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

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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 economic losses 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 help in surviving 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 involve 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 Brandão 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 2016; 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. 2011; 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 et al. 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 by

using fine-grained spatial controls and by 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 an untested context (New York City).

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

[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).

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

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 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

[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.

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 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

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

[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).

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. We generate counts of establishments, by borough-block-year, and our sample includes 187,758 block-year observations, covering 20,862 borough-blocks.[9]

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 from 2008 to 2015.[10] The LODES data are 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

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

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 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-year), 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-quarter-year observations.

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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.

[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.

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-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 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 the retail and non-retail classifications (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]

[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; resiliency planner at the New York City Department of City Planning, phone interview, September 15, 2015) 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.

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-year in the 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 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 to shut down entirely. In addition, standalone businesses may be

[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.

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).

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 zone A, prior to the storm. We consider characteristics of both the establishment, as well as the structures where they

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

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 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 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. There are no other meaningful differences across sub-types of the firms, though the share of establishments that are restaurants is slightly lower in the higher risk areas and the share that are health and social services is slightly higher. Second, establishments in the evacuation zone are more likely to be located in industrial buildings than their counterparts outside the zone and are located in somewhat newer structures (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.

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

The second source of selection bias relates to unobserved differences across establishments inside and outside the zone, and perhaps most notably, 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 it could directly affect business resilience, and we do not have information on the establishments' activities leading up to the storm.

In order to address both sets of 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 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] To capture the impact from flood exposure, we divide blocks in the evacuation zone into two categories: (i) blocks inside the evacuation zone that did not experience any flooding (*Evacuation_only*), and (ii) blocks in the 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 an example of how blocks are allocated with respect to evacuation designation and flooding (within one sample Sub-Borough Area (SBA), a collection of census tracts with aggregate population of at least 100,000). The grey blocks are in the *Evacuation_only* zone, the black blocks in the *Evacuation_surge* zone, the dotted blocks are those that got flooded, but were not in the evacuation zone, and the white blocks were neither in the evacuation zone nor flooded.

The 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 into 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

[20] We replicate the analyses using information on observed damage, as reported by FEMA. The observed damage and surge levels 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 levels as it is arguably more exogenous than the subjectively determined damage classifications provided by FEMA (which can also be endogenously determined by mitigation efforts by the property owner or business).

unobservable factors driving differential exposure to storm surge are correlated with the observables that we can control for.[21]

Finally, to further refine our identification of the storm's effect, we differentiate between blocks that had higher and lower surge levels (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 designated "no surge").[22] The crosshatched block in Figure 6 depicts a "high surge" block within the *Evacuation_surge* zone. 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

[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).

[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.

For the establishment and jobs models the unit of analysis is the block.[23] The regression takes the following form:[24]

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

where *Sandy* takes on a value of 1 starting in 2013.[25] *High* and *Low* capture the intensity of the surge. *High* takes on a value of 1 if block *i* experienced more than 3 feet of water surge (averaged across all of the commercial properties on the block), and 0 otherwise. Similarly, *Low* takes on a 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 borough-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

[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.
[25] Hurricane Sandy hit New York City on October 29th, 2012.

after Sandy. We identify closure when the establishment ceases to exist in the InfoUSA NYC 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 on the inundated blocks, 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-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 borough-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 number of which

[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.

may also decline due to Sandy), and 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).

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:

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

Our dependent variable is the log of total sales in a zip-zone in order to facilitate the comparison between the 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).[28] $\boldsymbol{D}_{b,q}$ is a vector of borough-quarter-year dummies to control for macro changes over time and N_j is a zip-zone fixed effect. By including zip-zone fixed effects, we can estimate changes in sales over time within a single zip-zone (i.e. evacuation and surge) and how they vary with surge intensities. While the sales data do not allow us to isolate the blocks in the evacuation zone and still maintain precise estimates, 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

[28] 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.

number of tax filers in the zip-zone-quarter-year. 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

In this section we summarize findings for each of our outcomes. In each case, we present findings for the full sample and then the findings for only blocks in the evacuation zone, our preferred specification. For all models, we stratify the observations by retail and non-retail classifications. While we document 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-, high- and no-surge areas, for all samples.

4.1 What are the localized economic effects from Hurricane Sandy?

4.1.1 Number of establishments

Table 2 reports the estimates for equation (1) for the number of establishments, for the full sample of establishments and then for only those in the evacuation zone. When using the full sample (columns 1, 3, and 5), we see signs of establishment growth in blocks that experienced modest inundation (*Low*Sandy)*. At first blush, 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 columns 2, 4, and 6 of Table 2. The coefficients for the interaction terms *High*Sandy* and *Low*Sandy* 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 more inclusive 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 3. They show that while all of 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 we observe 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 more inclusive 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.[29] We run these for retail and non-retail samples separately and display the results in Table 4.[30]

Two key findings emerge from these regressions. First, there is no significant difference in the odds of closure after Sandy 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 after Sandy are significantly higher for retail establishments located in both high- and low-surge areas (compared to areas without any surge).[31] When we stratify by census tract the relative magnitude of the coefficients persists, but the

[29] Schoenfeld residual tests reject non-proportionality among all of the covariates, except for open year dummies.
[30] 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.
[31] The coefficients on *High*Sandy* and *Low*Sandy* are not significantly different.

significance goes away. Census tracts are quite small in New York, however, and 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 29 and 43 percent more likely to close when exposed to low and high levels of inundation, respectively. This suggests that the net loss for retail establishments observed in the block-level analysis is at least in part due to higher 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.[32] The stratified regressions are displayed in Table 5; 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,

[32] 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.

blocks in high-surge areas 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.

As for differences in impacts across chain and standalone establishments, our results again conform with theoretical expectations. Table 6 shows that the coefficient on *High*Sandy* is highly significant and negative for both retail and non-retail sectors for standalone establishments; but we see no effects for chain businesses.

4.2 Jobs

Table 7 shows employment results for the full and restricted samples. Here, even before restricting the sample to only evacuation zone blocks, the coefficient on *High*Sandy* is significant and negative for the retail sub-sample. When we restrict the sample to only blocks in the evacuation zone, this effect intensifies. Results in column 4 shows that blocks in high-surge areas lost on average about 10 retail jobs per year after Sandy, compared to blocks without any water surge.[33] This represents a 25 percent net loss for the typical block with non-zero employment prior to Sandy. Unlike the results for establishment counts, we see no significant net loss for non-retail establishments. Blocks with low surge levels are not significantly harmed either. Effects are concentrated among retail establishments in high-surge areas.

