DRAFT—Submitted to *Journal of Economic Geography*

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

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January 9th, 2020

Abstract:
This paper considers the localized economic impacts of a climate-related storm, Hurricane Sandy. Controlling for exposure to pre-storm risk, we exploit variation in post-storm inundation to identify the impact of storm-induced flooding on establishment survival, employment, and sales revenues. Results indicate that the economic losses from Sandy were significant and, as expected, concentrated among retail businesses with more localized consumer bases. After Sandy, retail establishments exposed to higher surge levels experienced higher rates of business closure and larger job and sales revenue declines compared to establishments with less exposure to inundation. Finally, closures are concentrated among smaller and standalone establishments.

Keywords:
Natural disaster; Retail; Resilience; Business

Classification codes:
Q51, Q53, R3

1. Introduction

The density that makes urban areas economically productive may also make them more vulnerable to damage in the face of climate change and the extreme weather events that accompany it. In this paper, we consider the localized economic impacts of one such event, Hurricane Sandy, on businesses in 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 survival 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 economic activity may be more vulnerable to hurricane-induced flooding than others.

We hypothesize that retail businesses that serve a more localized consumer base will be most harmed by flooding risk; businesses that do not rely on foot traffic and serve broader markets will be less affected. Our reasoning is that the risk for retail establishments is twofold: they may not only suffer physical damage from excessive flooding, but also risk losing local customers who are displaced by the storm and/or experience 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 maps that show us exactly where, and to what height, the flood waters rose during the storm. Because the city government publicly identified blocks in evacuation zone A as those most at risk of hurricane damage and issued a mandatory evacuation order for these blocks prior to Sandy, we restrict our core sample to establishments within evacuation zone A. To identify the storms' impact, we rely on variation in water surge heights within this evacuation zone.

Results indicate that neighborhood economic losses from Sandy are significant and, in certain cases, persistent. Consistent with theoretical expectations, losses are primarily concentrated among retail businesses, especially those that serve a more localized consumer base. We find evidence of higher rates of business closures among retail establishments located on blocks that experienced high surge levels. By contrast, non-retail establishments in high surge areas do not exhibit any differential change in rates of closure as compared to those located elsewhere in the evacuation zone. Furthermore, establishment closures are concentrated among smaller and standalone establishments.

We also find that the storm led to reductions in employment. Retail employment declined by 14 percent after Sandy on blocks that faced at least three feet of storm flooding relative to nearby blocks in the evacuation zone that saw no flooding. Non-retail businesses saw no differential job losses on high-surge blocks. Finally, retail businesses in areas with higher levels of inundation experienced a 9% decline in sales revenues after Sandy as compared to those in other areas. Sales declines were persistent, indicating little sign of recovery to pre-Sandy levels four years after the storm.

2. Global shocks and local commercial impacts

2.1 Background

Climate scientists warn that climate change will continue to bring more severe weather (Banholzer, Kossin, and Donner, 2014). While natural disasters, like hurricanes or earthquakes, typically cover large swaths of land area, their impacts are highly uneven. The force of the extreme event can vary significantly across neighborhoods within a single metropolitan area.

Outcomes are likely to vary across different types of businesses, depending on the predisposition to risk and harm. Specifically, we distinguish between retail (including restaurants and bars) and non-retail businesses, as retail businesses are more likely to rely on local patronage and depend on street traffic (Jacobs 1961; Meltzer and Capperis 2017; Waldfogel, 2008; Davis, 2006; Dinlersoz, 2004). The vulnerability of what we collectively refer to as retail establishments is twofold: in addition to losses from any direct physical damage to their location or inventory (which any other commercial establishment could similarly experience), they also face business interruptions due to 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 (Kolko and Neumark 2010; Jardim 2015; Brandao et al 2014).

In contrast, commercial activity that draws consumers from long distances or does not rely on face-to-face interactions is less vulnerable to localized demand shocks from extreme flooding. 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).

Within the retail sector, we expect those that rely on local customers (because they sell goods that are perishable and/or frequently consumed) to be particularly vulnerable to storms. We also expect smaller and standalone establishments to be more vulnerable as they are less likely to have the capital to invest in pre-storm preparation and post-storm repairs or the reserves to survive the business interruption.

2.2 Prior 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; Marshall et al. 2015; Sydnor et al. 2017).[1]

The literature considering micro-geographies yields a few common findings (whether disasters are tornados, hurricanes, floods or earthquakes). First, business characteristics 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; Marshall et al. 2015). A number of studies find that larger businesses, those that were performing relatively better prior to the disaster, and those with fewer credit constraints cope better in post-disaster circumstances (Tierney 1997b, Dahlhamer and Tierney 1998, Wasileski et al. 2011; Basker and Miranda 2017). Smaller establishments typically operate with tight margins (in good times), and 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 shut down or to cut back on staff to save on expenses. In addition, larger businesses do more to prepare leading up to the disaster, given their greater administrative and financial resources (Webb et al. 2000; Basker and Miranda 2017).

Businesses that are part of multi-establishment chains are also likely to fare better in the face of a storm, as establishments in unaffected areas with continuing operations can help cushion the economic blow for the flooded location (LeSage et al. 2011). Finally, 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).

[1] Basker and Miranda 2018 is an exception.

Second, business recovery is linked to the fate and fortune of the surrounding community. A few cross-sectional studies based on post-storm surveys of small or systematically selected samples suggest that business recovery 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 depends 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 shapes the degree of losses a business suffers. In addition, wholesale and retail businesses are more likely than other businesses 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 fail to control for pre-existing vulnerabilities and omit many of the businesses that may have closed due to disaster-induced damages.

Third, short-term outcomes can differ from long-term ones. LeSage et. al. (2011) consider the variation in post-disaster outcomes over time and space. In the short term, severity of the disaster (flood depth) reduces the probability of businesses reopening post-disaster, while sole proprietorship and local household income increases the probability of re-opening. Based on post-disaster observations only, the authors find that all of these associations diminish over time. Basker and Miranda (2018) also find evidence of higher short-term closure rates in the wake of Hurricane Katrina along the Mississippi coast. While larger and more productive businesses were more resilient in the short-term, the size advantage dissipated over the long-term. These findings are consistent with those of 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 current analysis contributes to the literature in several ways. First, we are able to isolate causal impacts by using fine-grained spatial controls and by narrowing the counterfactual to include other commercial establishments similarly at risk prior to the storm.[2] Second, we develop simple hypotheses about heterogeneity across businesses in their response to an extreme event and test those hypotheses empirically, in a context not yet studied. Finally, we contribute to understanding how recovery patterns can differ in the short- and long-term by observing measures of commercial activity over an extended period before and after the disaster.

3. Data and analytical strategy

In October of 2012, Hurricane Sandy struck the eastern seaboard of the United States. One of the strongest storms on record to strike the coast, Sandy hit New York City with particular force. The storm surge reached almost nine percent of all residential units in the city, and nearly four

[2] 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 property 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).

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). At the time, Hurricane Sandy was estimated to be the second-costliest hurricane on record in the U.S., after Hurricane Katrina in 2005.[3]

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, slightly to the north, 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 establishment and neighborhood levels. To capture the pre-storm vulnerability of businesses, we use the boundaries of local hurricane evacuation zones (defined by New York City officials).[4] We focus on blocks within Evacuation Zone A, since

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

[4] We use evacuation zones rather than FEMA zones, because FEMA zones are not as relevant or salient for businesses. Few businesses own their properties in New York City, and among those that do, only a very small set (those with federally subsidized mortgages) are required to purchase insurance. Thus, we do not expect that businesses would have taken into account the FEMA zone boundaries in making their location decisions. More importantly, the city's warnings about Hurricane Sandy were focused on the evacuation zone A and not the FEMA zones, and therefore were more salient to businesses. That said, FEMA zones and the evacuation zone overlap considerably, and when we replicate our analyses using the FEMA flood zones instead of the evacuation zone, we obtain consistent results.

these were deemed to be most at risk in advance of the storm, Indeed, in the days before Hurricane Sandy hit, New York City officials issued mandatory evacuation orders for residents and businesses in evacuation zone A and not for those in zones B and C, which are further from the shore and deemed less vulnerable to flooding and damage. The evacuation zone map, obtained from the New York City Mayor's Office of Recovery and Resiliency, can be seen in Figure 1.

We use FEMA's surge map to capture the storm's actual impact (from water inundation).[5] We obtain the surge map 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.[6] 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. The surge heights across blocks vary widely (see Appendix A). Figure 2 displays a map of surge levels for blocks across the city.[7] We exploit the variation in surge height for our identification strategy, discussed in the next section.

We obtain information on establishments from the Infogroup historical business database, a longitudinal panel of establishments constructed by Infogroup [8] Infogroup identifies

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[5] While FEMA also produces parcel-level damage estimates, one of the most significant inputs into this determination is the surge map. The additional information to determine the damage classification is likely to introduce noise into the measure and we expect the variation in surge heights to be a more exogenous measure of storm impact.
[6]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.
[7] Surge levels for the block are calculated as the average height across all of the commercial properties on the block
[8] See http://resource.referenceusa.com/available-databases/ for details.

establishments using yellow pages, phone books, and newspapers, and incorporates phone verification for the entire database (Lavin, 2000).[9] We use data from 2008 through 2016. Unlike publicly available government data on establishments, the Infogroup dataset provides the full street address for each establishment, and it is more likely to capture non-employer firms and small chain establishments than public records.[10] 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.[11] The dataset also reports on the number of employees at each establishment and distinguishes between chains and standalone businesses. Most importantly for this analysis, the data 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 includes 19,058 establishments operating in 2008.

