the coefficient on *High*Sandy* is negative and significant overall and then for both the retail and non-retail subsamples.

Next, we include ZIP-zone dummies, which allows us to compare outcomes across surge heights over time and within the same ZIP-zone (which is designated as evacuation or not). Table 11 shows results. We see that the coefficient on *High*Sandy* is significant and negative. When we stratify the sample by type of establishment (or filer, in this case), the negative coefficient on *High*Sandy* persists only for retail: sales drop by about 16 percent after Sandy compared to areas without any flooding. The coefficient on *High*Sandy* is marginally significant and positive for the non-retail subsample. Note that when we control for pre- and post-Sandy revenue trends, the significance goes away for not-retail filers (but persists for retail filers).[33]

[33] Recall that the sales revenue data only capture goods and services subject to sales tax and excludes items like packaged food, diapers, medications and laundry services. Therefore, it is possible that these observed effects are underestimates of the Sandy-induced revenue losses, if demand for exempt goods and services is similarly interrupted. However, it is also possible that demand for these exempt items, which tend to be more necessity goods, are less vulnerable to interruptions (Aladangady et al. 2016; Farrell and Ward 2018). The net effect is therefore ambiguous.

4.4 Robustness checks

4.4.1 Alternative surge metrics

In order to confirm that our results are not an artifact of how we set the *high* and *low* surge thresholds, we estimate models using alternative metrics. First, we re-estimate the preferred models using a continuous measure of surge height. Table 12 shows these results. The results are consistent with those that use a categorical surge measure, such that only coefficients for the retail regressions are significant and negative. However, in two cases, the non-retail establishment and retail sales analyses, the negative coefficient is not significant. These differences, and the smaller coefficient magnitudes across the board, indicate that the continuous measure does obscure nonlinearities in how inundation affects economic viability. Second, we use thresholds below and above three feet to classify *high* and *low* surge blocks. These results, displayed in Table 13, show that a similar pattern persists, but that the magnitude of the *high* effect increases as the threshold gets higher (with the exception of the sales estimation). Therefore, our findings should not be driven by our selection of a three foot cutoff.

4.4.2 Controlling for transit interruptions and relocations

While transportation networks, like the subway, were interrupted following the storm, they were not disabled for long. 80 percent of the city's subway system was operational one week after Sandy (Kaufman et al. 2012). Within two weeks after Sandy, about 95% of the subway lines were back to normal or partial operations (Zimmerman 2014). We do not expect that short-lived interruptions would drastically influence our estimates, which capture multiple years post-Sandy. However, there were a few places where transportation interruptions persisted (although no more than 8 months), like the Rockaways in Queens

(Flegenheimer 2013). In order to test the sensitivity of our results to these transit-related outages, we replicate our preferred specifications with the Rockaways omitted. These results are displayed in Table 14. The estimates are generally unchanged, suggesting that they are not driven by transit-related interruptions for local residents and potential consumers.

We also want to confirm that we are not overestimating economic losses by including in our count of establishment closures those that stay in business by relocating to another space in the city. Using the InfoUSA data, we can identify establishments that close and relocate (unfortunately we cannot follow establishments with the other datasets), and we re-estimate our preferred model excluding establishments that relocated during 2008-2016. These results are displayed in Table 15 (for the establishment outcome only) and they show very similar results to those produced by the evacuation sample. This is not surprising since the share of establishments that relocate is very small (in 2013, 2.3% businesses relocated).

4.4.3 Controlling for pre- and post-Sandy trends

Thus far, we have constrained the post-Sandy response to be a one-time persistent shock. However, it is possible that the response to Sandy-induced flooding could change over time, and that this temporal response could vary depending on the outcome. Looking at the impacts over time will provide a clearer picture of localized commercial resilience. To do this, we replicate the above models, but instead of including a single dummy for *Sandy* we specify year-specific (or quarter-specific, in the case of sales revenues) dummies that are individually interacted with *High Surge* and *Low Surge*. We plot the coefficients for these year-specific (or quarter-specific, in the case of sales revenues) interactions in Figures 7 - 9. All figures plot coefficients across retail and non-retail strata.

Even though the volatility of the trends varies across the three outcomes, the overall trajectory is similar. First, within industrial classification (i.e. retail and non-retail), we see parallel trends are upheld across *High* and *Low Surge* observations leading up to Hurricane Sandy at the end of 2012. We test this assumption more formally by estimating pre- and post-Sandy trends separately for *High* and *Low* surge areas. The results from these models are displayed in Table 16. They generally support the results from our preferred specification, with a couple of exceptions. Across all models, the pre-sandy trend controls are insignificant, mitigating concerns that any post-sandy effects are due to different trends across *Low* and *High* surge areas leading up to the storm. However, for the establishment analysis, the negative coefficients for the sandy-surge interactions (our impact estimates) are now insignificant; but the post-sandy trend variable is negative and significant, supporting the post-sandy effects we observe above. In addition, for the establishment analysis, there are now also significant losses for non-retail establishments (on *Low Surge* blocks only). As a share of the mean number of non-retail establishments, this is a 38 percent loss. These results are tempered, however, by possible multicollinearity across the trend and SBA-year fixed effects. For this reason we opt to not prioritize these results in the paper.

Second, the increasing gap between *High* and *Low* surge lines and the zero axis (which represents establishments, jobs or sales in areas without any surge) is evident for both sectors. However, the divergence is most severe for the *High* surge lines and, with the exception of establishments, is negative only for the retail sector (this is corroborated by the regression estimates presented above). Recall that while the drop in the number of non-retail establishments on *High* surge blocks is bigger in magnitude, it is actually smaller as a share of the baseline number of non-retail establishments (which tend to be more common). Third, for all three outcomes, the negative impacts manifest themselves within the first year post-Sandy. The one exception is sales revenues, which grow for non-retail entities immediately following Sandy, though they drop over time to below pre-Sandy levels. This could be capturing an increase in consumption of goods and services that are used during recovery, such as construction material and services. Finally, the divergence between *High* and *Low Surge* lines for both retail and non-retail observations persists until the end of the study period, indicating that economic activity has not returned to pre-storm levels .

5. Conclusions and policy implications

This paper explores how extreme events, like hurricanes, affect localized commercial activity in dense urban areas. Specifically, we examine how businesses in New York City fared in the face of severe flooding induced by Hurricane Sandy. We find that economic losses are primarily concentrated among retail businesses that tend to serve a more localized consumer base. While the number of both retail and non-retail establishments declines after Sandy, these losses appear to be at least partially driven by higher rates of business closures for retail establishments and lower rates of new business openings for non-retail establishments. Furthermore, any establishment declines are concentrated among smaller and standalone establishments--some of the most vulnerable businesses in good times. The number of jobs and sales revenues also decline after Sandy. And these losses are persistent over time.

Our findings have three important implications. First, the results from a natural disaster, like Sandy, were immediate (i.e. within the first year) and persistent--as of 2016 businesses still hadn't recovered to pre-storm activity. Second, establishments respond in different ways, both by shutting down and also by cutting back on how intensive their services are. Critically, closure is not inevitable and adjustments in employment, for example, suggest some level of resiliency among businesses. On the other hand, closures do occur, and are disproportionately borne by smaller, independent establishments.

Finally, the most significant impacts are caused by extreme flooding, or inundation of more than 3 feet. Holding all else constant, the city blocks with extreme flooding experienced aggregate net losses of 540 establishments, 3,700 jobs and $2 million in sales revenue, compared to blocks that had no water surge. Lower levels of water inundation did not appear to trigger similar losses. Therefore, any mitigation or recovery efforts should focus on places that experience severe flooding, as it more likely induces prolonged business disruption.

In short, neighborhoods experience shocks in different ways, partly due to the variation in the nature of economic activity that takes place across them and partly due to the variation in the intensity of the shock. Given the growing risk of climate-related threats, and their increasing presence in dense urbanized areas, the results have important policy implications. Both mitigation and recovery efforts need to take localized contexts into consideration and be tailored to the conditions of the neighborhood and the type of businesses at risk. The nature and capacity of resiliency varies across neighborhoods, and therefore the policy responses should as well. And while we observe economic losses in the context of a Hurricane shock, we can expect similar repercussions for establishments in the face of other profound shocks outside the control of the local neighborhood. For example, our results can shed light on how retail businesses might suffer as online e-commerce draw local consumers away from brick-and-mortar locations. There is a good chance that neighborhoods will increasingly face one, if not more, of these shocks.