[33] 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 also see signs of losses for the third outcome of interest, sales revenues, across the full sample (Table 8). Columns 1, 4, and 7 show that the coefficient on *High*Sandy* is negative and significant overall as well as for the retail subsamples.

Columns 2, 5, and 8 shows results when we retain the full sample and include zip-zone dummies, which allow us to compare outcomes across surge heights over time and within the same zip-zone (each of which is designated as evacuation or not). We see that the coefficient on *High*Sandy* declines in magnitude, but remains significant and negative. When we stratify the sample by type of establishment (or filer, in this case), the negative coefficient on *High*Sandy* persists 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.[34]

Columns 3, 6, and 9 show results when sample is restricted to only evacuation zip-zones. Unfortunately, restricting the sample to only evacuation zip-zones reduces its size considerably (by about 80 percent). Recall, the sales tax filers were aggregated into large enough geographies that identify their exposure to evacuation and inundation, but still maintain confidentiality requirements. Due to a smaller number of tax filers in the evacuation zone (and especially the part of the evacuation zone without any surge), we

[34] 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.

lose considerable estimation power. While the signs on the interactions terms are all negative (that for *Low*Surge* for non-retail is also marginally significant), we lose a great deal of precision (the standard errors increase by an order of magnitude). For the robustness checks that follow, we therefore rely on the full sample with zip-zone controls.

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 9 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 may obscure some nonlinearities in how inundation affects economic viability.

As a second test, we use different thresholds of height to classify *High* and *Low* surge blocks. These results, displayed in Table 10, show that a similar pattern persists as that when using a three-foot threshold, but as expected, the magnitude of the *High*Sandy* 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. Eighty percent of the city's subway system was operational one week after Sandy (Kaufman et al. 2012), and about 95% of the subway lines were back to normal or partial operations about two weeks after Sandy (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 11. 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 place 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 12 (for the establishment outcome only) and they show very similar results to those produced by the full sample of establishments.

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-year-specific, in the case of sales revenues) dummies that are individually interacted with *High* and *Low*. We plot the coefficients for these year-specific (or quarter-year-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* 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 13. They generally support the results from our preferred specification. Across all models, the coefficients on pre-sandy trend controls are insignificant, mitigating concerns that any post-sandy effects are due to different trends across *Low* and *High* leading up to the storm. As for retail establishments, while the

negative coefficients for the *High*Sandy* lose significance, the coefficient on the post-sandy trend variable is negative and significant, supporting the post-sandy effects we observe above. In addition, for the jobs analysis, there are now also significant losses for non-retail establishments (in 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.

A second feature of the estimates over time is that the increasing gap between *High* and *Low* 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* 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 larger in magnitude, the loss is smaller as a share of the baseline number of non-retail establishments (which are more prevalent).

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. And, finally, the widening divergence of the surge lines from the zero axis, 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 four important implications. First, the impacts of a natural disaster, like Sandy, appear to be 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 the volume of their services. 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.

Third, and not surprisingly, 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 annual net losses of 540 establishments, 3,700 jobs and $8 million in sales revenue, compared to blocks that had no water surge. Lower levels of water inundation did not appear to trigger similar losses.

Finally, regardless of the outcome observed, hurricane-induced damages were detrimental predominantly for retail enterprises. While any business type is threatened by physical damages to their space and inventory, retail establishments also suffer from interruptions to their localized consumer base. Our findings show that in relying on local patronage, retail businesses are more susceptible to economic losses that delay their recovery and, worst case, force their closure.

Given the growing risk of climate-related threats, and their increasing presence in dense urbanized areas, our results indicate that cities should invest in both mitigation and recovery strategies that are tailored to the conditions of the neighborhood and the type of businesses at risk. More broadly, 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. Urban neighborhoods are at increasing risk of facing one, if not more, of these shocks.

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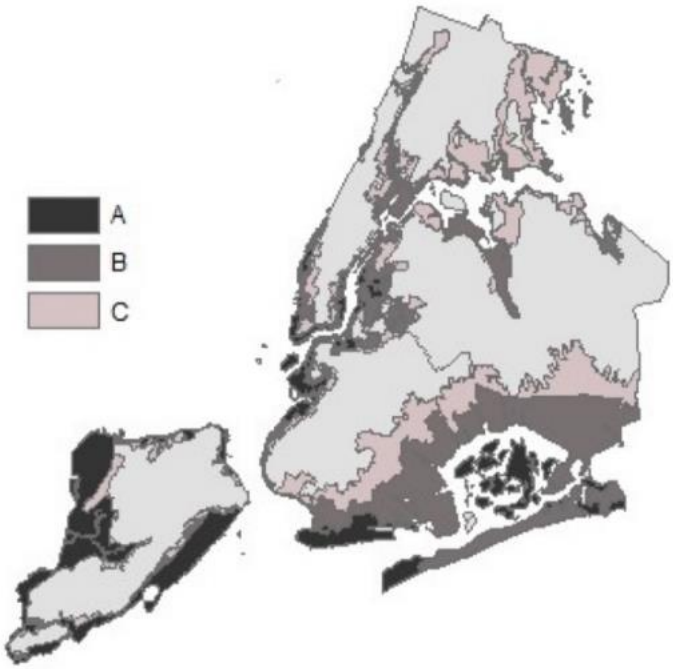
Figure 1: NYC Evacuation Map