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.[12] The LODES data are derived from state unemployment insurance

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[9] Every business in the database is contacted at least once a 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 Infogroup asks only basic information. Keeping track of defunct businesses has been a part of Infogroup's database maintenance, and Infogroup 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 Infogroup 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.

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

[11] 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).

[12] 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.

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).[13] We use the variable that records jobs based on the location of employment. Our sample for the employment analyses includes 9,995 block-year observations, covering 1,679 census blocks.

To capture sales, we use reported quarterly taxable sale revenues for all NYC commercial filers from the city's Department of Finance (NYC DOF).[14] Due to statutory restrictions on data sharing, we cannot access filer-level information. Instead, NYC DOF provided aggregated 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, or zones: blocks outside the evacuation zone and without any surge; blocks in the evacuation area but without any post-storm surge; blocks with surge but not in the evacuation zone; and blocks in the evacuation and with surge; (ii) filers were then grouped first according to their ZIP code, then according to their designation into one of these four zones[15] 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

[13] 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).

[14] 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.

[15] 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 and 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 fewer missing, but bigger, geographies. The results from regressions using this unit of analysis are substantively to the ZIP-zone ones presented in the paper.

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 across group-quarters is $65,407, and the standard deviation is $125,440.[16] In total, our sample for the sales analyses covers 307 ZIP-zones, comprised of 10,644 ZIP-zone-quarter-year observations.

Finally, we obtain building characteristics, like age and height from the New York City Department of City Planning's Primary Land Use Tax Lot Output (PLUTO) dataset. We use these variables to compare the physical structures in which establishments operate inside and outside the evacuation zone A.[17] We have this information for 2012.

Table 1 shows summary statistics for dependent variables: the time until closure from Infogroup, the number of jobs from LODES, and quarterly average sales revenues from DOF.

3.2 Identifying Commercial Economic Activity

We examine outcomes for all types of businesses but also conduct separate analyses for retail and non-retail sectors given that we want to observe how the response varies for businesses that draw more on neighborhood-based customers as compared to businesses that serve a

[16] 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.
[17] 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. Further, any insurance coverage for the property would only protect the structure and not the inventory or activity that takes place in the commercial space. We do not expect that insurance is widespread enough to affect the validity of our results.

geographically more dispersed clientele.[18] See Table 2 for a list of NAICS codes included in the retail and non-retail classifications. (Our definition of retail is consistent with that used in other studies; see Meltzer and Capperis, 2017; Bingham and Zhang, 1997; Stanback, 1981). In addition to the establishments classified as retail by NAICS (44-45), our retail category includes food services and other personal services that tend to rely on neighborhood-based markets.[19]

Our dependent variables capture three aspects of commercial economic performance. First, we examine the likelihood that an establishment closes, using the Infogroup dataset. We consider closure as the most severe outcome after the storm, or as the establishment's response along the extensive margin. Second, we track the number of jobs on each census block by year establishments using LODES data. Third, we examine sales revenues, using NYC DOF data.[20] Together, changes in these last two metrics (employment and sales) indicate whether and how establishments adjust their operations, or their response along the intensive margin.

We also explore the heterogeneity of effects across retail establishments. We use several variables from the Infogroup 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

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[18] There are likely to be other differences between retail and non-retail establishments, such as the fact that retail establishments tend to be on ground floors, and therefore more vulnerable to flooding damage. We are unable to test this directly as we do not know the building floor for the establishment.

[19] 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 Infogroup 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.

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

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.[21] Finally, we implement a more conservative definition of retail and separately consider the set of establishments most likely to serve local customers, like grocery stores, drug stores, and nail salons (see Appendix B for full list).

3.3 Addressing threats to validity

We are concerned about two threats to validity: selection bias and spatial spillovers. 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 that rely on immobile and expensive infrastructure could avoid flood-prone areas. Zoning could also drive certain kinds of establishments into more flood-prone areas.

To assess the severity of this threat, we compare differences between the characteristics of establishments and the structures located in evacuation zone A and those located elsewhere in NYC prior to the storm (Figure 3 shows that most establishments are located outside of the flood-prone areas of the city).[22] First, we consider the characteristics of establishments. Figure 4a shows establishments within the evacuation zone are 2.4 percentage points less likely to be micro, or very small, businesses (1-19 employees) and roughly one percentage point more likely

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

[22] This is also true for employment: over 90 percent of jobs are located outside of the evacuation zone A pre-Sandy. Sub-borough areas (SBA) without any area belonging to evacuation zone A or surge zone are dropped from the dataset. SBA is a collection of census tracts with aggregated population around 100,000.

to be chains (see Figure 4b).[23] Establishments in the evacuation zone are also slightly younger (1.4 percentage points more likely to be opened after 2008; see Figure 4c). Figure 4d shows that the retail share of establishments is 4.5 percentage points lower in the evacuation zone.[24]

Figures 5a through 5c reveal differences in property characteristics between businesses inside and outside of evacuation zones. First, establishments in the evacuation zone are 5.6 percentage points more likely than those outside to be located in one- and two-story buildings, increasing their exposure to flood-induced damage.[25] Second, establishments in the evacuation zone are 8 percentage points more likely to be located in industrial buildings than their counterparts outside the zone. Third, establishments in the evacuation zone are located in newer structures (though the overwhelming majority of all establishments in both areas were built before 1990, when new resilience standards were put into place). Although it is not displayed, average commercial property values per square foot (as a proxy for the cost of renting space) are very similar outside and inside the evacuation zone.[26]

In addition, there could be unobservable differences across establishments in higher and lower risk areas. Specifically, establishments located in riskier areas may better prepare for storm-induced damage or interruption given public warnings (i.e. moving inventory to avoid flooding and reinforcing windows and levee-type structures). Unfortunately, we do not have information on the establishments' activities leading up to the storm.

[23] All differences significant at the 99% level.
[24] The share of establishments that are restaurants is 2 percentage points lower in the higher risk areas and the share that are health and social services is slightly higher.
[25] All reported differences significant at the 99% level.

[26] The test statistic is 0.0173, and the P-value is 0.9862.

In order to address all of these concerns, we restrict the sample to establishments located on blocks in the pre-determined evacuation zone A, and therefore similarly subject to evacuation warnings. This restriction will also address any bias introduced from differences in establishment and structural composition across blocks located inside and outside the evacuation zone. In the year preceding Sandy, evacuation zone A included about ten percent of the city's gross commercial square footage and five percent of its gross residential square footage. We assume that establishments perceived relatively similar risk levels within evacuation zone A, and that any difference in preparedness was randomly distributed (controlling for observable property and establishment characteristics). For ease of presentation, we refer to evacuation zone A simply as the evacuation zone.

We also make the reasonable assumption that the distribution of severe flooding within the evacuation zone was random, and the error term in our regression is uncorrelated with this "treatment."[27] We use the variation in flooding within the evacuation zone to identify impacts of the storm. To capture the impact from flood exposure, we divide blocks in the evacuation zone into three categories: 1) blocks with three or more vertical feet of flooding are designated "high surge"; 2) blocks with flooding of less than three feet are labeled "low surge"; 3) blocks without any flooding are designated "no surge."[28] About 42 percent of the establishments in the

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[27] 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).

[28] The surge height by block is calculated as the average surge height for affected properties within a block. 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 60^{th} 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.

evacuation zone are located on “high surge” blocks, 51 percent are on “low surge” blocks, and 7 percent are on “no surge” blocks. Figure 6 provides an illustration of how blocks are classified into these three categories. We expect that any effects from the storm should be concentrated or more intense for the “high surge” blocks. These are the sites where water was deep enough to damage property and disrupt operations. Therefore, “high surge” will serve as our primary treatment indicator.

Since “low-surge” and “high-surge” blocks are naturally contiguous, “low-surge” indicators control somewhat for spillover effects from the “high-surge” areas; however, there could still be a certain amount of direct damage from the low-level flooding on those blocks. In order to more comprehensively address spatial spillovers, we further divide the low-surge area into a spillover area and a moderate-surge area. Specifically, “spillover” blocks are those that experienced only a modest amount of flooding (less than 0.5 feet), while the moderate-surge blocks experienced between 0.5 and 3 feet of flooding. The spillover blocks are by design contiguous to the other blocks in the surge area, and should capture any spillovers from the areas that experienced relatively more flooding. For example, if economic activity relocates from the severely affected areas to the less affected areas (where services are still intact), we will be able to directly estimate these effects by examining what happens to businesses on the spillover blocks as compared to the no-surge blocks.

3.4 Estimation

We estimate a series of regression models in which the dependent variable is one of three outcomes: establishment closure; employment; and average sales revenue.