References

Aladangady, A, et al. 2016. The effect of Hurricane Matthew on consumer spending. Federal Reserve Board, working paper

Alesch, Daniel J. and James N. Holly. 2002. When disasters and small businesses collide. Natural Hazards Observer 26:1–3.

Asgary, Ali, Muhammad Imtiaz Anjum, and Nooreddin Azimi.2012. Disaster recovery and business continuity after the 2010 flood in Pakistan: Case of small businesses. International journal of disaster risk reduction 2: 46-56.

Baade, Robert A., Robert Baumann, and Victor Matheson, 2007, Estimating the economic impact of natural and social disasters, with an application to Hurricane Katrina. Urban Studies 44.11: 2061-2076.

Bakkensen, Laura, and Lint Barragey. Do disasters affect growth? 2016, A macro model-based perspective on the empirical debate. No. 2016-9. Working Paper, Brown University, Department of Economics

Barr, Jason, Jeffrey P. Cohen, and Eon Kim. Storm Surges, 2017. Informational Shocks, and the Price of Urban Real Estate: An Application to the Case of Hurricane Sandy. No. 2017-002. Department of Economics, Rutgers University, Newark

Basker, Emek, and Javier Miranda. 2017, Taken by storm: business financing and survival in the aftermath of Hurricane Katrina. Journal of Economic Geography 18, no. 6: 1285-1313.

Bingham, Richard D., and Zhongcai Zhang. 1997, Poverty and economic morphology of Ohio central-city neighborhoods. Urban Affairs Review 32.6: 766-796.

Birch, Eugenie L. 2013. How to bring economies back after a natural disaster. The Atlantic Cities. Retrieved September 27, 2013, from http://www.theatlanticcities.com/jobs-and-economy/2013/09/how-bring-economies-back-after-natural-disaster/7008/.

Boarnet, Marlon G. 1996, Business losses, transportation damage and the Northridge Earthquake.

Boustan, L. P., Kahn, M. E., Rhode, P. W., & Yanguas, M. L. 2017. The effect of natural disasters on economic activity in us counties: A century of data (No. w23410). National Bureau of Economic Research.

Brandão, A., Correia-da-Silva, J. and Pinho, J., 2014. Spatial competition between shopping centers. Journal of Mathematical Economics, 50, pp.234-250.

Chang, Stephanie E., and Anthony Falit-Baiamonte. 2002, Disaster vulnerability of businesses in the 2001 Nisqually earthquake. Global Environmental Change Part B: Environmental Hazards 4.2: 59-71.

Clotfelter, Charles, et al. 2008 Would higher salaries keep teachers in high-poverty schools? Evidence from a policy intervention in North Carolina. Journal of Public Economics 92.5-6: 1352-1370.

Corey, Christy M. and Elizabeth A. Dietch. 2011. Factors affecting business recovery immediately after Hurricane Katrina. Journal of Contingencies and Crisis Management 19(3):169–181.

Cutter, Susan L., Jerry T. Mitchell, and Michael S. Scott. 2000. Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina. Annals of the Association of American Geographers, 90(4): 713-737.

Cutter, S.L., B.J. Boruff and W.L. Shirley. 2003. Social vulnerability to environmental hazards. Social Science Quarterly, 84(3): 242–61.

Cutter, Susan L., and Christina Finch. 2008. "Temporal and Spatial Changes in Social Vulnerability to Natural Hazards." Proceedings of the National Academy of Sciences, 105(7): 2301-2306.

Dahlhamer, James M. and Kathleen J. Tierney. 1998. Rebounding from disruptive events:

Business recovery following the Northridge Earthquake. Sociological Spectrum 18:121–141.

Davis P, 2006, Spatial competition in retail markets: Movie theaters. The RAND Journal of Economics 37(4): 964–982.

Davlasheridze, M. and Geylani, P.C., 2017. Small Business vulnerability to floods and the effects of disaster loans. Small Business Economics, 49(4), pp.865-888.

De Mel, Suresh, David McKenzie, and Christopher Woodruff. 2011, Enterprise recovery following natural disasters. The Economic Journal 122, no. 559 (2011): 64-91.

Dinlersoz EM, 2004, Firm organization and the structure of retail markets. Journal of Economics and Management Strategy 13(2): 207–240.

Dixon, Llloyd, Noreen Clancy, Bruce Bender, Aaron Kofner, David Manheim, and Laura Zakaras. 2013. Flood Insurance in New York City Following Hurricane Sandy. Santa Monica, CA: RAND Corporation.

Duranton, Gilles and Puga, Diego. 2004. Micro-Foundations of Urban Agglomeration Economies. In J.V. Henderson and J.F. Thisse, (Eds.) The Handbook of Regional and Urban Economics, Elsevier.

Eha, Brian P. 2013. Six months after Hurricane Sandy, many businesses are still struggling to recover. Entrepreneur. Retrieved September 27, 2013, from http://www.entrepreneur.com/ article/226520.

Farrell, Diana and Marvin Ward Jr. 2018, Local Consumer Commerce in the Wake of Hurricane Harvey. JPMorgan Chase Institute.

Finch, Christina, Christopher T. Emrich, and Susan L. Cutter. 2010. Disaster disparities and differential recovery in New Orleans. Population and Environment, 31(4): 179-202.

Fisher, Bonnie. 1991. A neighborhood business area is hurting: Crime, fear of crime, and disorders take their toll. NPPA Journal, 37(3): 363-373.

Flegenheimer, Matthew. 2013. Just in Time for Summer, the A Train Is Fully Restored, The New York Times.

Furman Center. 2013. Sandy's Effects on Housing in New York City. Policy Brief, Furman Center for Real Estate and Urban Policy.

Glaeser, Edward L., Jed Kolko, and Albert Saiz. 2001. Consumer city. Journal of Economic Geography 1(1):27–50.

Haynes, George W., Sharon M. Danes, and Kathryn Stafford. 2011. Influence of federal disaster assistance on family business survival and success. Journal of Contingencies and Crisis Management 19(2):86–98.

Hoehner, Christine M., and Mario Schootman. 2010, Concordance of commercial data sources for neighborhood-effects studies. Journal of Urban Health 87.4: 713-725.

Hotelling, Harold, 1929. "Stability in Competition." The Economic Journal, 39(153): 41-57.

Huffington Post. 2013. NYC Hurricane Evacuation Zones Map Updated Months After Hurricane Sandy. Retrieved June 18, 2013 from https://www.huffingtonpost.com/2013/06/18/nyc-hurricane-evacuation-zones-map_n_3460565.html.

Jacobs, Jane. 1961. Death and Life of Great American Cities. Vintage.

Jardim, Eduardo, 2015. All in the mix: Spillovers and the agglomeration of neighborhood retail. Duke University Working Paper.

Kaufman, Sarah, Carson Qing, Nolan Levenson and Melinda Hanson. 2012. Transportation During and After Hurricane Sandy. New York: Rudin Center for Transportation.

Kellenberg, D. and Mobarak, A.M., 2011. The economics of natural disasters. Annual Review of Resource Economics Vol. 3:297-312

Kliesen, K.L. and Mill, J.S., 1994. The economics of natural disasters. The regional economist, 332.

Kolko, Jed and David Neumark. 2010. Does local business ownership insulate cities from economic shocks? Journal of Urban Economics 67(1):103–115.

Kroll, Cynthia A., John D. Landis, Qing Shen, and Sean Stryker. 1990. The economic impacts of the Loma Prieta Earthquake: A focus on small business. Berkeley Planning Journal 5(1):39–58.

Lavin, Michael R. 2000, An Interview with Daniel K. German, Senior Vice President of Database Creation and Maintenance, info USA, Inc. Journal of Business & Finance Librarianship 5.3: 27-42.

Leiter, A. M., Oberhofer, H., & Raschky, P. A. 2009. Creative disasters? Flooding effects on capital, labour and productivity within European firms. Environmental and Resource Economics, 43(3), 333-350.