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

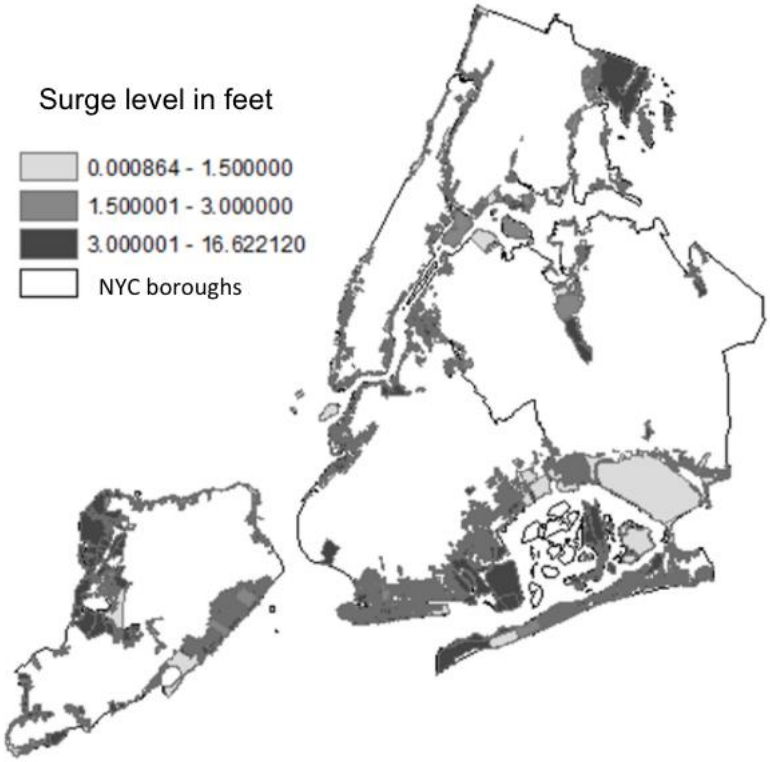
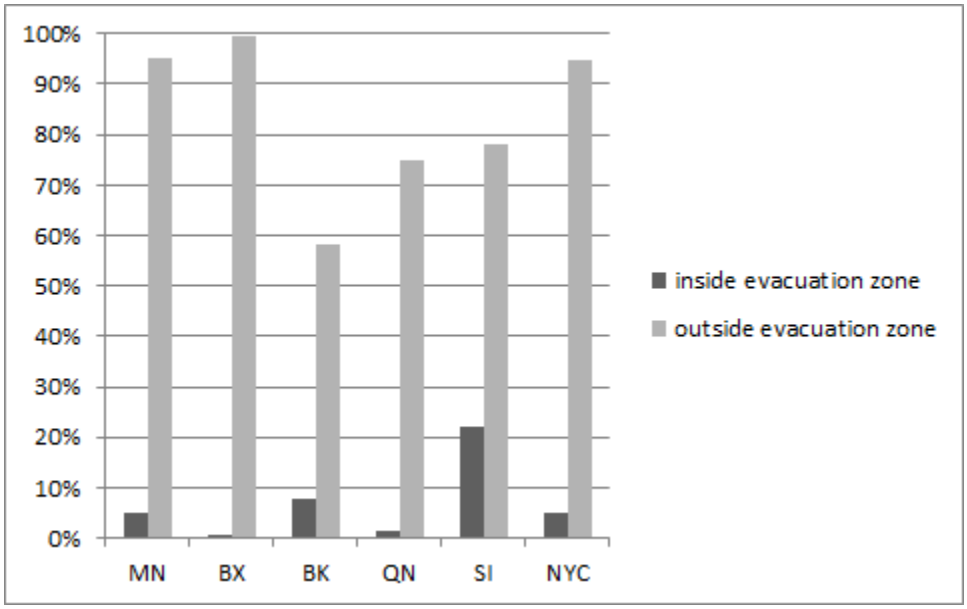
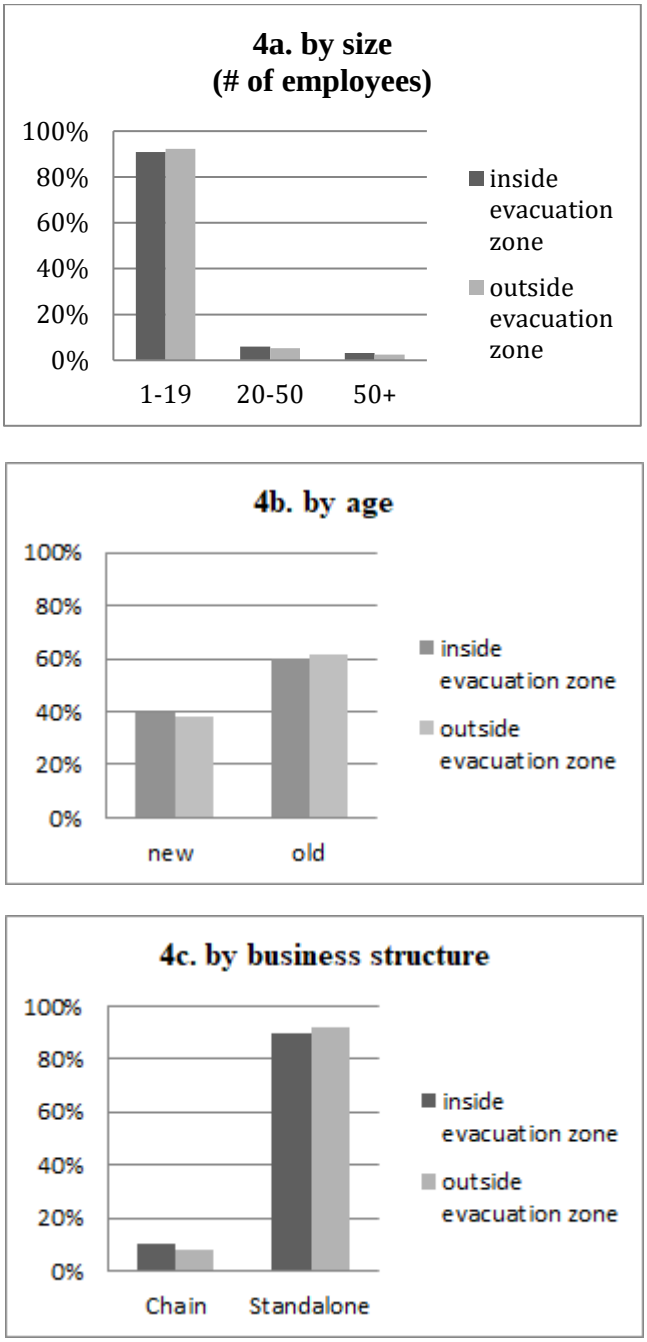