3.4.1 Establishments

Because we can follow establishments' locations and operations over time, we estimate an establishment-level survival model to test for any changes in the probability of closure after Sandy. We identify closure when the establishment ceases to exist in the Infogroup NYC data or when we observe a move to a different location within New York City.[29] For the cohort of establishments in existence as of 2008, we test whether the time until closure shortens after Hurricane Sandy for the establishments on the inundated blocks compared to those on block without any flooding. We use a Cox model with non-proportional hazards to estimate the likelihood that an establishment closes between time *t* and Δ*t*, 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.[30]

$$h_{i,j}(t) = h_0(t)\exp(\lambda PostSandy_t + \beta High_j + \gamma Low_j + \eta High_i * PostSandy_t + \zeta Low_i * PostSandy_t + \delta Chain_i + \theta Employee_i + \alpha Cluster_j) \quad (1)$$

$h_{i,j}(t)$ 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.

[29] Results are qualitatively the same when we look specifically at closures and not movements to a different location.
[30] 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.

PostSandy takes on a value of 1 starting in 2013.[31] *High* takes on the value of 1 if the establishment is on a block with more than 3 feet of surge; *Low* equals 1 if the establishment is on a lower-surge block, as defined above. We are interested in η and ζ, which capture the post-Sandy impacts relative to areas without any flooding, and we expect that η will have a larger magnitude than ζ. Chain takes on the value of 1 if the establishment is part of a multi-establishment chain, $Employee_i$ captures the number of employees at establishment i in 2008 (baseline), $Cluster_j$ is the baseline number of retail/non-retail establishments on block j.[32] The *Cluster* covariate controls for any effect of being located in a cluster with other businesses, Finally, we stratify the model, to allow for different hazard rates across ZIP Codes and types of businesses, as measured by three-digit NAICS codes.

3.4.2 Jobs

For the employment model the unit of analysis is the census block. The regression takes the following form:[33]

$$Jobs_{it} = \lambda + \beta\ High_i * PostSandy_t + \gamma\ Low_i * PostSandy_t + \delta N_i + \theta D_{b,t} + e_{it} \qquad (2)$$

where the indicators, *PostSandy*, *High*, and *Low* are defined the same as in equation (1). We include N_i, a census block fixed effect, and $D_{b,t}$, a vector of SBA-year dummies to control for

[31] Hurricane Sandy hit New York City on October 29th, 2012, and the InfoUSA data provide a snapshot of establishments at the start of the year. Therefore, observations in 2013 should capture activity within a few months post-Sandy.
[32] 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. In addition, we estimated specifications that did not restrict to only businesses open in 2008 and found similar results (controlling for year of opening).
[33] We also run, and display, log-linear models and the results are substantially the same.

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.

3.4.3 Sales Revenues

Since sales revenues are only available at an aggregate unit of analysis (ZIP-zone), we estimate our sales regression at a higher level of aggregation:

$$log(Sales_{j,q}) = \lambda+\beta High_j*PostSandy_t+\gamma Low_j*PostSandy_t+ \delta \boldsymbol{N}_j + \theta \boldsymbol{D}_{b,q} +e_{j,q} \quad (3)$$

Our dependent variable is the log of average sales in sector q in ZIP-zone j. We use log of average sales to account for difference in sales volume across retail and non-retail filers. The indicators, *PostSandy*, *High*, and *Low* are defined as they are in equation (1).[34] $\boldsymbol{D}_{b,q}$ is a vector of borough-quarter-year dummies to control for macro changes over time and $\boldsymbol{N}_j$ is a ZIP-zone fixed effect. Unfortunately because they are aggregated, 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.[35] 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. All of the regressions are weighted by the number of tax filers in the ZIP-zone-quarter-year. We also estimate regressions where the post-Sandy impact varies across time, by interacting the *High* and *Low* dummies with year-specific indicators for retail and non-retail sub-samples.

[34] 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.
[35] The sample still excludes Sub-borough areas without evacuation zone A or inundation.

4. Effects on Business Closures and Employment

In this section we summarize the results of our regression models of business closures and employment, which use a similar identification strategy.

4.1 Business Closures

Table 3 shows our hazard model estimates of the difference in time to closure across pre- and post-Sandy periods and across high-, low-, and no-surge blocks.[36] The second column of Table 3 shows results for the retail sub-sample, incorporating ZIP Code and three-digit NAICS code strata. For retail establishments, the hazard ratios on *High*PostSandy* and *Low*PostSandy* are greater than one, indicating a higher probability of closing after the storm (relative to blocks without any surge). On blocks with surges higher than 3 feet, retail establishments experienced a change in closure rate after Sandy that was twice as high as that for establishments in areas without any surge. This is off of a base of 5.24 retail establishments on the typical "high-surge" block (compared to 4.22 establishments on a block without any inundation). The significant coefficient on *Low*PostSandy* suggests that establishments in less inundated areas are also threatened, albeit to a lesser degree than those hit directly by higher surges. In contrast, the hazard ratios for the non-retail subsample (column 3) are far smaller in magnitude (less than one for *Low*PostSandy*) and statistically insignificant.[37] Appendix C shows the survival curves for the retail and non-retail sub-samples and illustrates the divergence in survival estimates across

[36] Schoenfeld residual tests reject non-proportionality among all of the covariates.

[37] We also estimate hazard models controlling for Census Tract strata instead of ZIP Code. Although the coefficients are no longer significant for the retail sub-sample, the same patterns of relative magnitude remain. We lose quite a bit of variation when we use Census Tract strata.

surge and non-surge areas for the retail establishments after Sandy, but much smaller changes for non-retail businesses.

The Infogroup 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.[38] These results are displayed in column 4 of Table 3. The hazard ratios of interest are still highly significant and far larger in magnitude, suggesting that what we observe among retailers is even more pronounced for a more restrictive set of neighborhood-based businesses.

In Column 5, we explore heterogeneity within the non-retail category. Specifically, we use detailed industrial classifications to create a category for establishments providing recovery-related goods or services (i.e. construction materials, building material dealers, outpatient care, and community relief services). We want to confirm that the results for non-retail are not obscuring significant outcomes for establishments that might benefit, economically, from storm recovery. These results are displayed in the final column of Table 3, and neither of the coefficients of interest is significant.

Finally, we also run similar models testing for the likelihood of establishment *openings* on affected blocks. The coefficients on both *High*PostSandy* and *Low*PostSandy* are statistically insignificant, indicating that the flooded blocks suffered net losses in establishments that were driven by increased closures not reduced openings. These results are displayed in Appendix D.

[38] 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.

4.1.1 Testing for heterogeneous effects among retail establishments

Thanks to the detailed nature of our establishment data, we can test for heterogeneous effects across retail establishments. These results are displayed in Table 4.[39] We first consider establishment size, proxied by number of employees. We define discrete size categories based on the distribution of establishments in New York City. Over 80 percent of establishments have fewer than 10 employees. As predicted, closures are concentrated among these smaller establishments—those with fewer than 10 employees. These size differences are not evident in the non-retail sample.

As for differences in impacts across chain and standalone establishments, our results again conform with theoretical expectations. The coefficient on *High*Sandy* is highly significant in column 3, indicating a higher probability of closure for stand-alone establishments on inundated blocks. The same coefficients for the models run on chain businesses are smaller in magnitude and statistically insignificant. Of course, part of the difference here could be related to sample size: the number of standalone establishments far outweighs the number of chains in the sample and so standard errors are larger for models estimated on the latter set of establishments.

4.2 Jobs

[39] We do not display results for different types of non-retail establishments, but we tested for heterogeneity by size and structure and found little variation. We confirm that differences in the results are not due to differences in composition; small and standalone establishments are similarly represented in the retail and non-retail sub-samples. Results available upon request.

As for employment, Figure 7 shows that for both retail and non-retail establishments leading up to Sandy, the trend in the number of employees on high- and low-surge blocks is not significantly different from that on blocks without any surge, supporting the parallel trends assumption for our difference-in-difference estimation approach.[40] However, after Hurricane Sandy, the number of retail employees in high-surge areas falls significantly compared to no-surge areas; there is no significant change in employment on the low-surge blocks. There appears to be a slight recovery on the high-surge blocks in 2015, but employment remains low compared to no-surge areas. By comparison, non-retail employment does not change significantly after the storm.

Full regression results are displayed in Table 5. The first column shows that the storm appears to have had no significant impact on total employment on inundated blocks. However, when we divide the sample into retail and non-retail classifications, the results are consistent with what we observed in terms of establishment closures. Employment on "high-surge" blocks lost an average of about 10 retail jobs after Sandy, compared to blocks without any water surge.[41] This represents a 14 percent net loss for the typical block with non-zero employment prior to Sandy. Blocks with low surge levels are not significantly harmed. Again, there is no significant response for non-retail establishments (and the coefficients are positive). Columns 4-6 show that results are consistent when we use log-transformed employment counts as the dependent variable.[42]

[40] Statistical tests show high-surge and low-surge trends are also parallel before 2013.
[41] The *High*Sandy* and *Low*Sandy* coefficients are significantly different at the 5 percent level for the retail sample.
[42] We lose a large number of observations for retails when the dependent variable is log-transformed due since a large share of observations (65%) have fewer than 3 employees in retails, and 52% have zero.

4.3 Spillover effect

To examine whether Hurricane Sandy might generate positive spillovers on areas close to inundated areas, we divide the *low-surge* area into *spillover* blocks, with a surge height of more than zero but less than 0.5 feet, and *moderate-surge* blocks, with a surge height between 0.5 and 3 feet.