LeSage, James P., R. Kelley Pace, Nina Lam, Richard Campanella, and Xingjian Liu. 2011. New Orleans business recovery in the aftermath of Hurricane Katrina. Journal of the Royal Statistical Society: Series A (Statistics in Society), 174(4): 1007-1027.

Makridis, Christos A., and Michael Ohlrogge. 2017, Validating RefUSA micro-data with the Longitudinal Employer-Household Dynamics Data. Economics Letters 152: 83-87

Marshall, Alfred. 1890. Principles of Economics. London: MacMillan.

Meltzer, Rachel and Capperis, Sean, 2017. Neighbourhood differences in retail turnover: Evidence from New York City. Urban Studies, 54(13): 3022{3057.

Nelson, Richard Lawrence, 1958. The Selection of Retail Locations. FW Dodge Corporation.

Ono, Arito 2015. How do natural disasters affect the economy? World Economics Forum. Retrieved February 11, 2015, from https://www.weforum.org/agenda/2015/02/how-do-natural-disasters-affect-the-economy/.

Ortega, Francesc, and Suleyman Taspinar. 2017, Rising Sea Levels and Sinking Property Values: The Effects of Hurricane Sandy on New York's Housing Market.

Runyan, Rodney C. 2006. Small Business in the Face of Crisis: Identifying Barriers to Recovery from a Natural Disaster. Journal of Contingencies and Crisis Management, 14(1): 12-26.

Skidmore, M. and Toya, H. 2002. Do natural disasters promote long-run growth? Economic Inquiry, 40(4):664–687

Smith, Gavin P., and Dennis Wenger. 2007. Sustainable disaster recovery: operationalizing an existing agenda. Handbook of Disaster Research. New York: Springer.

Stanback, T.M., 1981. Services, the new economy (Vol. 20). Allanheld, Osmun.

Sydnor, Sandra, Linda Niehm, Yoon Lee, Maria Marshall, and Holly Schrank. 2017, Analysis of post-disaster damage and disruptive impacts on the operating status of small businesses after Hurricane Katrina. Natural Hazards 85, no. 3: 1637-1663.

Tanaka, A 2015, The impacts of natural disasters on plants' growth: Evidence from the Great Hanshin-Awaji (Kobe) earthquake, Regional Science and Urban Economics 50, 31-41.

Tierney, Kathleen J. 1997a. Business impacts of the Northridge Earthquake. Journal of Contingencies and Crisis Management 5(2):87–97.

Tierney, Kathleen J. 1997b. Impacts of recent disasters on businesses: The 1993 Midwest Floods and the 1994 Northridge Earthquake. In Barclay G. Jones (ed.) Economic Consequences of Earthquakes: Preparing for the Unexpected. Buffalo, NY: Multidisciplinary Center for Earthquake Engineering Research.

Van Zandt, Shannon, Walter Gillis Peacock, Dustin W. Henry, Himanshu Grover, Wesley E. Highfield, and Samuel D. Brody. 2012. Mapping Social Vulnerability to Enhance Housing and Neighborhood Resilience. Housing Policy Debate, 22(1): 29-55.

Waldfogel J 2008, The median voter and the median consumer: Local private goods and population composition. Journal of Urban Economics 63: 567–582.

Wasileski, Gabriela, Havidán Rodríguez, and Walter Diaz. 2011. Business closure and relocation: A comparative analysis of the Loma Prieta Earthquake and Hurricane Andrew. Disasters 35(1):102–129.

Webb, Gary R., Kathleen J. Tierney, James M. Dahlhamer. 2000. Businesses and disasters: Empirical patterns and unanswered questions. Natural Hazards Review 1(2):83–90.

Xiao, Y., & Nilawar, U. 2013. Winners and losers: analysing post-disaster spatial economic demand shift. Disasters, 37(4), 646-668.

Xiao, Yu, and Shannon Van Zandt. 2012. Building community resiliency: Spatial links between household and business post-disaster return. Urban Studies, 49(11): 2523-2542.

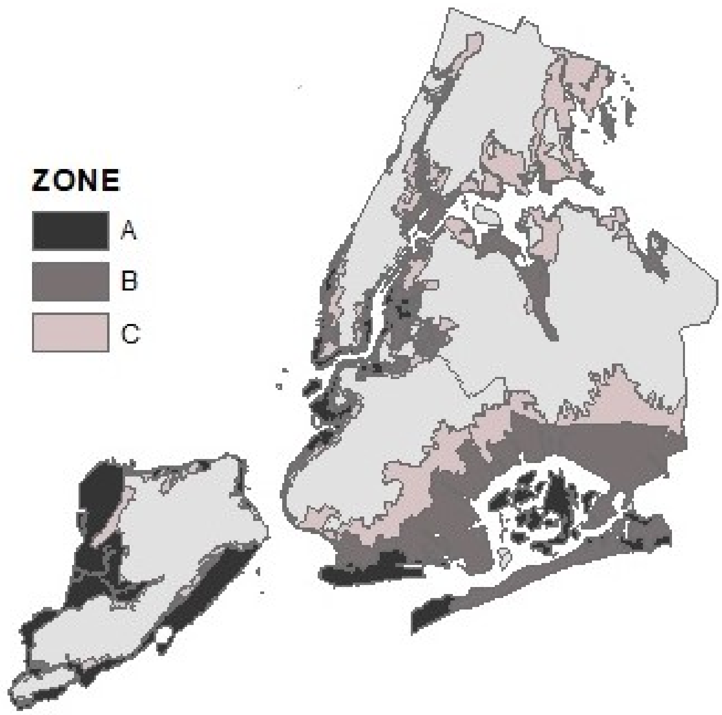
Yoshida, Kaori, and Robert E. Deyle. 2005, Determinants of small business hazard mitigation. Natural Hazards Review 6.1: 1-12.

Zimmerman, Rae. 2014, Planning restoration of vital infrastructure services following Hurricane Sandy: Lessons learned for energy and transportation. Journal of Extreme Events 1.01: 1450004.

Zissimopoulos, Julie, and Lynn A. Karoly. 2010, Employment and self-employment in the wake of Hurricane Katrina. Demography 47, no. 2 : 345-367.

Figures

Figure 1: NYC Evacuation Map



Notes: The dark area is Zone A, the evacuation zone that was instructed to evacuate prior to Sandy. The lighter shaded areas are also evacuation zones, but were not told to evacuate for Superstorm Sandy. We use only Zone A areas to define our evacuation zones in the analysis.