Figure 3: Distribution of businesses across zones, 2012



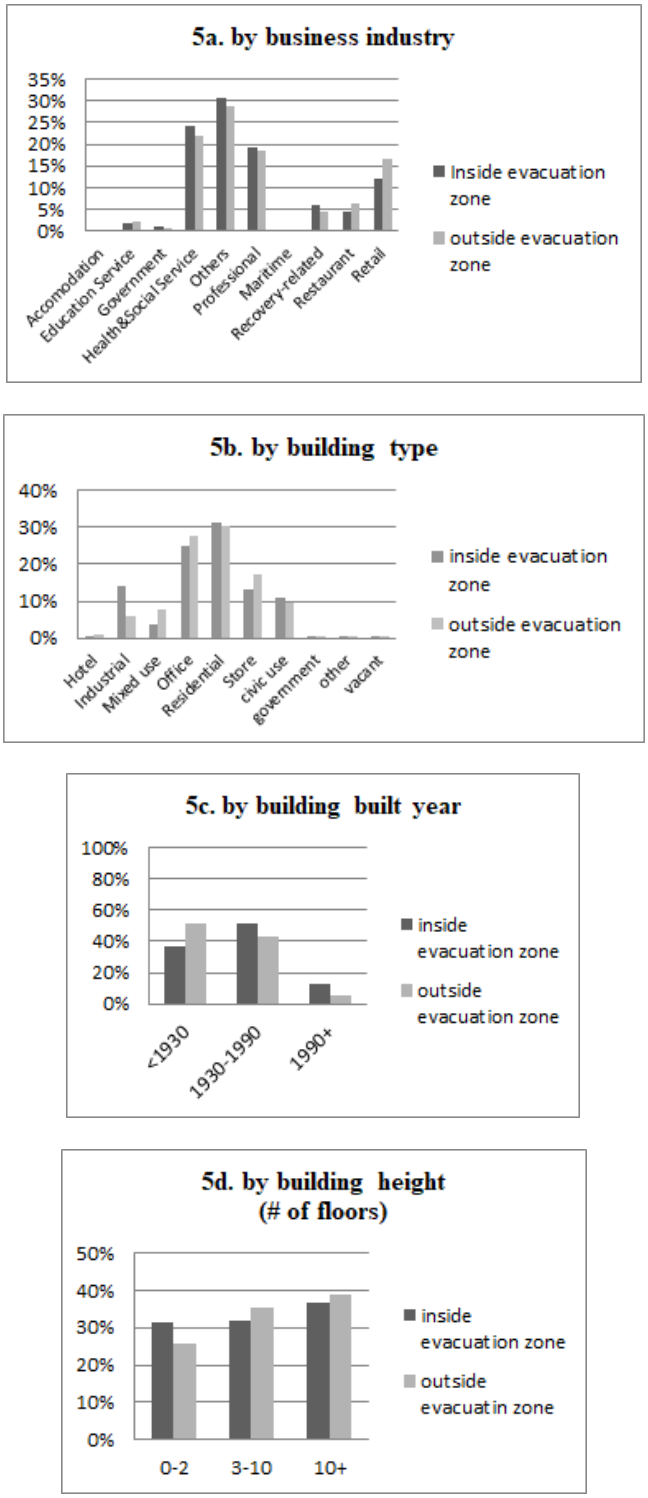
Notes: Y-axis reports shares (%)

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



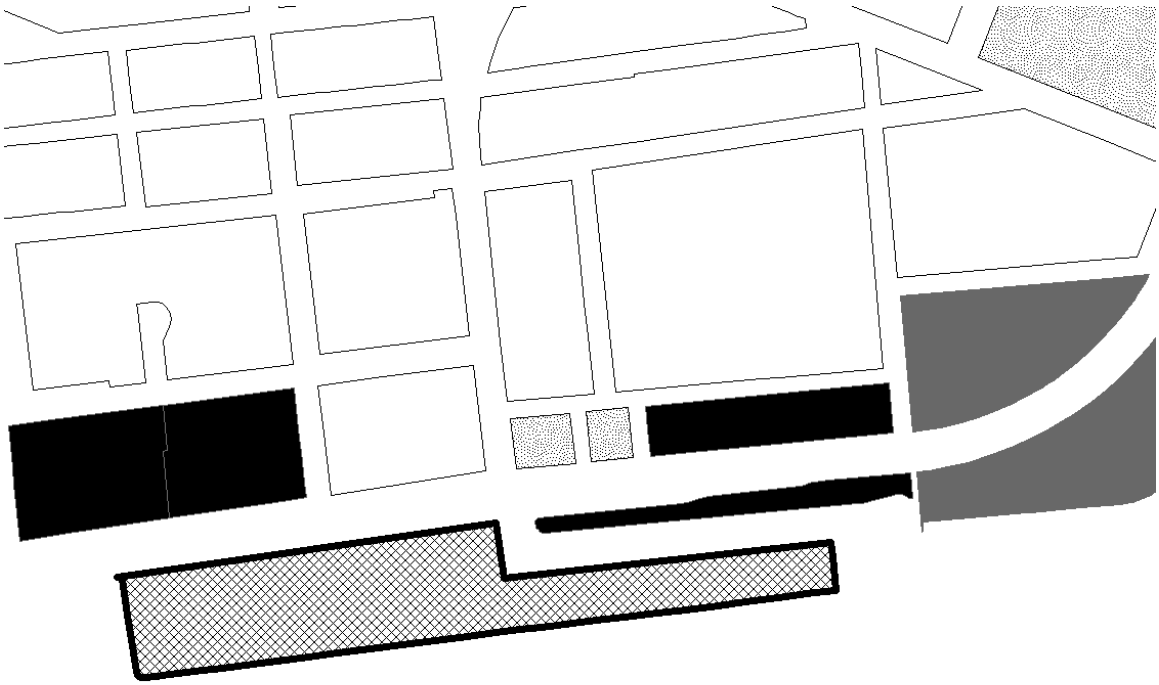
Notes: old establishments open before 2009, and new establishments open after 2008; Y-axis reports shares (%)