Table 6 shows the regression results. The coefficients on *High*PostSandy* and *Moderate*PostSandy* are largely unchanged, and the coefficient on *Spillover*PostSandy* is not statistically significant in any of the regressions. We see no evidence, in other words, that Hurricane Sandy had a significant effect on business closures or jobs in *spillover* areas.

5. Sales revenues

Figure 8 confirms parallel trends in sales revenues between surge areas and the comparison area without any surge for retail businesses. The figures also suggest a sharp and persistent decline in sales for retail businesses in high-surge areas after the storm. We also see some weak evidence of a positive effect in on retail sales in the low-surge area, which could reflect spillovers to these areas. Also, we see some evidence of an upward trend in sales for non-retail firms, prior to the storm, which clouds our interpretation of the results for non-retail businesses.

Table 7 presents regression results. For comparison, we present results for the evacuation-only sample alongside the full sample (with ZIP-zone controls), though the sample size falls significantly, and so we interpret these results with caution.[43] Columns 1, 3, and 5 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). The coefficients in the first two columns show no significant impacts after Sandy for the full set of businesses.

When we stratify the sample by type of establishment (or filer, in this case), the coefficient on *High*PostSandy* becomes statistically significant for retail establishments when not restricting to evacuation ZIP-zones: sales drop by about 9 percent after Sandy compared to areas without any flooding. When we restrict to only evacuation ZIP-zones, the coefficient on *High*PostSandy* loses significance, and we actually see a marginally significant positive coefficient on *Low*Post Sandy*. However, again, due to a smaller number of tax filers in the evacuation zone (and especially the part of the evacuation zone without any surge), we lose considerable estimation power.[44] The persistence of the "high-surge" effects displayed in column 3 is evident in Figure 8: retail sales do not recover and the null effect in "low-surge" areas is stable over time.

As for non-retail filers, the coefficient on *High*PostSandy* is significant and positive in the broader sample, while the coefficient on *Low*PostSandy* is not significant for either sample. We think the apparent positive effect on non-retail sales is explained by the fact that pre-Sandy sales trends, displayed in Figure 8, show an upward trend relative to no-surge areas leading up to the

[43] It is important to note that "high-surge" areas and "low-surge" areas in the sales analysis are not the same as their counterparts in the jobs and establishment analyses. The average surge height is calculated for the ZIP-zone rather than block. Some blocks belonging to "high-surge" in the jobs and establishments analysis are categorized as "low surge" in sales analysis, and vice versa.
[44] There are only 96 observations in the non-surge areas for retail analysis.

storm. Therefore, any positive effects after the storm are likely to be a continuation of that upward trajectory.[45]

6. Robustness checks

6.1 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. Appendix E1 shows these results. The results are consistent with those that use a categorical surge measure, and once again, only coefficients for the retail regressions are significant and negative. The smaller coefficient magnitudes across the board indicate that the continuous measure may obscure some nonlinearities in how inundation affects economic viability.

We also experiment with different thresholds of height to classify *High* and *Low* surge blocks. These results, displayed in Appendix E2, show that they are robust to adjustments in to surge height. Our findings are clearly not driven by our selection of a three-foot cutoff, and as expected, the magnitude of the *High*PostSandy* coefficient generally increases as the threshold gets higher.

6.2 Controlling for transit interruptions and relocations

While transportation networks, like the subway, were interrupted following the storm, they were not disabled for long.[46] Eighty percent of the city's subway system was operational one week

[45] In addition, around the time of Sandy, there was a reclassification of taxable goods and services such that more of them became tax-eligible; most of these goods and services fall into the non-retail category. This could also be driving the upward trend.

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 Appendix F1. The estimates are generally unchanged, suggesting that impacts 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 Infogroup 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 2009-2016. These results are displayed in Appendix F2 (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 (less than 6% of establishments that close in one location in our sample relocated to another site in the city between 2009-2016).

5. Conclusions and policy implications

[46] We are not concerned with lifeline utility outages ((Tierney 1997a and 1997b, Alesch and Holly 2002, Wasileski et al. 2011, Corey and Dietch 2011), as those were even more short-lived than the transit ones.

This paper explores how climate-related 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 establishments that tend to serve a more localized consumer base. Retail establishments are more likely to close after Sandy, without any significant replacement from new business openings. Furthermore, the establishment declines appear to be concentrated among smaller and standalone establishments--some of the most vulnerable businesses in good times. Retail employment and sales revenues also decline after Sandy; again there is not a similar shock to non-retail activity. And some of these losses appear to be fairly 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, in some cases, persistent--as of 2016 retail establishment closures had not subsided and sale revenues had not recovered. 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. However, in the case of closures, establishments exposed to less dramatic flooding were also vulnerable. There do not appear to be significant positive spillovers into nearby, less affected areas. Holding all else constant, retail establishments on city blocks with extreme flooding were on average two times more likely close and those blocks experienced 14 percent decrease in jobs and 9 percent decrease 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.

These business interruptions could generate meaningful fiscal losses, in the form of reduced sales and payroll tax revenues. In addition, neighborhoods are left without services and street activity, both of which could be vital for post-disaster recovery. 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 localized and tailored to the type of businesses at risk.

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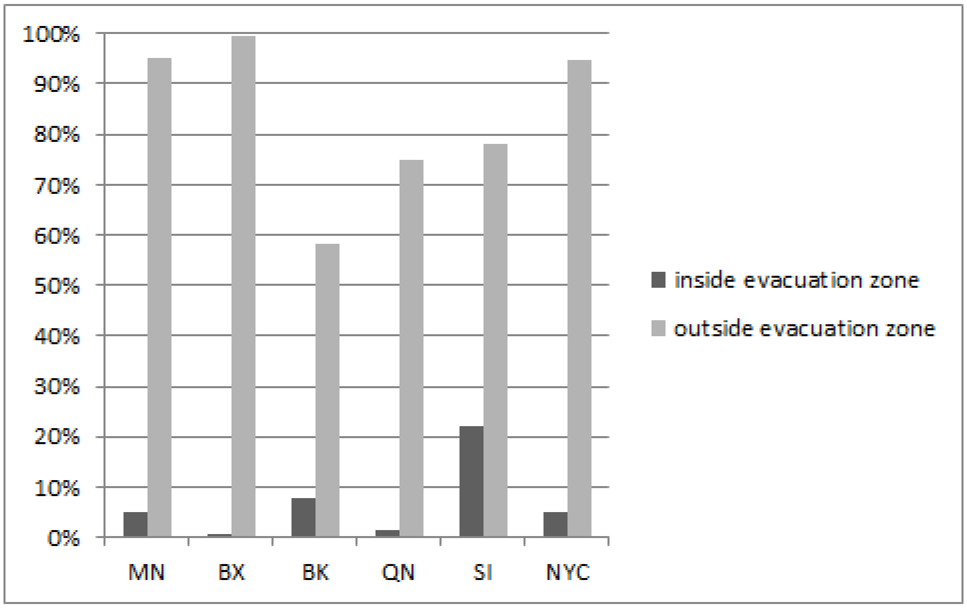
Figure 1: NYC Evacuation Map

Notes: The black area is Zone A, the evacuation zone that was instructed to evacuate prior to Sandy. The grey area is Zone B, and the crosshatched area is Zone C.

Figure 2: Surge Levels by borough-block

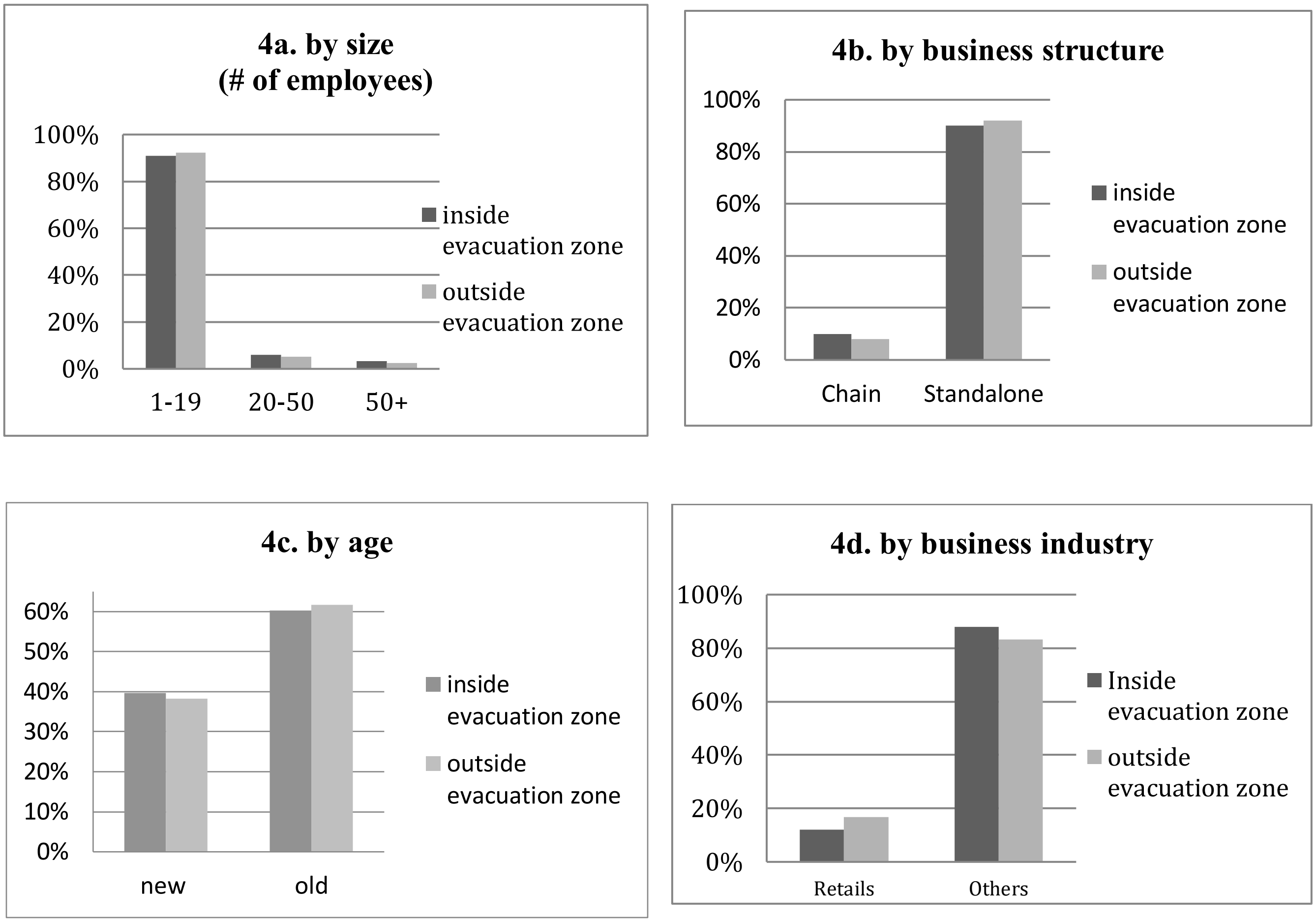
Notes: The surge height by block is higher than 3 feet in black areas, 1.5-3 feet in grey areas, and smaller than 1.5 feet but higher than 0 in crosshatched areas.