Figure 2: Surge Level by borough-block

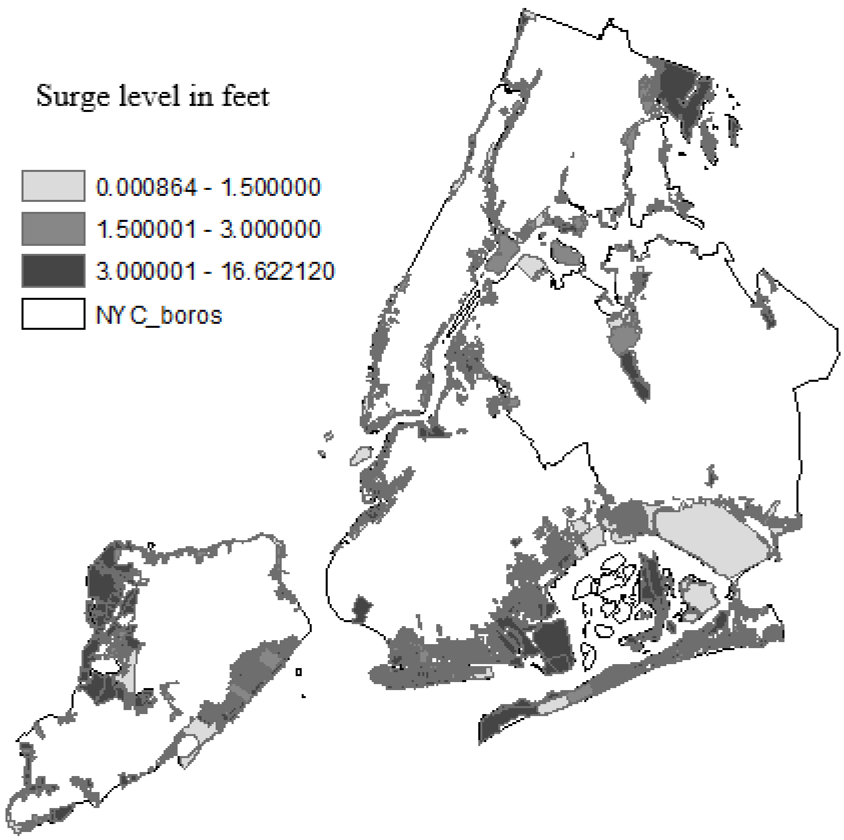
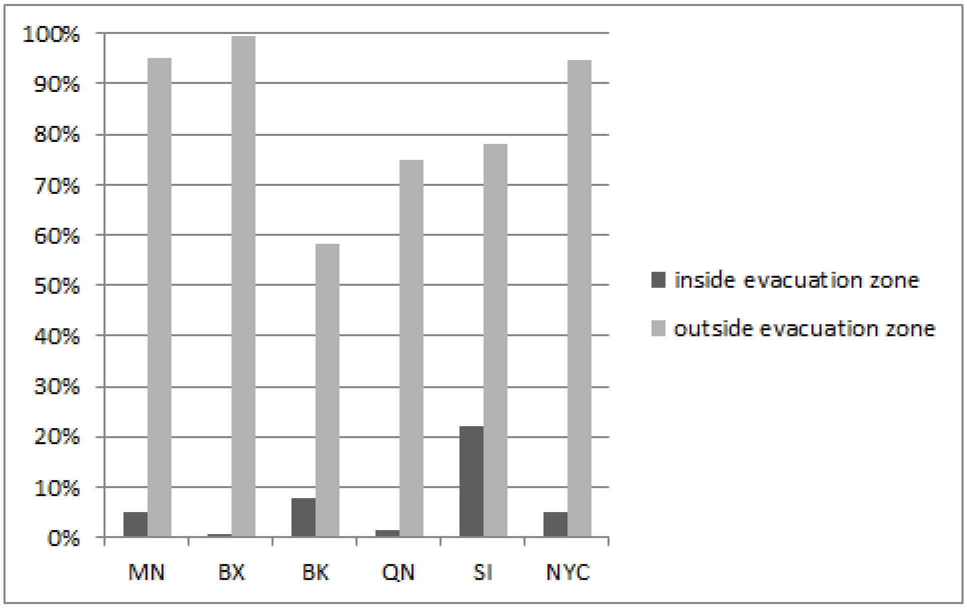
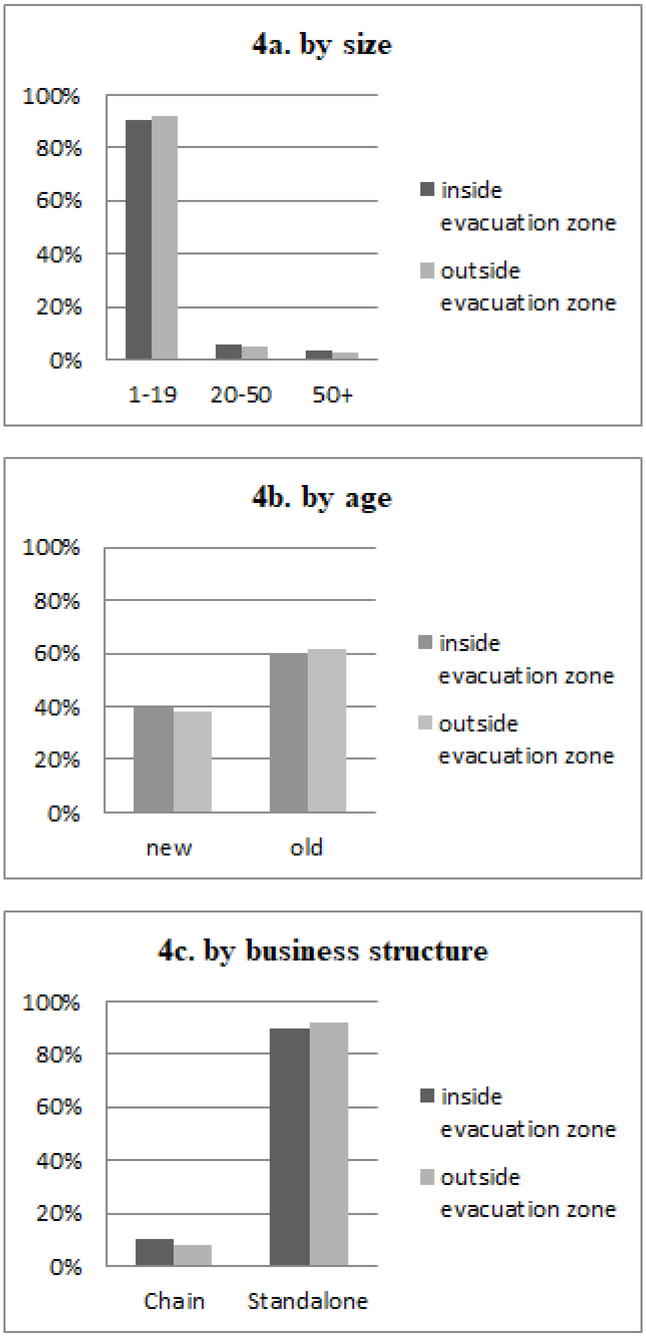


Figure 3: Distribution of businesses across zones, 2012



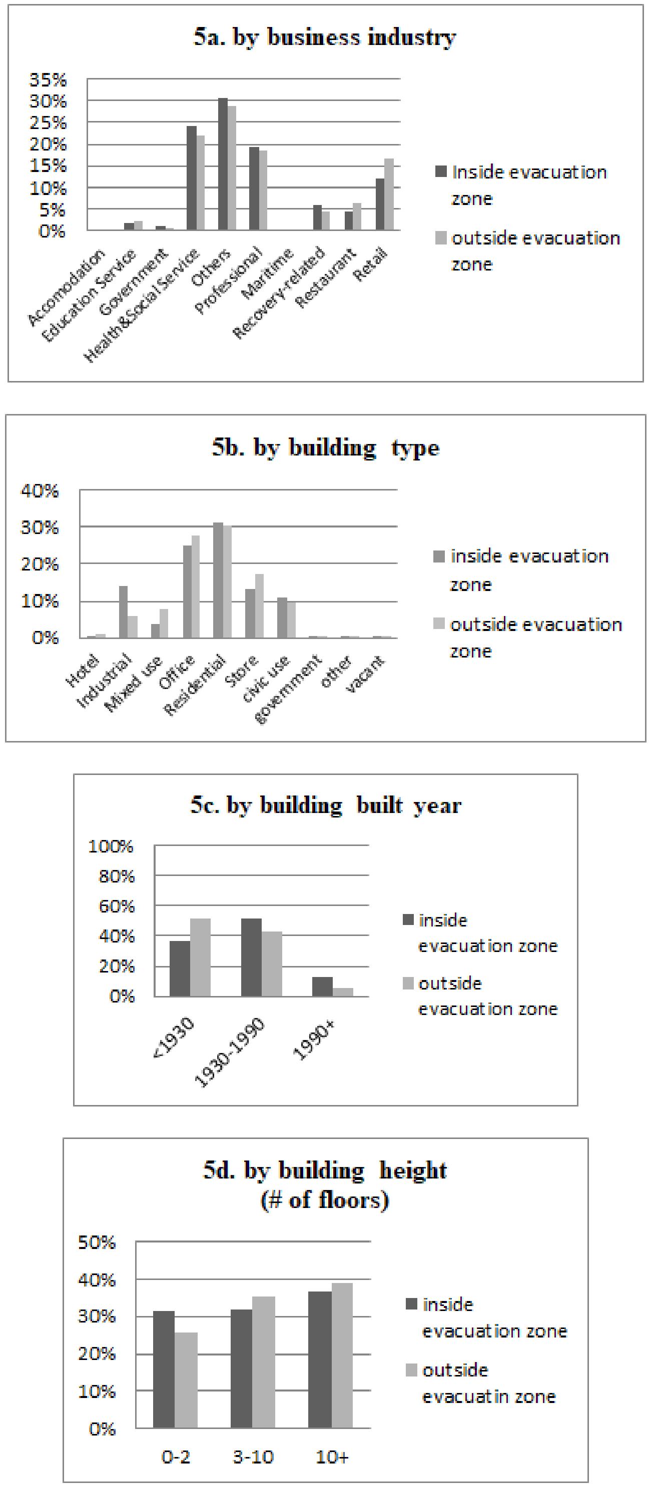
Notes: **Y-axis reports shares (%)**

Figure 4: Distribution of businesses, Citywide, inside/outside evacuation zone, 2012