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



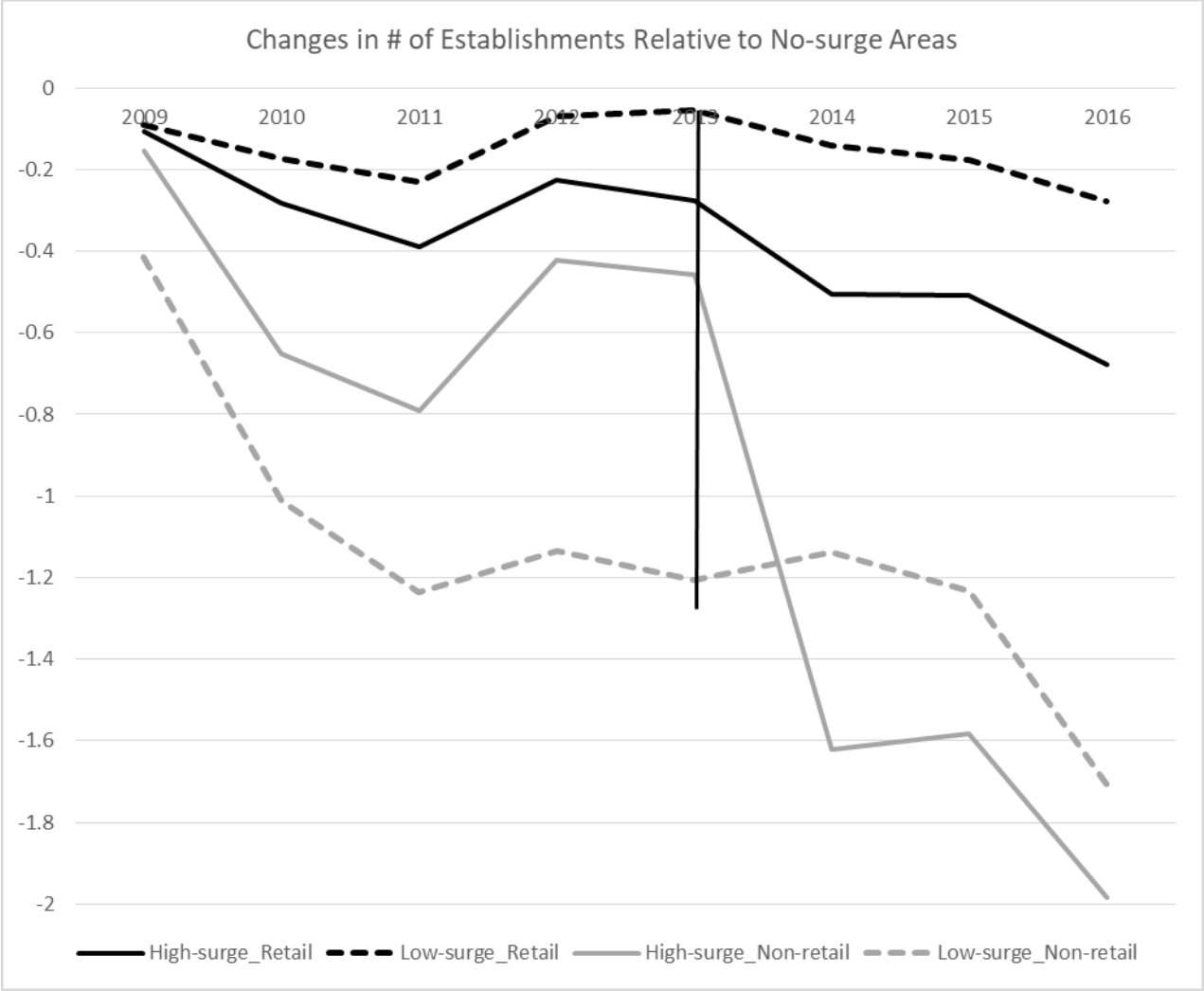
Notes: Y-axis reports shares (%)

Figure 6: Evacuation and Surge Zones



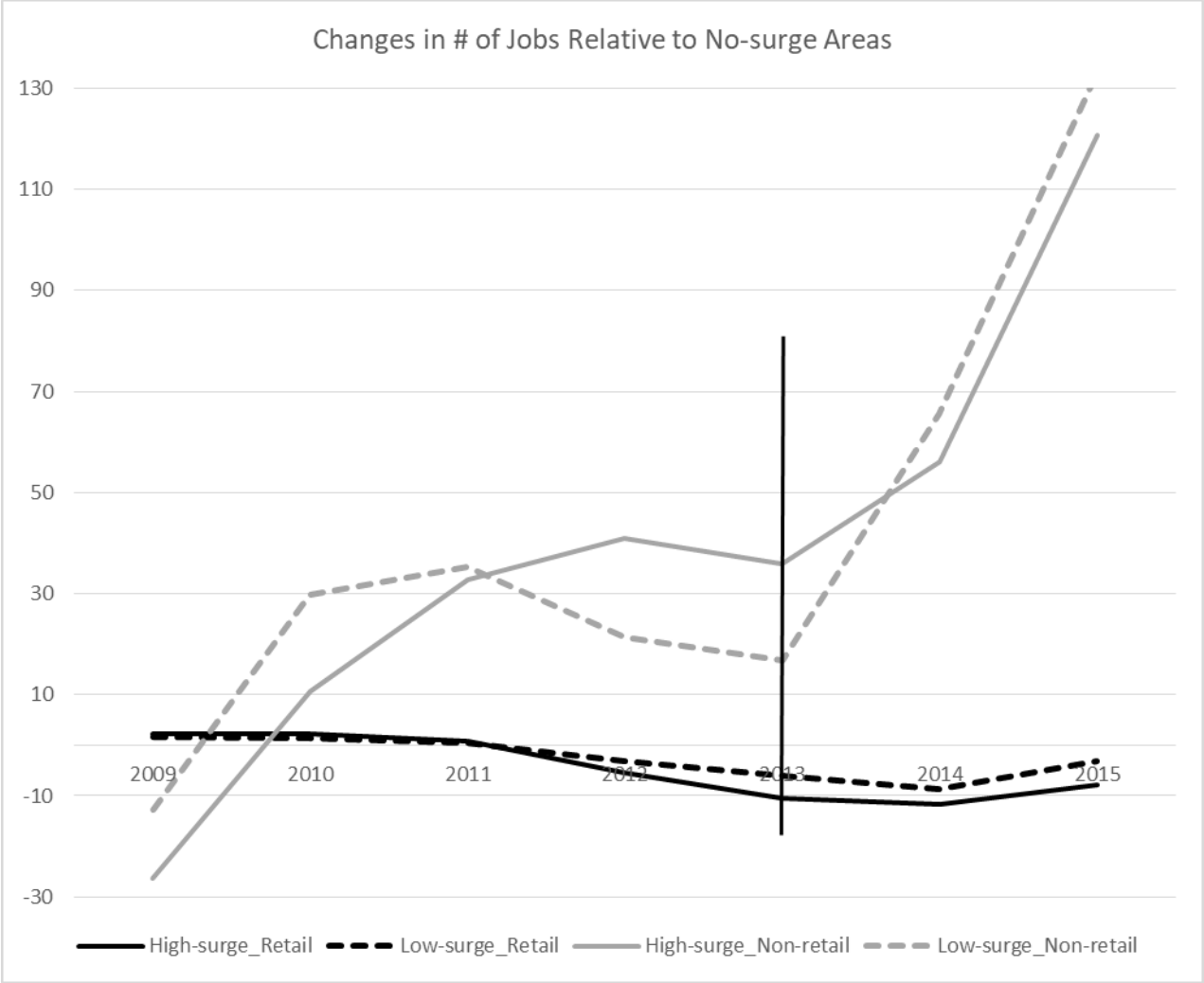
Notes: The grey blocks are in the *Evacuation_only* zone; the black blocks are in the *Evacuation_surge* zone; the dotted blocks are those that got flooded, but were not in the evacuation zone; and the white blocks were neither in the evacuation zone nor flooded. The crosshatched block is in the *Evacuation_surge* area with high-surge levels.