Figure 3: Distribution of businesses across zones, 2012



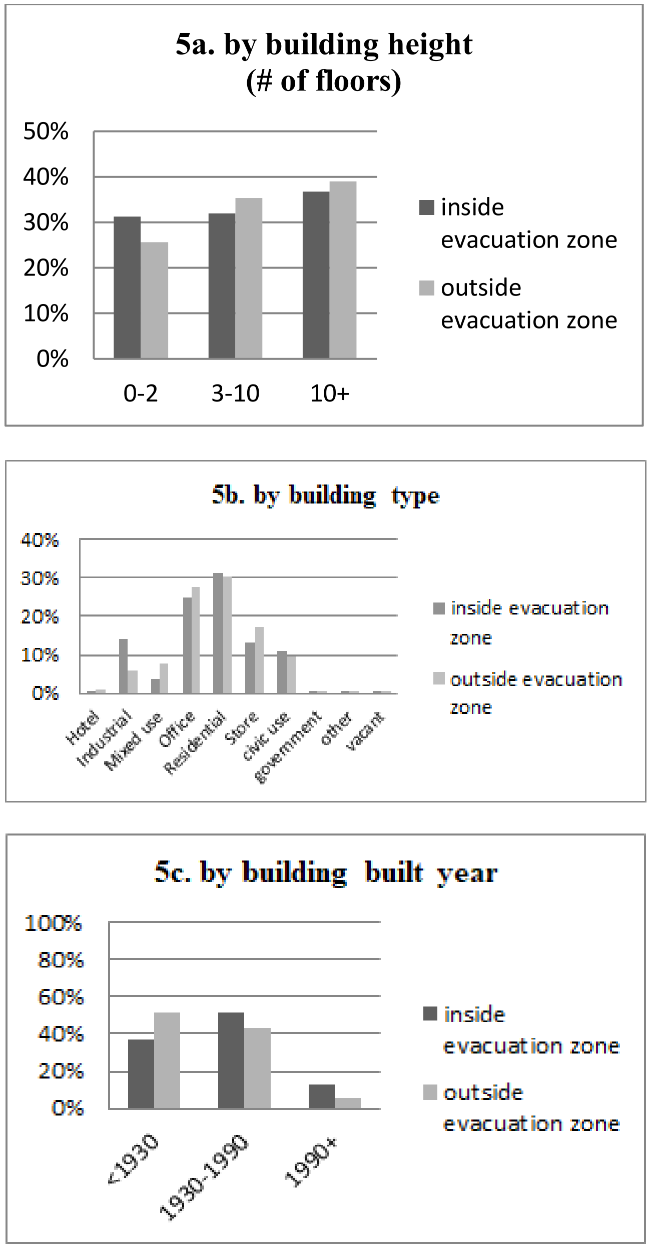
Notes: Y-axis reports shares (%)

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



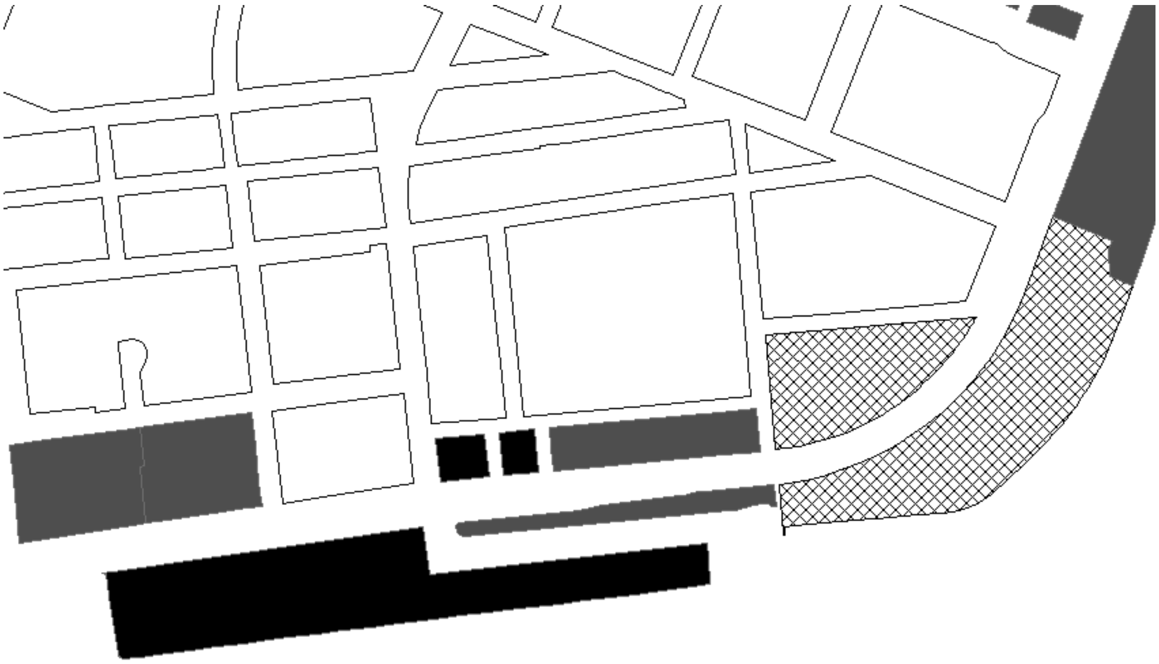
Notes: old establishments open before 2009, and new establishments open after 2008; Y-axis reports shares (%)

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



Notes: Y-axis reports shares (%)

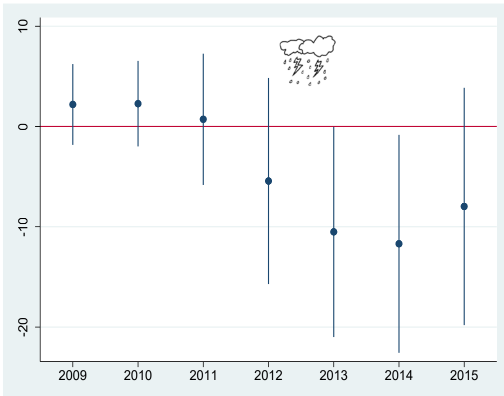
Figure 6,: Evacuation and Surge Zones



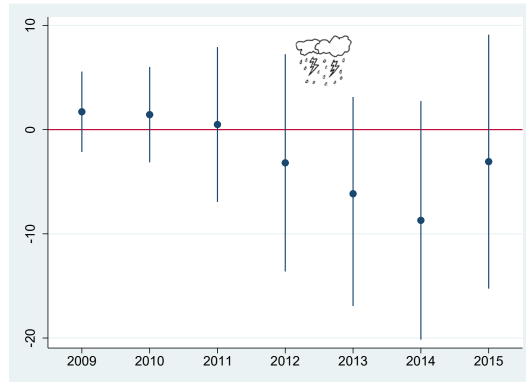
Notes: This is a part of Lower East Side. The black areas are “high surge” blocks, the grey areas are “low surge” blocks, and the crosshatched areas are “non-surge” blocks, which all belong to the evacuation zone A. The unshaded blocks are outside the evacuation zone A.
.