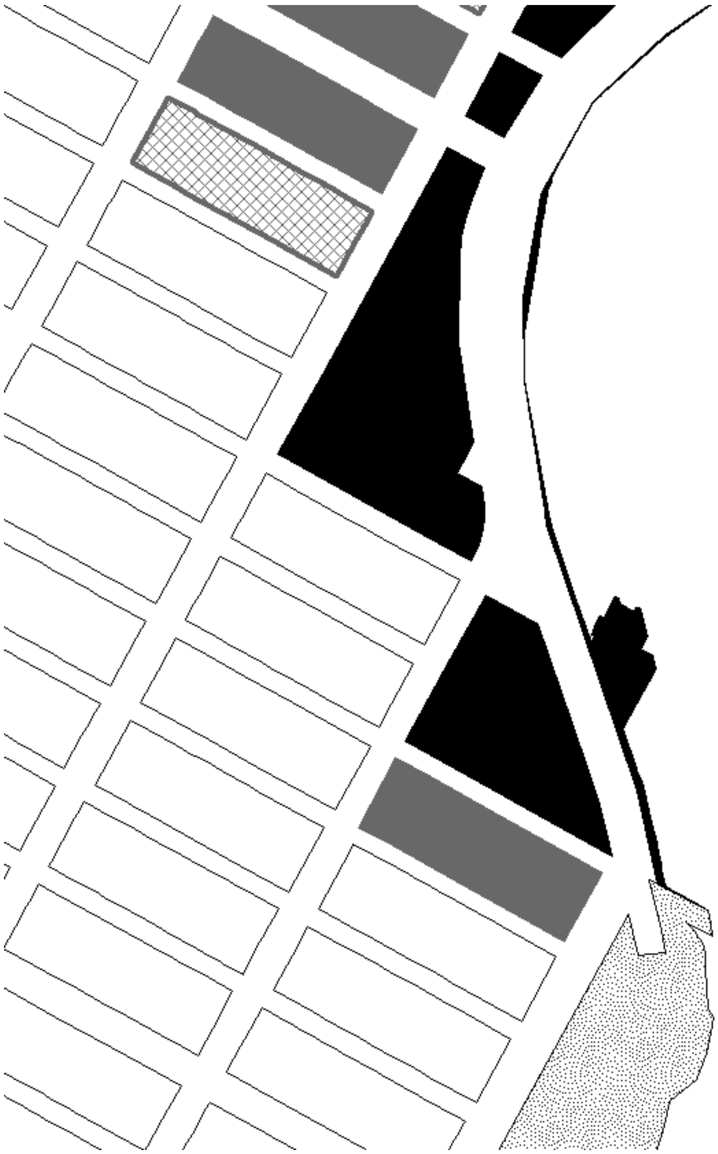
Notes: **old establishments open before 2009, and new establishments open after 2008; Y-axis reports shares (%)**

Figure 5: Distribution of businesses, Citywide, inside/outside evacuation zone, 2012



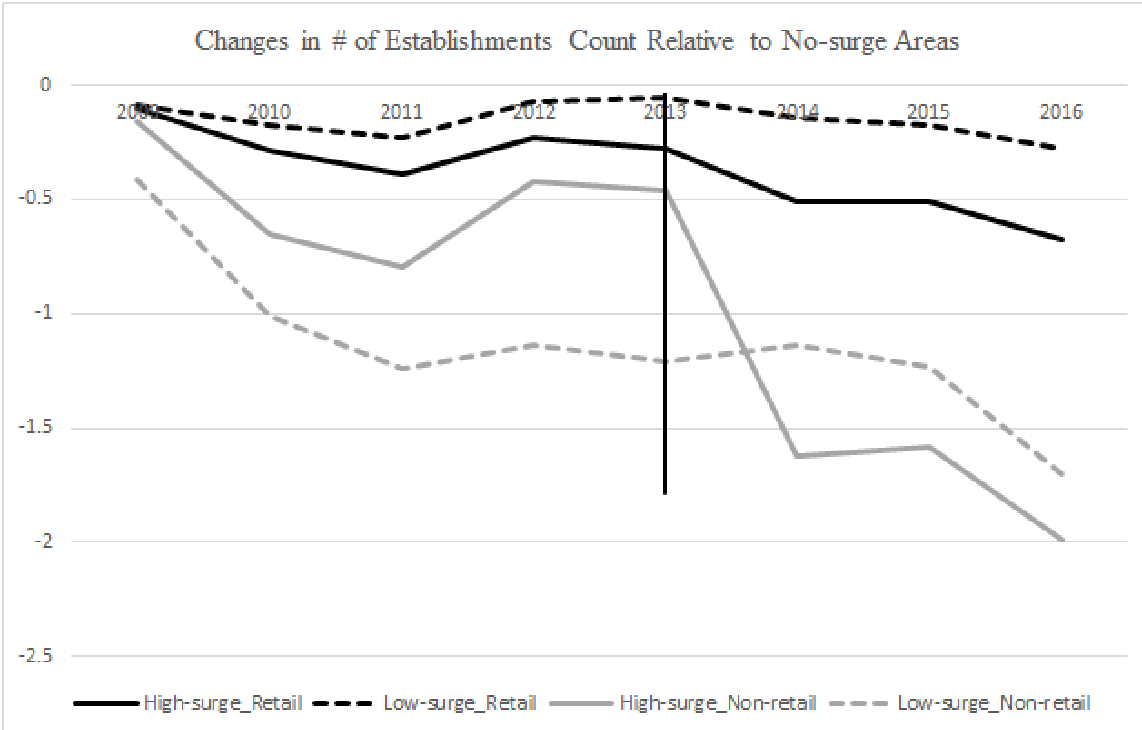
Notes: **Y-axis reports shares (%)**

Figure 6: Evacuation and Surge Zones



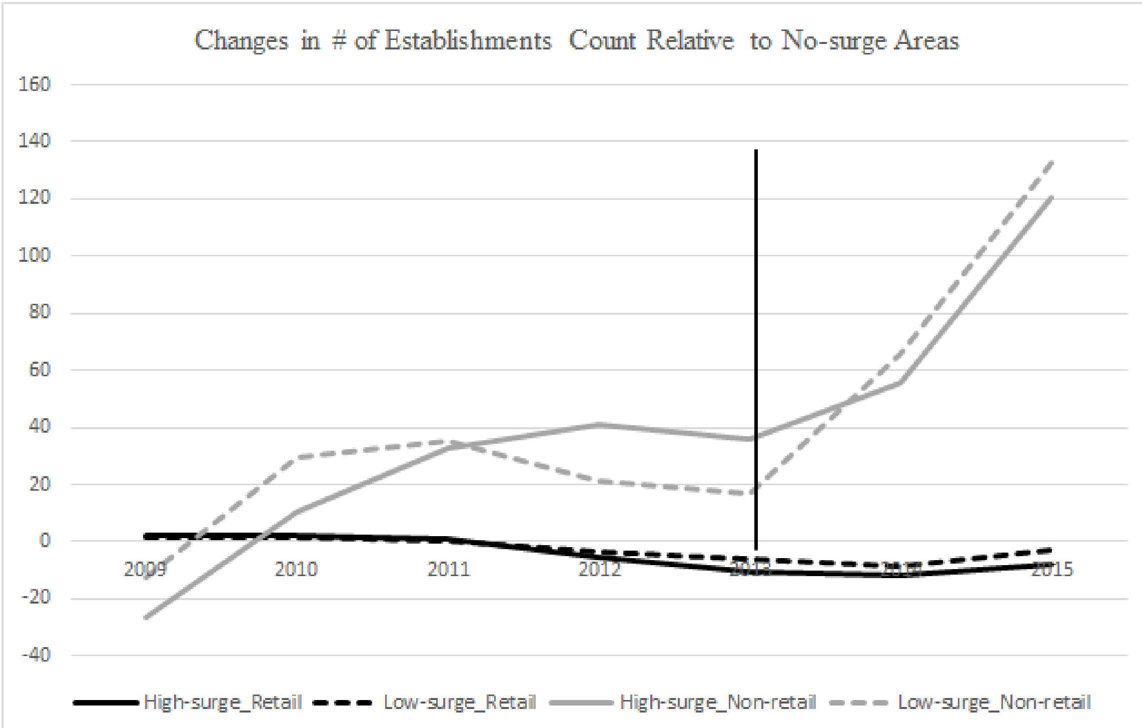
Notes: **Black blocks are in both evacuation and surge zones; grey blocks are in surge only zones; dotted blocks are in evacuation only zones; and hollow blocks are not in any zones. The crosshatched area is high-surge.**