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



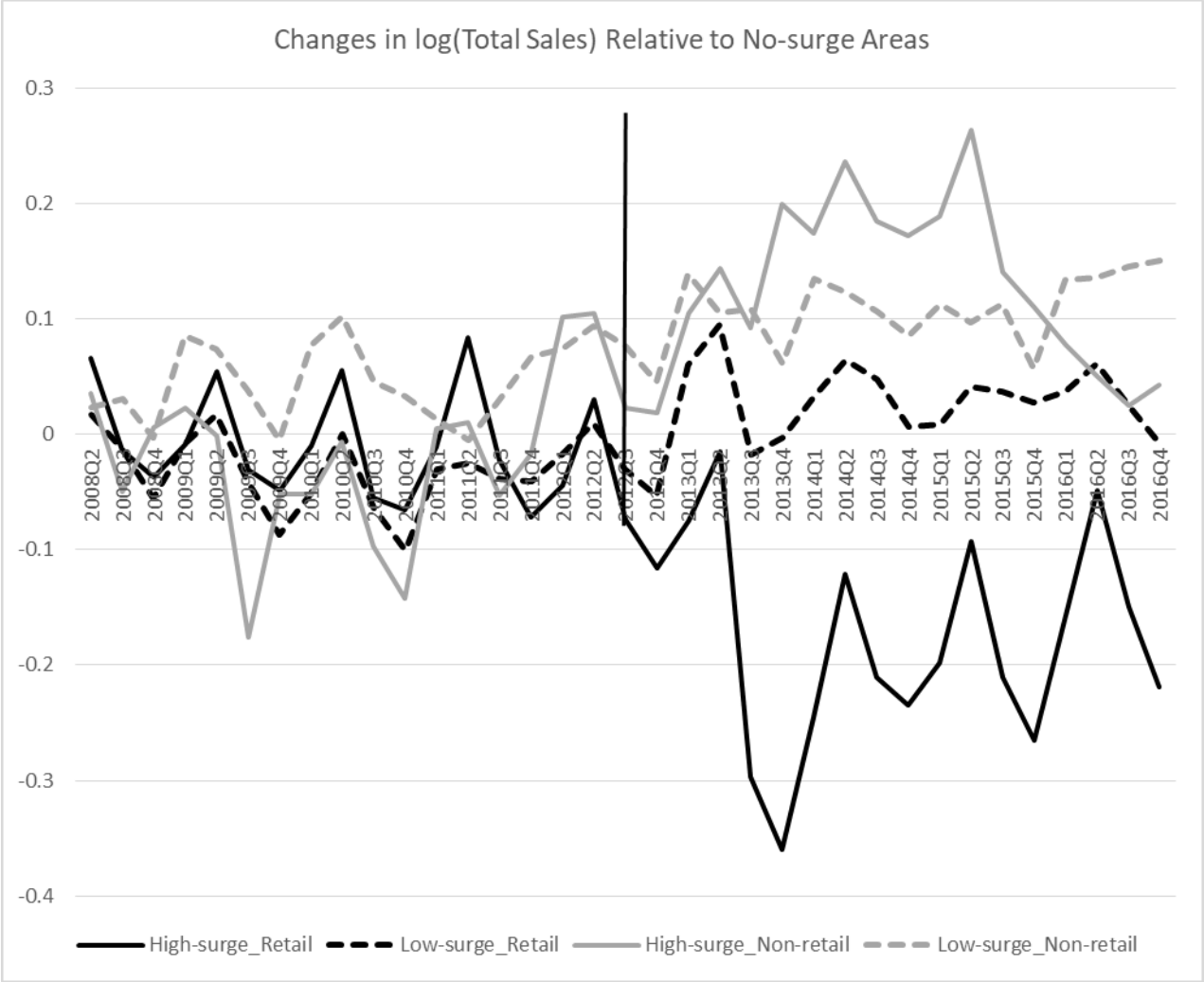
Notes: Plotted points are adjusted values, controlling for block fixed effects, and SBA-year dummies.

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



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

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-quarter-year dummies.

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	Dry cleaning and Laundry Services (except Coin-Operated)
Non-retail	11	Agriculture, Forestry, Fishing and Hunting
	21	Mining, Quarrying, and Oil and Gas Extraction
	22	Utilities
	23	Construction
	31-34 (except for 311811)	Manufacturing
	42	Wholesale Trade
	48-49	Transportation and Warehousing
	51	Information
	52	Finance and Insurance
	53	Real Estate and Rental and Leasing
	54	Professional, Scientific, and Technical Services
	55	Management of Companies and Enterprises
	56	Administrative and Support and Waste Management and Remediation
	61	Educational Services
	62	Health Care and Social Assistance

	71	Arts, Entertainment, and Recreation
	81 (except for 812111, 812112, 812113, 812310, 812320)	Other Services
	92	Public Administration
LODES[35]		
Retail	44-45	Retail Trade
	72	Accommodation and Food Services
Non-retail	11	Agriculture, Forestry, Fishing and Hunting
	21	Mining, Quarrying, and Oil and Gas Extraction
	22	Utilities
	23	Construction
	31-34	Manufacturing
	42	Wholesale Trade
	48-49	Transportation and Warehousing
	51	Information
	52	Finance and Insurance
	53	Real Estate and Rental and Leasing
	54	Professional, Scientific, and Technical Services
	55	Management of Companies and Enterprises
	56	Administrative and Support and Waste Management and Remediation
	61	Educational Services
	62	Health Care and Social Assistance
	71	Arts, Entertainment, and Recreation
	81	Other Services

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

	92	Public Administration
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
	81	Other Services
Non-retail	11	Agriculture, Forestry, Fishing and Hunting
	21	Mining, Quarrying, and Oil and Gas Extraction
	22	Utilities
	23	Construction
	31-34	Manufacturing
	42	Wholesale Trade
	48-49	Transportation and Warehousing
	51	Information
	52	Finance and Insurance
	53	Real Estate and Rental and Leasing
	54	Professional, Scientific, and Technical Services
	55	Management of Companies and Enterprises
	56	Administrative and Support and Waste Management and Remediation