Figure 7: Retail and Non-Retail Jobs by Year

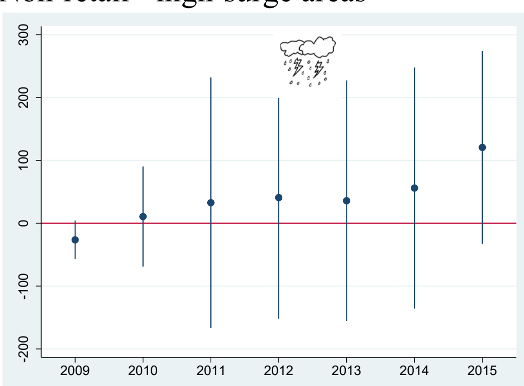
Retail: high-surge areas



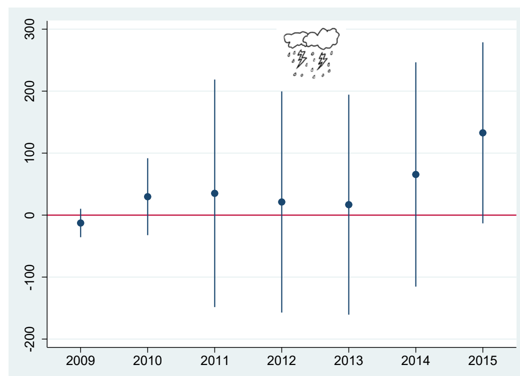
Retail: low-surge areas



Non-retail - high-surge areas



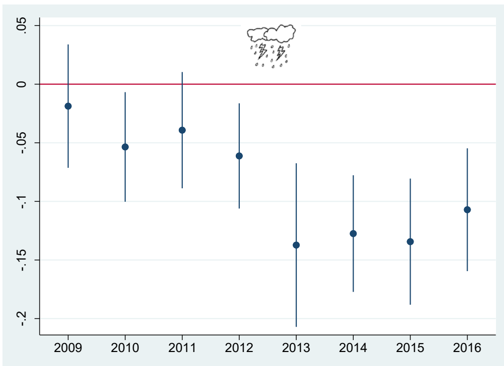
Non-retail - low-surge areas



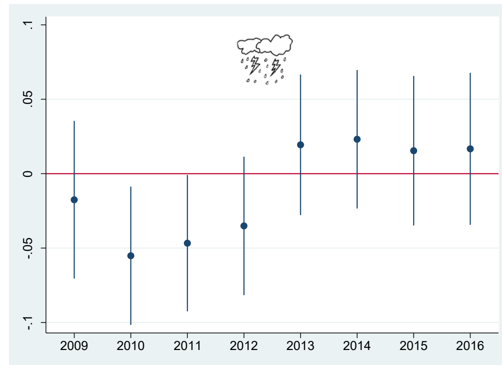
Notes: Plotted points are adjusted values, controlling for block fixed effects, and SBA-year dummies.

Figure 8: Retail and Non-Retail log(Average Sales)

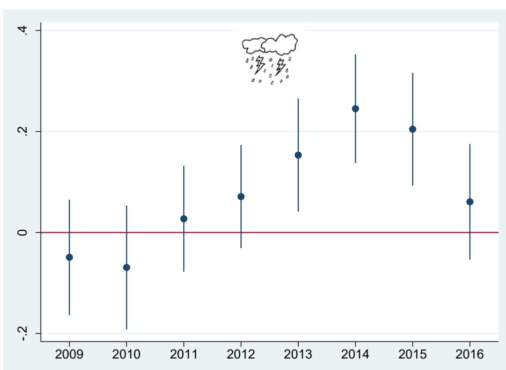
Retail: high-surge areas



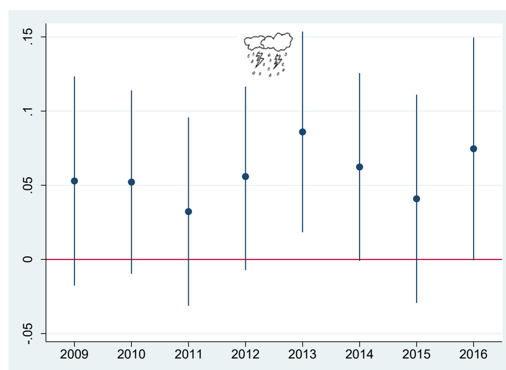
Retail: low-surge areas



Non-retail: high-surge areas



Non-retail: low-surge areas



Notes: Plotted points are adjusted values, controlling for ZIP-zone fixed effects, borough-quarter-year dummies. The OLS regression is weighted by the number of filers per ZIP-zone.

Table 1: Summary Statistics

Variable	# of Obs	Mean	Std. Dev.	Min	Max
Probability of closure	19,058	0.669	0.471	0	1
Probability of closure (retails)	3,574	0.623	0.485	0	1
Probability of closure (non-retails)	15,484	0.680	0.467	0	1
# of years until closure	12,750	3.695	2.338	1	8
# of years until closure (retails)	2,226	3.715	2.313	1	8
# of years until closure (non-retails)	10,529	3.691	2.344	1	8
# of jobs	9,995	176.6043	783.3688	1	12226
# of jobs (retails)	9,995	18.02401	65.63417	0	1274
# of jobs (non-retails)	9,995	158.5803	766.3436	0	12168
quarterly average sales $1,000	10,644	65407.32	36646.89	3044.32	363173.8
quarterly average sales $1,000 (retails)	8,610	69794.58	42208.05	6326.21	430204.8
quarterly average sales $1,000 (non-retails)	8,574	48963.95	32346.64	1582.13	265601.4

Table 2: Retail and Non-retail Classification

Category	NAICS	Description
Infogroup		
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[47]	
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

[47] 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 3: Hazard Model Regression Result, Establishments

	(1) All		(2) Retail		(3) Non-retail		(4) Neighborhood-based Retail		(5) Recovery-related Non-retails	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
PostSandy	-39.48	0	-39.29	0	-37.28	0	-40.38	0	-40.03	0
	(0)		(0)		(0)		(0)		(0)	
High	-0.0548	0.947	-0.0399	0.961	-0.0567	0.945	-0.425	0.654	-0.200	0.818
	(0.0733)		(0.197)		(0.0790)		(0.376)		(0.195)	
Low	-0.0689	0.933	-0.0117	0.988	-0.0741	0.929	-0.504	0.604	-0.199	0.819
	(0.0715)		(0.193)		(0.0772)		(0.379)		(0.176)	
*High*PostSandy*	0.253**	1.288**	0.728**	2.071**	0.129	1.138	1.724***	5.609***	0.420	1.522
	(0.119)		(0.297)		(0.130)		(0.546)		(0.344)	
*Low*PostSandy*	0.119	1.127	0.674**	1.961**	-0.0293	0.971	1.321**	3.746**	0.436	1.547
	(0.117)		(0.292)		(0.128)		(0.548)		(0.315)	
Chain	-0.116**	0.891**	-0.146	0.864	-0.110**	0.896**	-0.619***	0.539***	-0.155	0.856
	(0.0486)		(0.109)		(0.0548)		(0.239)		(0.186)	
Employee	-0.000122	1.000	-0.00120	0.999	-7.39e-05	1.000	0.00335	1.003	-0.00234	0.998
	(0.000151)		(0.000954)		(0.000151)		(0.00300)		(0.00183)	
Cluster	5.98e-05	1.000	-0.00259	0.997	-3.52e-07	1.000	0.00381	1.004	0.000596	1.001
	(0.00110)		(0.00230)		(0.000102)		(0.00543)		(0.000503)	
Observations	19,058	19,058	3,574	3,574	15,484	15,484	863	863	1,335	1,335

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Cluster is calculated as the # of retails/non-retails by block. Regressions are stratified by ZIP code and three-digit NAICS code.

Table 4: Hazard Model Regression Result, Retail Establishments, Heterogeneity Analysis

	(1) <10 employee		(2) >=10 employee		(3) Standalone		(4) Chain	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
PostSandy	-37.84	0	-37.30	0	-39.28	0	-37.54	0
	(1.993e+06)		(4.967e+06)		(0)		(8.025e+06)	
High	-0.107	0.899	-0.0241	0.976	-0.0796	0.923	-0.184	0.832
	(0.261)		(0.385)		(0.215)		(1.165)	
Low	-0.0924	0.912	0.00389	1.004	-0.0700	0.932	-0.113	0.893
	(0.257)		(0.392)		(0.211)		(1.304)	
*High*PostSandy*	0.973**	2.646**	0.0143	1.014	0.769**	2.157**	0.583	1.791
	(0.382)		(0.712)		(0.328)		(1.559)	
*Low*PostSandy*	0.941**	2.562**	-0.193	0.825	0.723**	2.061**	0.747	2.112
	(0.375)		(0.713)		(0.323)		(1.656)	
Chain	-0.361**	0.697**	-0.143	0.867				
	(0.167)		(0.197)					
Employee			-0.00327	0.997	-0.00130	0.999	-0.000427	1.000
			(0.00216)		(0.00110)		(0.00298)	
Cluster	-0.00142	0.999	-0.00291	0.997	-0.00200	0.998	-0.0197	0.980
	(0.00280)		(0.00492)		(0.00238)		(0.0138)	
Observations	2,758	2,758	816	816	3,225	3,225	349	349

Note: Cluster is calculated as the # of retail/non-retail establishments by block. Regressions are stratified by ZIP code and three-digit NAICS code.