Figure 7: Retail vs. Non-Retail Establishment counts, Before and After Sandy



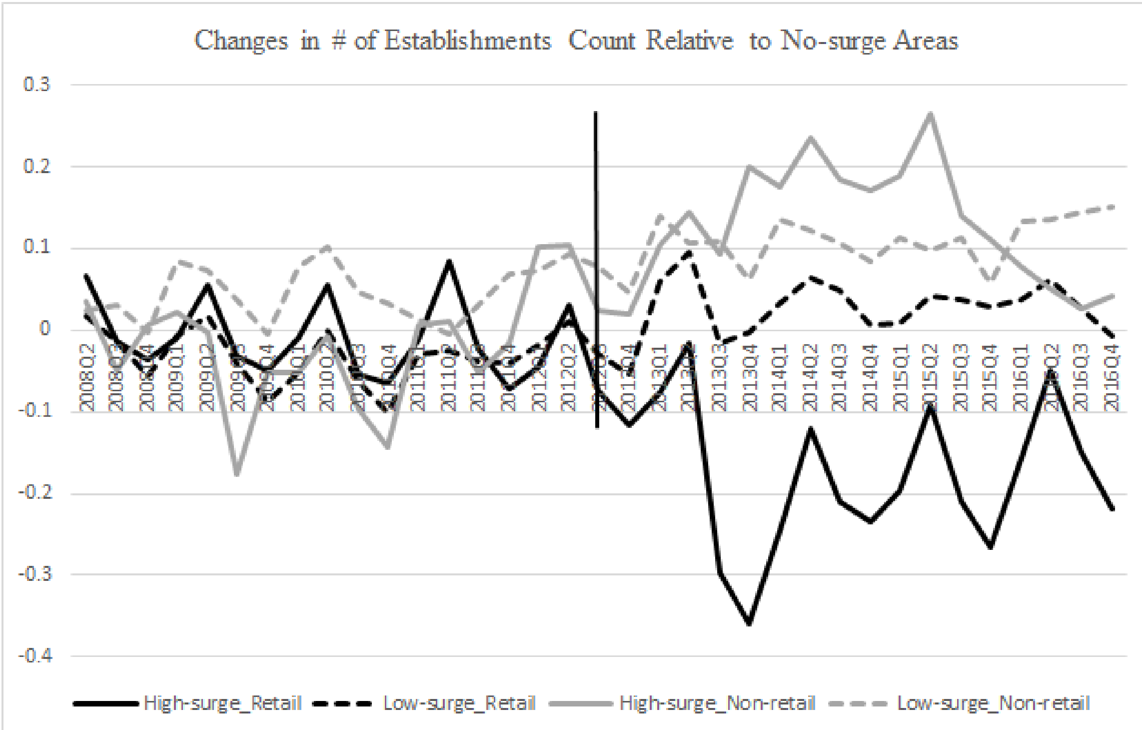
Notes: Plotted points are adjusted values, controlling for borough-block fixed effects, and SBA-year indicators.

Figure 8: Retail vs. Non-Retail Jobs, Before and After Sandy



Notes: Plotted points are adjusted values, controlling for census block fixed effects, and SBA-year indicators.

Figure 9: Retail vs. Non-Retail log(Total Sales), Before and After Sandy



Notes: Plotted points are adjusted values, controlling for Zip-zone fixed effects, borough-YearQuater indicators.

Tables

Table 1: Retail and Non-retail Classification

Category	NAICS	Description
		InfoUSA
Retail	311811	Retail Bakery
	44-45	Retail Trade
	72	Accommodation and Food Services
	812111	Barber Shops
	812112	Beauty Salons
	812113	Nail Salons
	812310	Coin-Operated Laundries and Drycleaners
	812320	Drycleaning and Laundry Services (except Coin-Operated)
Non-retail	Other	
		LODES[34]
Retail	44-45	Retail Trade
	72	Accommodation and Food Services
Non-retail	Other	
		Sales from DOF
Retail	44-45	Retail Trade
	61	Educational Services
	62	Health Care and Social Assistance
	71	Arts, Entertainment, and Recreation
	72	Accommodation and Food Services
Non-retail	Other	

[34] LODES has 2-digit NAICS rather than 6-digit NAICS

Table 2: Regression Results, Establishments, Full-sample

# of establishment per borough-block (bb)	(1) Total	(2) Total	(3) Retail	(4) Retail	(5) Non-retail	(6) Non-retail
sandy	2.354***	2.298***	-0.0224	-0.0480	2.377***	2.346***
	(0.627)	(0.627)	(0.163)	(0.163)	(0.615)	(0.614)
high_sandy		0.470		0.00952		0.461
		(0.363)		(0.0768)		(0.343)
low_sandy		0.371**		0.189***		0.182
		(0.165)		(0.0440)		(0.149)
Constant	17.36***	17.36***	4.163***	4.163***	13.20***	13.20***
	(0.0861)	(0.0861)	(0.0126)	(0.0126)	(0.0814)	(0.0814)
borough-block f.e.	Y	Y	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y	Y	Y
Observations	187,758	187,758	187,758	187,758	187,758	187,758
R-squared	0.098	0.098	0.098	0.099	0.085	0.085
Number of bb	20,862	20,862	20,862	20,862	20,862	20,862

Robust standard errors in parentheses

***** p<0.01, ** p<0.05, * p<0.1**

Table 3: Regression Results, Establishments, Evacuation Zone Sample

# of establishment per borough-block (bb)	(1) Total	(2) Retail	(3) Non-retail
sandy	10.17	6.464	3.710
	(7.602)	(5.181)	(2.443)
high_sandy	-1.299**	-0.292**	-1.007**
	(0.553)	(0.122)	(0.510)
low_sandy	-0.610	-0.0496	-0.561
	(0.474)	(0.0988)	(0.427)
Constant	14.00***	2.595***	11.40***
	(0.347)	(0.0321)	(0.341)
borough-block f.e.	Y	Y	Y
SBA*Year dummies	Y	Y	Y
Observations	12,312	12,312	12,312
R-squared	0.120	0.074	0.121
Number of bb	1,368	1,368	1,368

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Retail Sub-sector Regression Results, Establishments, Evacuation Zone Sample

# of establishment per borough-block (bb)	(1) Neighborhood-based	(2) Accommodation	(3) Restaurant	(4) Other
sandy	1.099	0.0194	1.951	6.510*
	(1.434)	(0.0310)	(1.435)	(3.939)
high_sandy	-0.128*	-0.00995	-0.114	-0.166
	(0.0695)	(0.0339)	(0.0971)	(0.118)
low_sandy	-0.0991	-0.0194	0.0494	-0.0103
	(0.0674)	(0.0310)	(0.0949)	(0.113)
Constant	1.091***	0.0367***	1.056***	2.023***
	(0.0230)	(0.00551)	(0.0226)	(0.0420)
SBA*Year dummies	Y	Y	Y	Y
borough-block f.e.	Y	Y	Y	Y
Observations	7,596	7,596	7,596	7,596
R-squared	0.048	0.063	0.038	0.082
Number of bb	844	844	844	844

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Hazard Model Regression Result, Establishments, Evacuation Zone Sample