Table 2: Regression Results, Establishments

	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Total	Retail	Retail	Non-retail	Non-retail
	Full	**Evac**	**Full**	**Evac**	**Full**	**Evac**
	Sample	**Zone**	**Sample**	**Zone**	**Sample**	**Zone**
Sandy	2.298***	10.17	-0.0480	6.464	2.346***	3.710
	(0.627)	(7.602)	(0.163)	(5.181)	(0.614)	(2.443)
*High*Sandy*	0.470	-1.299**	0.00952	-0.292**	0.461	-1.007**
	(0.363)	(0.553)	(0.0768)	(0.122)	(0.343)	(0.510)
*Low*Sandy*	0.371**	-0.610	0.189***	-0.0496	0.182	-0.561
	(0.165)	(0.474)	(0.0440)	(0.0988)	(0.149)	(0.427)
Constant	17.36***	14.00***	4.163***	2.595***	13.20***	11.40***
	(0.0861)	(0.347)	(0.0126)	(0.0321)	(0.0814)	(0.341)
block fixed effects	Y	Y	Y	Y	Y	Y
SBA-year dummies	Y	Y	Y	Y	Y	Y
Observations	187,758	12,312	187,758	12,312	187,758	12,312
R-squared	0.098	0.120	0.099	0.074	0.085	0.121
Number of blocks	20,862	1,368	20,862	1,368	20,862	1,368

Robust standard errors in parentheses

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

Table 3: Retail Sub-sector Regression Results, Establishments, Evacuation Zone Sample

	(1)	(2)	(3)	(4)
	Neighborhood-based	Accommodation	Restaurant	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)
block fixed effects	Y	Y	Y	Y
SBA-year dummies	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 blocks	844	844	844	844

Robust standard errors in parentheses

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

Table 4: Hazard Model Regression Result, Establishments, Evacuation Zone Sample

	(1)	(2)	(3)	(4)
	Retail	Retail	Non-retail	Non-retail
Sandy	0.0185***	0.0225***	0.0270***	0.0271***
	(0.00283)	(0.00363)	(0.00191)	(0.00194)
High	0.957	1.052	1.053	1.060
	(0.107)	(0.129)	(0.0541)	(0.0563)
Low	1.022	1.094	1.024	1.036
	(0.111)	(0.130)	(0.0512)	(0.0542)
*High*Sandy*	1.432**	1.153	1.093	1.076
	(0.210)	(0.181)	(0.0752)	(0.0753)
*Low*Sandy*	1.288*	1.072	1.018	1.008
	(0.185)	(0.164)	(0.0690)	(0.0696)
Chain	0.747***	0.768***	0.756***	0.768***
	(0.0506)	(0.0527)	(0.0254)	(0.0259)
Employee	0.999**	0.999*	1.000*	1.000
	(0.000708)	(0.000731)	(7.97e-05)	(8.01e-05)
Cluster	1.000*	1.000	1.000	1.000
	(0.000176)	(0.000210)	(5.24e-06)	(6.45e-06)
Stratified by	Zip code	Census Tract	Zip code	Census Tract
Open Year dummies	Y	Y	Y	Y
Observations	6,833	6,833	31,126	31,126

Standard error in parentheses

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

p<0.1

Table 5: Regression Results, Establishments, Evacuation Zone Sample, Stratify by Size

	(1)	(2)	(3)	(4)	(5)	(6)
	Retail 1-19	Retail 20-50	Retail 50+	Non-retail 1-19	Non-retail 20-50	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)
block fixed effects	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 blocks	844	844	844	1343	1343	1343

Robust standard errors in parentheses

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

Table 6: Regression Results, Establishments, Evacuation Zone Sample, Stratify by Chain/Standalone

	(1)	(2)	(3)	(4)
	Retail Chain	Retail Standalone	Non-retail Chain	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)
block fixed effect.	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 blocks	844	844	1343	1343

Robust standard errors in parentheses

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

Table 7: Regression Results, Jobs

VARIABLES	(1) Total **Full** **Sample**	(2) Total **Evac** **Zone**	(3) Retail **Full** **Sample**	(4) Retail **Evac** **Zone**	(5) Non-retail **Full** **Sample**	(6) Non-retail **Evac** **Zone**
Sandy	47.01***	280.5	4.065**	314.3	42.94***	-33.75
	(12.55)	(246.7)	(1.941)	(232.6)	(12.22)	(44.38)
*High*Sandy*	5.489	47.86	-3.108*	-9.790***	8.598	57.65
	(11.61)	(42.54)	(1.605)	(3.730)	(11.44)	(42.47)
*Low*Sandy*	5.287	50.32	0.101	-5.931	5.186	56.25
	(8.287)	(42.66)	(1.416)	(3.809)	(8.048)	(42.27)
Constant	133.7**	2,776	21.89***	451.7	111.8**	2,325
	(56.37)	(9,370)	(6.322)	(753.3)	(55.29)	(9,149)
block fixed effects	Y	Y	Y	Y	Y	Y
SBA-year dummies	Y	Y	Y	Y	Y	Y
Observations	160,776	9,995	160,776	9,995	160,776	9,995
R-squared	0.006	0.039	0.026	0.085	0.004	0.035
Number of blocks	24,929	1,679	24,929	1,679	24,929	1,679

Robust standard errors in parentheses

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

Table 8: Regression Results, Sales Revenues

VARIABLES	(1) Total	(2) Total	(3) Total	(4) Retail	(5) Retail	(6) Retail	(7) Non-retail	(8) Non-retail	(9) Non-retail
Sandy	0.245***	0.246***	0.136	0.304***	0.291***	0.283**	0.112**	0.105***	0.596**
	(0.0233)	(0.0190)	(0.153)	(0.0253)	(0.0190)	(0.139)	(0.0528)	(0.0391)	(0.231)
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**	-0.0966*	0.0651	-0.241***	-0.161**	-0.182	0.128	0.140*	-0.332
	(0.0698)	(0.0581)	(0.137)	(0.0799)	(0.0658)	(0.128)	(0.0934)	(0.0774)	(0.226)
*Low*Sandy*	0.0334	0.0328	0.243*	0.0517	0.0524	0.141	0.118**	0.0629	-0.450*
	(0.0362)	(0.0316)	(0.138)	(0.0568)	(0.0475)	(0.138)	(0.0580)	(0.0473)	(0.234)
Constant	18.08***	16.35***	16.33***	17.71***	15.88***	15.88***	16.95***	15.38***	15.24***
	(0.129)	(0.0203)	(0.0531)	(0.124)	(0.0263)	(0.0888)	(0.200)	(0.0343)	(0.135)
Evacuation Zone Only	N	N	Y	N	N	Y	N	N	Y
zip-zone dummies	N	Y	Y	N	Y	Y	N	Y	Y
borough-quarter-year	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,644	10,644	1,965	8,610	8,610	1,154	8,574	8,574	1,150
R-squared	0.484	0.991	0.971	0.455	0.989	0.971	0.418	0.983	0.918