Table 5: Regression Results, Jobs

	# of jobs			ln(# of jobs)		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Total	Retail	Non-retail	Total	Retail	Non-retail
*High*PostSandy*	47.86	-9.790***	57.65	-0.0320	-0.142*	0.0269
	(42.54)	(3.730)	(42.47)	(0.0907)	(0.0829)	(0.0989)
*Low*PostSandy*	50.32	-5.931	56.25	0.0359	-0.129	0.122
	(42.66)	(3.809)	(42.27)	(0.0888)	(0.0800)	(0.0959)
Constant	2,776	451.7	2,325	3.003***	2.198***	2.866***
	(9,370)	(753.3)	(9,149)	(0.0291)	(0.0373)	(0.0311)
block fixed effects	Y	Y	Y	Y	Y	Y
SBA-year dummies	Y	Y	Y	Y	Y	Y
Observations	9,995	9,995	9,995	9,995	4,842	9,396
R-squared	0.039	0.085	0.035	0.046	0.080	0.042
Number of blocks	1,679	1,679	1,679	1,679	1,000	1,622

standard errors are clustered by block

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

Table 6: Regression Results, Spillover Effects

	(1) Hazard-Retail Coefficient	Hazard Ratio	(2) Hazard-Non-retail Coefficient	Hazard Ratio	(3) Jobs-Retail	(4) Jobs-Non-retail
PostSandy	-38.86	0	-37.23	0		
	(2.095e+06)		(0)			
High	-0.0492	0.952	-0.0552	0.946		
	(0.197)		(0.0792)			
Moderate	-0.0339	0.967	-0.0674	0.935		
	(0.195)		(0.0788)			
Spillover	0.109	1.115	-0.101	0.904		
	(0.243)		(0.0935)			
*High*PostSandy*	0.770***	2.159***	0.115	1.122	-9.678**	55.72
	(0.298)		(0.130)		(3.758)	(42.61)
*Moderate*PostSandy*	0.751**	2.119**	-0.0741	0.929	-5.336	47.71
	(0.298)		(0.130)		(4.168)	(42.98)
*Spillover*PostSandy*	0.383	1.467	0.116	1.122	-6.734	66.23
	(0.369)		(0.155)		(4.227)	(51.00)
Constant					166.2	3,431
					(743.0)	(6,347)
Observations	3,574	3,574	15,484	15,484	9,995	9,995
R-squared					0.085	0.035
Number of blocks					1,679	1,679

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Column (1) and (2) are stratified by ZIP code and three-digit NAICS code, chain, employee, and cluster are controlled. In Column (3) and (4), block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block.

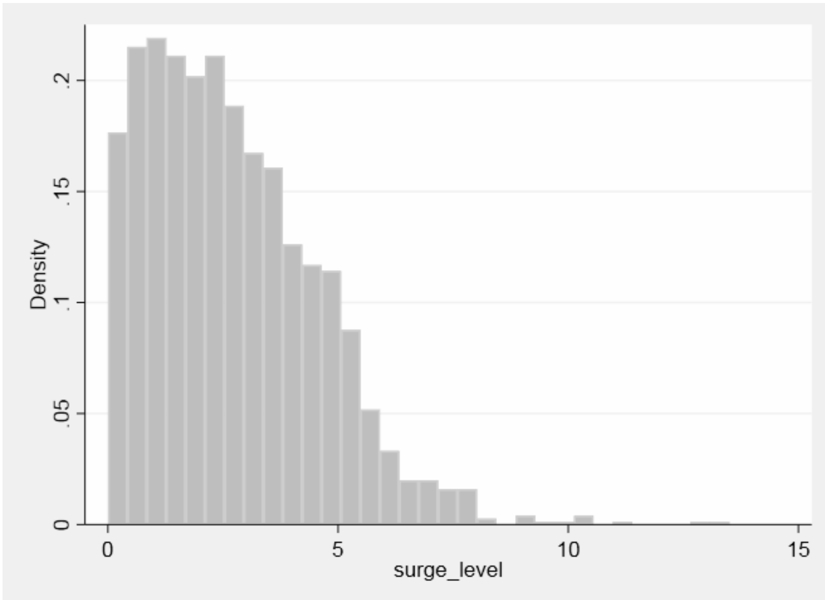
Table 7: Regression Results, Sales Revenues

ln(average sales)	(1) Total	(2) Total	(3) Retail	(4) Retail	(5) Non-retail	(6) Non-retail
*High*PostSandy*	-0.0436	0.114	-0.0946***	0.0122	0.156**	-0.167
	(0.0334)	(0.114)	(0.0345)	(0.0838)	(0.0781)	(0.243)
*Low*PostSandy*	0.0235	0.162	0.0379	0.187*	0.0250	-0.399
	(0.0256)	(0.115)	(0.0374)	(0.0959)	(0.0447)	(0.245)
Constant	11.10***	11.13***	11.25***	11.28***	10.89***	10.84***
	(0.0157)	(0.0370)	(0.0210)	(0.0726)	(0.0297)	(0.123)
evacuation zone A only	N	Y	N	Y	N	Y
ZIP-zone dummies	Y	Y	Y	Y	Y	Y
borough-quarter-year	Y	Y	Y	Y	Y	Y
Observations	10,644	1,965	8,610	1,154	8,574	1,150
R-squared	0.961	0.885	0.968	0.901	0.896	0.837

Standard errors are clustered by Zip-zone in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: OLS regressions are weighted by the number of filers by industry and ZIP-zone.

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

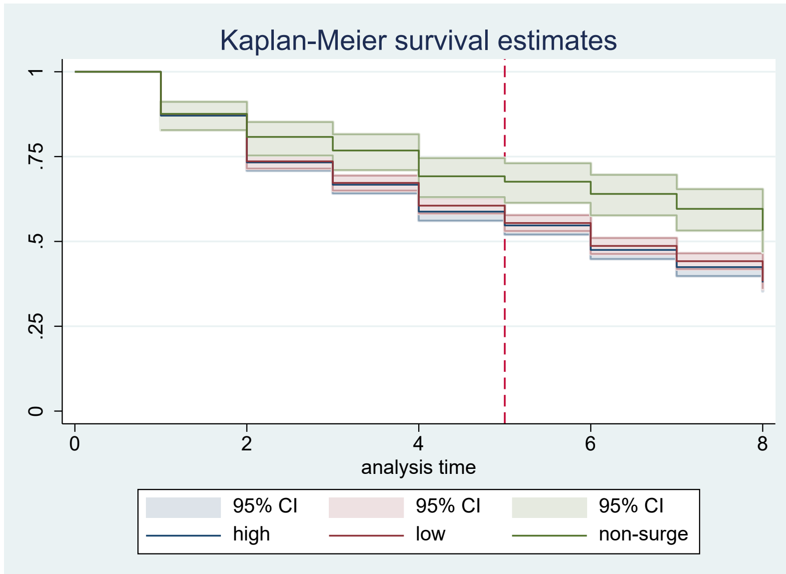
Category	NAICS	Description
Neighborhood-based Retail	311811	Retail Bakery
	444130	Hardware stores
	445110	Grocery stores
	445120	Convenience food stores
	445210	Meat markets
	445220	Seafood markets
	445230	Fruit markets
	445291	Baked goods stores, retailing only (except immediate consumption)
	445292	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 Retail	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

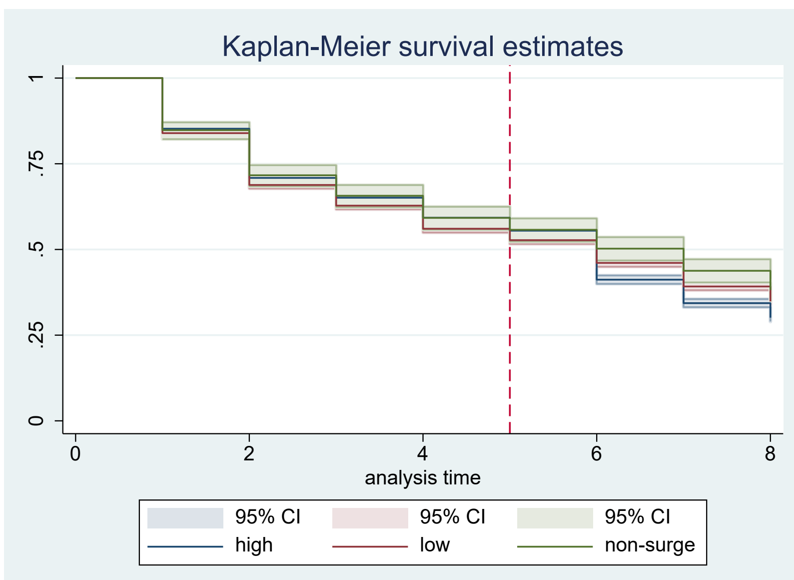
	448150	Clothing accessories stores
	448190	Other Clothing stores, like bridal and school uniform
	448210	Shoe (except bowling, golf, spiked) stores
	448310	Jewelry stores, precious
	448320	Luggage and leather stores
	451110	Athletic equipment and supply stores (including uniforms)
	451130	Needlecraft 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

Appendix C: Retail vs. Non-Retail Establishment counts, Before and After Sandy

Retail



Non-retail



Note: Kaplan-Meier survival estimates are not controlled by any establishment characteristic or stratified by any group.