Hazard Ratio	(1) Retail	(2) Retail	(3) Non-retail	(4) Non-retail
sandy	0.0185***	0.0225***	0.0270***	0.0271***
high	0.957	1.052	1.053	1.060
low	1.022	1.094	1.024	1.036
high_sandy	1.432**	1.153	1.093	1.076
low_sandy	1.288*	1.072	1.018	1.008
chain_dummy	0.747***	0.768***	0.756***	0.768***
employee	0.999**	0.999*	1.000*	1.000
Cluster	1.000*	1.000	1.000	1.000
Stratified by	ZipCode	Census Tract	ZipCode	Census Tract
Open Year Dummies	Y	Y	Y	Y
Observations	6,833	6,833	31,126	31,126

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Regression Results, Establishments, Evacuation Zone Sample, Stratify by Size

# of establishment per borough-block (bb)	(1) Retail 1-19	(2) Retail 20-50	(3) Retail 50+	(4) Non-retail 1-19	(5) Non-retail 20-50	(6) Non-retail 50+
sandy	3.050	3.530	2.512	4.206*	-0.396	0.0267
	(2.155)	(2.506)	(1.790)	(2.410)	(0.372)	(0.0379)
high_sandy	-0.387**	-0.0175	-0.00512	-0.865*	-0.121*	-0.0507
	(0.182)	(0.0462)	(0.0256)	(0.483)	(0.0625)	(0.0421)
low_sandy	-0.0504	-0.0305	-0.0124	-0.548	-0.0879*	-0.00269
	(0.169)	(0.0435)	(0.0240)	(0.395)	(0.0525)	(0.0344)
Constant	3.847***	0.264***	0.0924***	10.47***	0.692***	0.404***
	(0.0500)	(0.0122)	(0.00765)	(0.300)	(0.0155)	(0.0123)
borough-block f.e.	Y	Y	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y	Y	Y
Observations	7,596	7,596	7,596	12,087	12,087	12,087
R-squared	0.085	0.062	0.096	0.115	0.046	0.034
Number of bb	844	844	844	1343	1343	1343

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: InfoUSA Regression Results, Evacuation Zone Sample, Stratify by Chain/Standalone

# of establishment per borough-block (bb)	(1) Retail Chain	(2) Retail Standalone	(3) Non-retail Chain	(4) Non-retail Standalone
sandy	8.486	1.093	4.054	1.280***
	(6.086)	(0.732)	(2.848)	(0.432)
high_sandy	0.0287	-0.446***	-0.0610	-1.008**
	(0.0585)	(0.165)	(0.0864)	(0.481)
low_sandy	0.0138	-0.0933	-0.0471	-0.552
	(0.0548)	(0.152)	(0.0755)	(0.407)
Constant	0.371***	3.835***	0.702***	10.91***
	(0.0173)	(0.0475)	(0.0235)	(0.345)
borough-block f.e.	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y
Observations	7,596	7,596	12,087	12,087
R-squared	0.130	0.087	0.168	0.119
Number of bb	844	844	1343	1343

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Regression Results, Jobs, Full-sample

# of jobs per census block	(1) Total	(2) Total	(3) Retail	(4) Retail	(5) Non-retail	(6) Non-retail
sandy	47.52***	47.01***	4.051**	4.065**	43.46***	42.94***
	(12.55)	(12.55)	(1.936)	(1.941)	(12.23)	(12.22)
high_sandy		5.489		-3.108*		8.598
		(11.61)		(1.605)		(11.44)
low_sandy		5.287		0.101		5.186
		(8.287)		(1.416)		(8.048)
Constant	133.7**	133.7**	21.98***	21.89***	111.7**	111.8**
	(56.40)	(56.37)	(6.327)	(6.322)	(55.31)	(55.29)
census block f.e.	Y	Y	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y	Y	Y
Observations	160,776	160,776	160,776	160,776	160,776	160,776
R-squared	0.006	0.006	0.026	0.026	0.004	0.004
Number of blocks	24,929	24,929	24,929	24,929	24,929	24,929

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regression Results, Jobs, Evacuation Zone Sample

# of jobs per census block	(1) Total	(2) Retail	(3) Non-retail
sandy	280.5	314.3	-33.75
	(246.7)	(232.6)	(44.38)
high_sandy	47.86	-9.790***	57.65
	(42.54)	(3.730)	(42.47)
low_sandy	50.32	-5.931	56.25
	(42.66)	(3.809)	(42.27)
Constant	2,776	451.7	2,325
	(9,370)	(753.3)	(9,149)
census block f.e.	Y	Y	Y
SBA*Year dummies	Y	Y	Y
Observations	9,995	9,995	9,995
R-squared	0.039	0.085	0.035
Number of blocks	1,679	1,679	1,679

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10: Regression Results, Sales Revenues, Full Sample

log(total sales)	(1) Total	(2) Total	(3) Retail	(4) Retail	(5) Non-retail	(6) Non-retail
sandy	0.238***	0.245***	0.295***	0.304***	0.118**	0.112**
	(0.0240)	(0.0233)	(0.0271)	(0.0253)	(0.0536)	(0.0528)
high		-1.288***		-0.966**		-1.586***
		(0.425)		(0.447)		(0.283)
low		-1.748***		-1.696***		-1.248***
		(0.142)		(0.157)		(0.201)
high_sandy		-0.160**		-0.241***		0.128
		(0.0698)		(0.0799)		(0.0934)
low_sandy		0.0334		0.0517		0.118**
		(0.0362)		(0.0568)		(0.0580)
Constant	17.96***	18.08***	17.62***	17.71***	16.86***	16.95***
	(0.142)	(0.129)	(0.132)	(0.124)	(0.211)	(0.200)
Borough*YrQuarter dummies	Y	Y	Y	Y	Y	Y
Observations	10,644	10,644	8,610	8,610	8,574	8,574
R-squared	0.309	0.484	0.308	0.455	0.336	0.418

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 11: Regression Results, Sales Revenues, Within Evacuation Zones

log(total sales)	(1) Total	(2) Retail	(3) Non-retail
sandy	0.246***	0.291***	0.105***
	(0.0190)	(0.0190)	(0.0391)
high_sandy	-0.0966*	-0.161**	0.140*
	(0.0581)	(0.0658)	(0.0774)
low_sandy	0.0328	0.0524	0.0629
	(0.0316)	(0.0475)	(0.0473)
Constant	16.35***	15.88***	15.38***
	(0.0203)	(0.0263)	(0.0343)
ZipCode*Zone f.e.	Y	Y	Y
Borough*YrQuater dummies	Y	Y	Y
Observations	10,644	8,610	8,574
R-squared	0.991	0.989	0.983

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 12: Regression Results, Continuous Surge Height, Evacuation Zone Sample

	(1) Estab. - Retail	(2) Estab. - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retail	(6) Sales - Non-retail
sandy	6.421	3.065	308.8	17.39	0.292***	0.167***
	(5.198)	(2.461)	(232.5)	(15.78)	(0.0189)	(0.0341)
Sandy_surge height	-0.062***	-0.0456	-1.02***	4.323	-0.0156	0.0227*
	(0.0226)	(0.0803)	(0.359)	(3.595)	(0.0177)	(0.0132)
Constant	2.595***	11.40***	20.30***	149.0**	15.93***	15.38***
	(0.0321)	(0.341)	(3.891)	(60.69)	(0.0273)	(0.0295)
SBA*Year dummies	Y	Y	Y	Y	N	N
Block f.e.	Y	Y	Y	Y	N	N
Borough*YrQuarter Dummies	N	N	N	N	Y	Y
ZipCode*Zone f.e.	N	N	N	N	Y	Y
Observations	12,312	12,312	9,995	9,995	8,581	8,545
R-squared	0.074	0.120	0.084	0.035	0.989	0.983

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 13: InfoUSA Key Coefficients using Different Threshold, Evacuation Zone Sample

Threshold	Coefficients	(1) Estab. - Retail	(2) Estab. - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales- Retail	(6) Sales - Non-retail
3 feet	high_sandy	-0.292**	-1.007**	-9.79***	57.65	-0.16**	0.140*
		(0.122)	(0.51)	(3.73)	(42.47)	(0.0658)	(0.0774)
	low_sandy	-0.0496	-0.561	-5.931	56.25	0.0524	0.0629
		(0.0988)	(0.427)	(3.809)	(42.27)	(0.0475)	(0.0473)
2 feet	high_sandy	-0.196*	-0.585	-8.787**	56.58	-0.0442	0.0761*
		(0.113)	(0.535)	(3.766)	(43.03)	(0.0543)	(0.0426)
	low_sandy	-0.0684	-0.740*	-5.952	57.15	0.0147	0.123
		(0.1000)	(0.407)	(3.955)	(42.75)	(0.126)	(0.111)
4 feet	high_sandy	-0.368**	-0.638	-11.3***	73.27*	-0.0665	0.0686
		(0.149)	(0.597)	(3.805)	(40.07)	(0.0677)	(0.133)
	low_sandy	-0.0577	-0.693*	-5.931	50.65	-0.0309	0.0865**
		(0.0966)	(0.419)	(3.718)	(42.61)	(0.0552)	(0.0437)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Sandy dummy, constant, block fixed effects, and SBA*Year dummies are controlled for InfoUSA and LODES; Sandy dummy, constant, Zip-zone fixed effects, and Boro*YearQuater dummies are controlled for log(total sales).