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regression Results, Continuous Surge Level, Evacuation Zone Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Estab. - Retail	Estab. - Non-retail	Jobs - Retail	Jobs – Non-retail	Sales – Retail	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)
*Surge Level*Sandy*	-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)
block fixed effects	Y	Y	Y	Y	N	N
SBA-year dummies.	Y	Y	Y	Y	N	N
zip-zone fixed effects	N	N	N	N	Y	Y
borough-quarter-year	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 10: 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*, constant, block fixed effects, and SBA-year dummies are controlled for establishments and jobs; *Sandy*, constant, zip-zone fixed effects, and borough*quarter-year dummies are controlled for log(total sales).

Table 11: Regression Results, Excluding Transit-Interrupted Areas, Evacuation Zone Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Estab. - Retail	Estab. - Non-retail	Jobs - Retail	Jobs - Non-retail	Sales - Retail	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)
block fixed effects	Y	Y	Y	Y	N	N
SBA-year dummies.	Y	Y	Y	Y	N	N
zip-zone fixed effects	N	N	N	N	Y	Y
borough-quarter-year dummies	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 12: Regression Results, Establishments, Excluding Relocated Businesses, Evacuation Zone Sample

	(1)	(2)	(3)
	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)
block fixed effects	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 blocks	1,359	1,359	1,359

Robust standard errors in parentheses

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

Table 13: Regression Results, Controlling for Pre/Post Sandy Trend, Evacuation Zone Sample

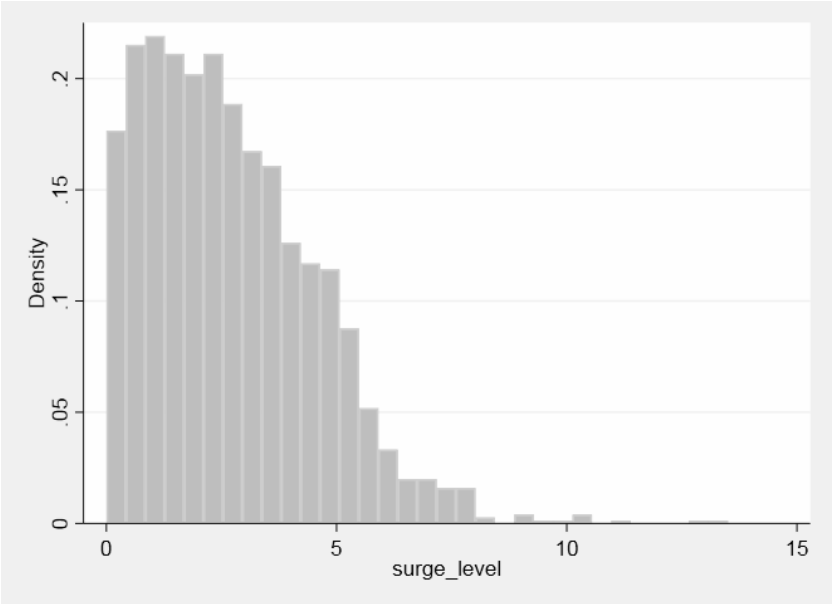
	(1)	(2)	(3)	(4)	(5)	(6)
	Estab. - Retail	Estab. - Non-retail	Jobs - Retail	Jobs - Non-retail	Sales – Retail	Sales - Non-retail
Sandy	6.736	4.737*	312.8	-99.60	0.293***	0.104***
	(5.163)	(2.520)	(232.7)	(77.75)	(0.0190)	(0.0394)
*High*Sandy*	-0.0675	-0.335	-7.832**	-57.25	-0.149***	0.0639
	(0.106)	(0.409)	(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[36]	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[37]	-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)

[36] High Trend is *High**(year-2010) for establishments and jobs; *High**(year-2009) for sales
[37] Sandy High Trend is *High**(year-2013)**Sandy* for establishments and jobs; *High**(year-2012)**Sandy* for sales

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 establishments and jobs; *High/Low**2008, zip-zone fixed effects, and borough-quarter-year dummies are controlled for log(total sales).

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 Retails	441110	New car dealers
	441120	Used car dealers
	441210	Recreational vehicle (RV) dealers
	441221	Bike and motorcycle dealers
	441229	Utility trailer dealers
	441310	Auto supply stores
	441320	Automotive tire dealers
	442110	Furniture stores (e.g., household, office, outdoor)
	442210	Floor covering stores (except wood or ceramic tile only)
	442291	Window treatment stores
	442299	All Other Home Furnishing Stores
	443111	Appliance stores, household-type
	443112	Electric Stores
	443120	Computer equipment stores
	443130	Camera shops, photographic
	444110	Home improvement centers
	444120	Paint stores
	444190	Other building material
	444210	Garden power equipment stores
	444220	Farm supply stores (feed)
	445299	All Other Specialty Food Stores
	445310	Liquor stores, package
	447110	Gasoline stations with Convenience Stores
	447190	Other Gasoline Stations
	448110	Clothing stores, men's and boys'
	448120	Clothing stores, women's and girls'
	448130	Apparel stores, children's and infants' clothing
	448140	Clothing stores, family

	448150	Clothing accessories stores
	448190	Other Clothing stores, like bridal and school uniform
	448210	Shoe (except bowling, golf, spiked) stores
	448310	Jewelry stores, precious
	448320	Luggage and leather stores
	451110	Athletic equipment and supply stores (including uniforms)
	451130	Needlecraft sewing supply stores
	451140	Music stores (i.e., instrument)
	451220	Music stores (e.g., cassette, compact disc, record, tape)
	452111	Department stores
	452910	Superstores (i.e., food and general merchandise)
	452990	All Other general merchandise stores
	453210	Office supply stores
	453220	Gift shops
	453310	Antique dealers (except motor vehicles)
	453920	Art dealers
	453930	Manufactured (mobile) home parts and accessory dealers
	453998	All other miscellaneous store retailers