Appendix D: Establishments openings by block

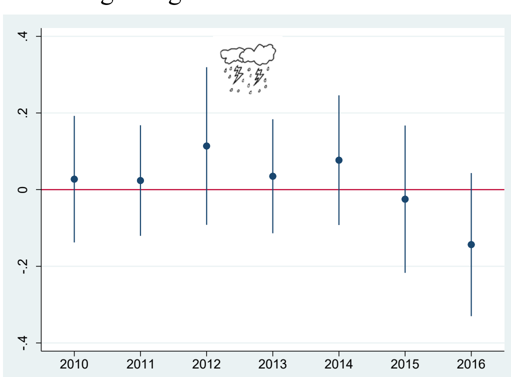
	(1)	(2)	(3)
# of openings by block	**Total**	**Retail**	**Non-retail**
*High*PostSandy*	-0.191	-0.0554	-0.136
	(0.220)	(0.0492)	(0.201)
*Low*PostSandy*	-0.0588	0.0311	-0.0900
	(0.190)	(0.0414)	(0.169)
Constant	2.050***	0.297***	1.753***
	(0.0893)	(0.0179)	(0.0825)
Block fixed effects	Y	Y	Y
SBA-year dummies	Y	Y	Y
Observations	9,832	9,832	9,832
R-squared	0.136	0.071	0.136
Number of blocks	1,229	1,229	1,229

Clustered errors in parentheses

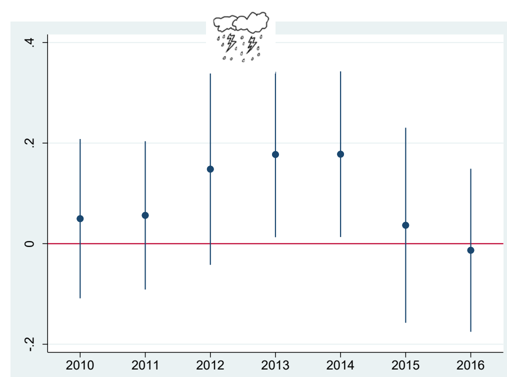
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note: block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block.

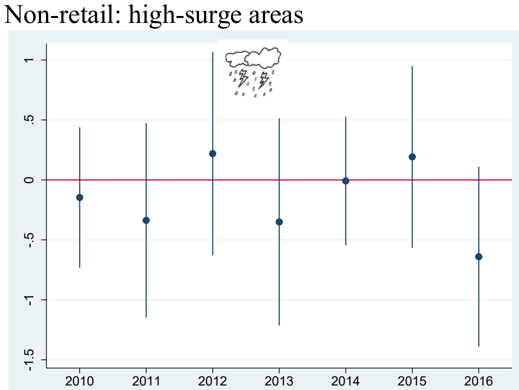
Retail: high-surge areas



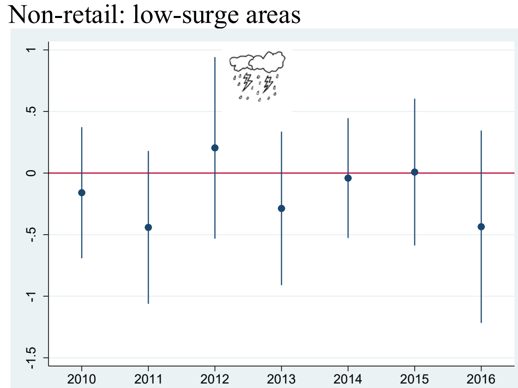
Retail: low-surge areas



Non-retail: high-surge areas



Non-retail: low-surge areas



Appendix E1: Regression Results, Continuous Surge Level

	(1)		(2)		(3)	(4)	(5)	(6)
	Hazard - Retail		Hazard - Non-retail		Jobs - Retail	Jobs – Non-retail	Sales – Retail	Sales - Non-retail
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio				
Surge Level	-0.0156	0.985	0.000986	1.001				
	(0.0231)		(0.0106)					
*Surge Level*PostSandy*	0.0926**	1.097**	0.00628	1.006	-1.02***	4.323	-0.00784	0.0167
	(0.0371)		(0.0174)		(0.359)	(3.595)	(0.00988)	(0.0145)
Constant					20.30***	149.0**	11.27***	10.87***
					(3.891)	(60.69)	(0.0179)	(0.0277)
Observations	3,574	3,574	15,484	15,484	9,995	9,995	8,581	8,545
R-squared					0.084	0.035	0.968	0.897

Standard errors in parentheses

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

Note: Column (1) and (2) are stratified by ZIP code and three-digit NAICS code, *PostSandy*, chain, employee, and cluster are controlled. In Column (3) and (4), block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block. ZIP-zone fixed effects, and borough*quarter-year dummies are controlled in Column (5) and (6).

Appendix E2: Key Coefficients using Different Threshold, Evacuation Zone Sample

Threshold	Coefficients	(1) Hazard - Retail Coefficient	Hazard Ratio	(2) Hazard - Non-retail Coefficient	Hazard Ratio	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retail	(6) Sales - Non-retail
2 feet	*High*PostSandy*	0.700**	2.014**	0.0209	1.021	-8.787**	56.58	-0.0190	0.0601
		(0.292)		(0.127)		(3.766)	(43.03)	(0.0313)	(0.0444)
	*Low*PostSandy*	0.691**	1.995**	0.0660	1.068	-5.952	57.15	0.000543	0.0762
		(0.300)		(0.132)		(3.955)	(42.75)	(0.0995)	(0.102)
3 feet	*High*PostSandy*	0.728**	2.071**	0.129	1.138	-9.79***	57.65	-0.095***	0.156**
		(0.297)		(0.130)		(3.73)	(42.47)	(0.0345)	(0.0781)
	*Low*PostSandy*	0.674**	1.961**	-0.0293	0.971	-5.931	56.25	0.0379	0.0250
		(0.292)		(0.128)		(3.809)	(42.27)	(0.0374)	(0.0447)
4 feet	*High*PostSandy*	0.877***	2.403***	0.106	1.112	-11.3***	73.27*	-0.0944**	0.0384
		(0.306)		(0.136)		(3.805)	(40.07)	(0.0436)	(0.140)
	*Low*PostSandy*	0.627**	1.872**	0.0163	1.016	-5.931	50.65	-0.00823	0.0651
		(0.290)		(0.126)		(3.718)	(42.61)	(0.0343)	(0.0432)

Note: Column (1) and (2) are stratified by ZIP code and three-digit NAICS code, *PostSandy*, *High, Low,* chain, employee, and cluster are controlled. In Column (3) and (4), block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block. ZIP-zone fixed effects, and borough*quarter-year dummies are controlled in Column (5) and (6).

Appendix F1: Regression Results, Excluding Transit-Interrupted Areas

	(1)		(2)		(3)	(4)	(5)	(6)
	Hazard - Retail		Hazard - Non-retail		Jobs - Retail	Jobs - Non-retail	Sales - Retails	Sales - Non-retails
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio				
*High*PostSandy*	0.721**	2.056**	0.132	1.141	-10.02***	57.92	-0.095**	0.183**
	(0.297)		(0.13)		(3.788)	(42.88)	(0.0369)	(0.0781)
*Low*PostSandy*	0.678**	1.971**	-0.0314	0.969	-5.895	56.78	0.0395	0.0252
	(0.292)		(0.128)		(3.856)	(42.76)	(0.0380)	(0.0452)
Constant					20.78***	158.0***	11.24***	10.89***
					(3.751)	(57.27)	(0.0212)	(0.0299)
Observations	3,508		15,176		9,296	9,296	8,458	8,422
R-squared					0.086	0.035	0.969	0.897

Standard errors in parentheses

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

Note: Column (1) and (2) are stratified by ZIP code and three-digit NAICS code, *PostSandy, High, Low*, chain, employee, and cluster are controlled. In Column (3) and (4), block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block. ZIP-zone fixed effects, and borough*quarter-year dummies are controlled in Column (5) and (6).

Appendix F2: Hazard Model Regression Results, Close only

	(1)		(2)		(3)	
	All		Retail		Non-retail	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
PostSandy	-34.92	0	-37.93	0	-37.22	0
	(194,090)		(2.215e+06)		(0)	
High	-0.0411	0.960	0.0353	1.036	-0.0496	0.952
	(0.0750)		(0.200)		(0.0810)	
Low	-0.0380	0.963	0.0542	1.056	-0.0454	0.956
	(0.0778)		(0.205)		(0.0843)	
*High*PostSandy*	0.138	1.148	0.687**	1.989**	-0.00408	0.996
	(0.121)		(0.306)		(0.132)	
*Low*PostSandy*	0.188	1.207	0.680**	1.974**	0.0446	1.046
	(0.126)		(0.313)		(0.138)	
Chain	-0.110**	0.896**	-0.129	0.879	-0.105*	0.900*
	(0.0504)		(0.113)		(0.0568)	
Employee	-0.000217	1.000	-0.00128	0.999	-0.000142	1.000
	(0.000186)		(0.000956)		(0.000187)	
Cluster	-0.000412	1.000	-0.00256	0.997	4.98e-05	1.000
	(0.00116)		(0.00254)		(0.000107)	
Observations	18,314	18,314	3,427	3,427	14,887	14,887

Standard error in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Cluster is calculated as the # of retails/non-retails by block. Regressions are stratified by ZIP code and three-digit NAICS code.