Table 14: Regression Results, Excluding Transit-Interrupted Areas, Evacuation Zone Sample

	(1) Estab. - Retail	(2) Estab. - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retail	(6) Sales - Non-retail
sandy	6.458	3.637	314.5	-33.20	0.398***	0.167***
	(5.182)	(2.439)	(232.6)	(44.08)	(0.0216)	(0.0340)
high_sandy	-0.294**	-0.964*	-10.02***	57.92	-0.155**	0.174**
	(0.128)	(0.535)	(3.788)	(42.88)	(0.0716)	(0.0757)
low_sandy	-0.0401	-0.473	-5.895	56.78	0.0565	0.0626
	(0.100)	(0.430)	(3.856)	(42.76)	(0.0484)	(0.0478)
Constant	2.852***	12.56***	20.78***	158.0***	15.88***	15.38***
	(0.0356)	(0.382)	(3.751)	(57.27)	(0.0266)	(0.0344)
SBA*Year dummies	Y	Y	Y	Y	N	N
block f.e.	Y	Y	Y	Y	N	N
Boro*YrQuater Dummies	N	N	N	N	Y	Y
ZipCode*Zone f.e.	N	N	N	N	Y	Y
Observations	10,998	10,998	9,296	9,296	8,458	8,422
R-squared	0.074	0.121	0.086	0.035	0.989	0.983

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15: InfoUSA Regression Results, Excluding Relocated Businesses, Evacuation Zone Sample

	(1)	(2)	(3)
VARIABLES	Total	Retail	Non-retail
sandy	10.47	6.774	3.699
	(7.473)	(5.051)	(2.447)
high_sandy	-1.221**	-0.251**	-0.970**
	(0.529)	(0.118)	(0.492)
low_sandy	-0.599	-0.0353	-0.564
	(0.458)	(0.0945)	(0.413)
Constant	13.54***	2.501***	11.04***
	(0.348)	(0.0308)	(0.344)
borough-block f.e.	Y	Y	Y
SBA*Year dummies	Y	Y	Y
Observations	12,231	12,231	12,231
R-squared	0.120	0.076	0.121
Number of bb	1,359	1,359	1,359

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 16: Regression Results, Controlling for Pre/Post Sandy Trend, Evacuation Zone Sample

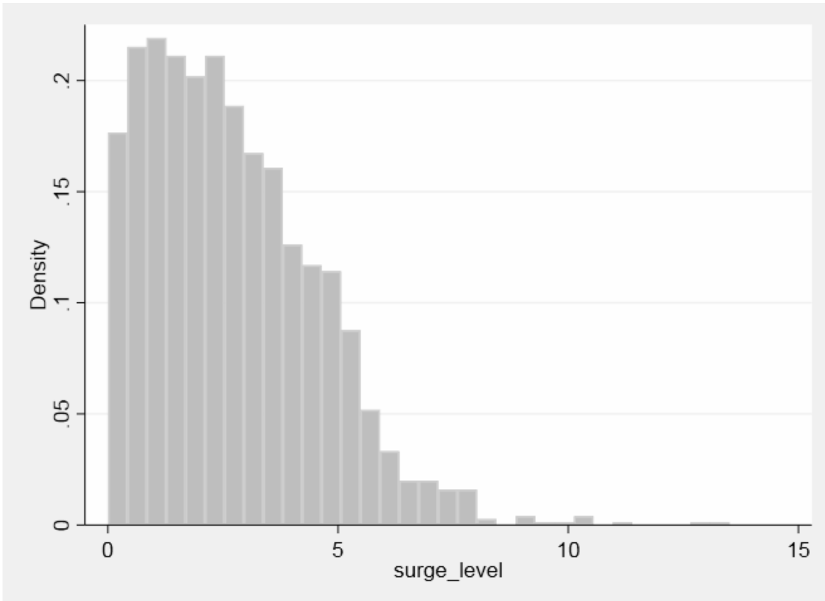
	(1) Estab. - Retail	(2) Estab. - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales – Retail	(6) Sales - Non-retail
sandy	6.736	4.737*	312.8	-99.60	0.293***	0.104***
	(5.163)	(2.520)	(232.7)	(77.75)	(0.0190)	(0.0394)
high_sandy	-0.0675	-0.335	-7.832**	-57.25	-0.149***	0.0639
	(0.106)	(0.409)	(3.676)	(35.16)	(0.0376)	(0.0806)
low_sandy	-0.00385	0.168	-6.249*	-68.49**	0.0235	0.0184
	(0.0887)	(0.250)	(3.412)	(33.71)	(0.0302)	(0.0318)
high_trend[35]	0.0278	0.114	-3.911	15.04	0.00177	0.0453
	(0.0557)	(0.232)	(2.391)	(39.94)	(0.0165)	(0.0316)
low_trend	0.0523	-0.0614	-2.342	-4.304	0.00712	0.00313
	(0.0449)	(0.162)	(2.375)	(39.26)	(0.0177)	(0.0199)
sandy_high_trend	-0.148*	-0.568	5.228	27.56	-0.00726	-0.0440
	(0.0807)	(0.409)	(4.780)	(68.93)	(0.0162)	(0.0432)
sandy_low_trend	-0.122*	-0.0973	3.907	62.41	0.00255	0.0109
	(0.0636)	(0.229)	(4.619)	(65.15)	(0.0175)	(0.0239)
Constant	2.372***	10.56***	485.0	2,581	15.87***	15.38***
	(0.0958)	(0.420)	(745.5)	(9,236)	(0.0367)	(0.0471)
Observations	12,312	12,312	9,995	9,995	8,610	8,574
R-squared	0.075	0.121	0.086	0.037	0.989	0.983

Note: Since we assume the trend started three years before Sandy, High/Low*2008, High/Low*2009, block fixed effects, and SBA*Year dummies are controlled for InfoUSA and LODES; High/Low*2008, Zip-zone fixed effects, and Boro*YearQuater dummies are controlled for log(total sales).

[35] High trend is high*(year-2010) for InfoUSA and LODES; high*(year-2009) for sales

Appendices

Appendix A: Surge level (in feet) distribution



Notes: the X-axis represents water levels in feet.

	Percentiles
1%	0.056109
5%	0.279842
10%	0.526056
25%	1.222088
50%	2.431354
75%	3.863869
90%	5.178217
95%	5.94011
99%	7.688412

Appendix B: Retail Sub-sector Classification

Category	NAICS	Description
Neighborhood-based Retail	311811	Retail Bakery
	444130	Hardware stores
	445110	Grocery stores
	445120	Convenience food stores
	445210	Meat markets
	445220	Seafood markets
	445230	Fruit markets
	445291	Baked goods stores, retailing only (except immediate consumption)
	445292	Candy stores, packaged, retailing only
	446110	Pharmacies
	446130	Optical goods stores (except offices of optometrists)
	446191	Nutrition (i.e., food supplement) stores
	446199	All Other Health and Personal Care Stores
	451120	Hobby, toy, and game stores
	451211	Book stores
	451212	Newsstands (i.e., permanent)
	453110	Flower shops, fresh
	453910	Pet shops
	453991	Tobacco stores
	812111	Barber Shops
	812112	Beauty Salons
	812113	Nail Salons
	812310	Coin-Operated Laundries and Drycleaners
	812320	Dry cleaning and Laundry Services (except Coin-Operated)
Accommodation	721	Accommodation
Restaurant	722	Food Services and Drinking Places
Other	Other	