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

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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 there were economic losses from Sandy and, as expected, they were concentrated among retail businesses with more localized consumer bases. After Sandy, retail establishments exposed to higher surge levels experienced significantly higher rates of business closure and larger sales revenue declines compared to establishments with less exposure to inundation. In addition, closures were concentrated among standalone establishments. These losses appear to be fairly persistent, showing no sign of recovery to pre-storm levels by 2016. The evidence for jobs is more tentative—at most, they exacerbated an existing downward trend for retail establishments after Sandy.

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1. Introduction

The density that makes urban areas economically productive may also make them more vulnerable to damage in the face of extreme events, like natural disasters, terrorist attacks and global pandemics. 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 an extreme event like Sandy; 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. 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. We compare changes in employment, revenues and closures before and after the storm for establishments that saw storm surge with changes for nearby establishments that did not. 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 focus on a restricted sample of establishments located within evacuation zone A. To identify the storm's impact, we use 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. Our results suggest that non-retail establishments in high surge areas did not see a similarly large hit. Furthermore, establishment closures are mitigated by new establishment openings and are concentrated among 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 that saw no flooding. In comparison, non-retail businesses saw no differential job losses on high-surge blocks. However, employment declines on blocks with high surges appear to have started in the year prior to Sandy, although the pre-trend is not significant and declines are larger after the storm. Still, this suggests some caution in interpreting our difference-in-difference results for employment. 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 less inundated 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 also 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). In a study of larger firms after the 1959 Ise Bay Typhoon in

[1] Basker and Miranda 2018 is an exception.

Japan, the authors find that on average, older manufacturing firms survived for longer after the disaster and that construction firms saw employment increases (Okubo and Strobl 2020). However, the analysis did not control for different exposures to flooding risk leading up to the typhoon.

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).

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.

Indaco, Ortega and Taspinar (2019) have produced the study most closely related to ours; they also estimate localized business outcomes in post-Sandy NYC. They build a panel of parcels for the city and control for location inside the FEMA designated flood zones. Using unemployment insurance employment data (QCEW) they find bigger employment and wage declines and more establishment exits in the parcels more damaged by the storm. They find differential impacts by borough, suggesting that the industrial composition of businesses could be mediating the economic impacts. The current analysis takes a different approach from this paper and 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 (specifically those mandated to evacuate before Sandy). Second, we develop simple hypotheses about heterogeneous responses to extreme events, across a bigger universe of businesses, and directly test those hypotheses empirically, in a dense urban 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 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.[2]

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

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). We focus on blocks within Evacuation Zone A, since 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 (see Figure 1).

We use evacuation zones rather than FEMA flood 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, when we replicate our analyses using the FEMA flood zones instead of the evacuation zone, we obtain fairly consistent results. 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). 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.[3] 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.[4] We exploit the variation in surge height for our identification strategy, discussed in the next section. 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.

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[3]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.

[4] Surge levels for the block are calculated as the average height across all of the commercial properties on the block

We obtain information on establishments from the Infogroup 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 their data from 2010 through 2016. 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.[7] 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 establishments 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. The sample for New York City as a whole includes 372,500 establishments operating in 2010. For purposes of comparison, this sample is larger than the 220,034 establishments recorded in the County Business Patterns, because the Infogroup dataset is more likely to capture non-employer firms and small chain establishments than public records. [8] Our core sample includes 17,320 establishments operating in 2010 in Evacuation Zone A.

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

[6] 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.

[7] 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).

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

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.[9] 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).[10] 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 in Evacuation Zone A.

To capture sales, we use reported quarterly taxable sale revenues for all NYC commercial filers from the city's Department of Finance (NYC DOF).[11] 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

[9] We can access LODES data back to 2002. We replicate the analyses with this longer time frame and the results are substantively the same.

[10] 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).

[11] 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.

into one of these four zones[12] 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 ZIP-zone-quarter-year, 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 per establishment across group-quarters is $65,407, and the standard deviation is $36,647.[13] 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.[14] We have this information for 2012.

3.2 Identifying Commercial Economic Activity

[12] 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.

[13] 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.

[14] 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.

We examine outcomes for all types of businesses but also conduct separate analyses for retail and non-retail sectors to observe how the response varies for businesses that draw more on neighborhood-based customers as compared to businesses that serve a geographically more dispersed clientele.[15] See Table 1 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 (722) and other personal services that tend to rely on neighborhood-based markets.[16]

Our dependent variables capture three aspects of commercial economic performance. First, we examine 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.[17] 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.

[15] 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.

[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 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.

[17] 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.

Table 2 shows summary statistics for these dependent variables: the probability of closure for establishments operating in 2010 (during 2010 to 2016), the time until closure for establishments that closed before 2016, the number of jobs from LODES (at block-level), and quarterly average sales revenues per business tax filer from DOF.

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 from 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] Finally, we separately consider the set of retail establishments most likely to serve local customers, such as 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. In terms of selection bias, the worry is that 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.

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

When comparing the characteristics of establishments and the structures located in evacuation zone A and those outside evacuation zone A but in SBAs with at least one block that experienced a surge, we find several significant differences.[19] Establishments within the evacuation zone A are slightly younger, 2.4 percentage points less likely to have fewer than 20 employees and roughly one percentage point more likely to be chains.[20] The retail share of establishments is 4.5 percentage points lower in the evacuation zone.[21] Further retail establishments in the evacuation zone A are less likely to be clothing, shoes, jewelry and personal care services as compared to those outside.[22]

As for differences in property characteristics between businesses inside and outside of evacuation zone A, 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.[23] 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 resiliency

[19] Over 90 percent of establishments and 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.
[20] All differences significant at the 99% level.
[21] 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.
[22] Outside Evacuation Zone A, 17% of retail establishments sell clothing, shoes, or jewelry while 15% offer personal care services. By contrast, among retail establishments inside Evacuation Zone A, 10% sell clothing, shoes, or jewelry, while 9% offer personal care services.
[23] All reported differences significant at the 99% level.

standards were put into place). 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.[24]

Perhaps more importantly, there could be unobservable differences across establishments in higher and lower risk areas. Specifically, establishments located in evacuation zone A 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), especially given that New York City officials issued mandatory evacuation orders for residents and businesses in evacuation zone A. Unfortunately, we do not have information on the establishments' activities leading up to the storm.

In order to address these potential differences, we restrict the sample to establishments (and blocks and ZIP-zones) located 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. We assume that establishments perceived relatively similar risk levels within evacuation zone A, and that any unobserved differences in preparedness were randomly distributed (controlling for observable property and establishment characteristics). Again, we think the evacuation zones are more relevant for the establishments' perception of (and therefore behavior related to) risk; the FEMA flood zones communicate risk primarily through mortgage-triggered insurance requirements that apply to property owners but not the commercial tenants. For ease of presentation, we refer to evacuation zone A simply as the evacuation zone. In the

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

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 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."[25] 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."[26] (We experiment with different thresholds, and find qualitatively similar results; see Appendix F). Approximately 42 percent of the establishments in the evacuation zone are located on "high surge" blocks, 51 percent are on "low surge" blocks, and 7 percent are on "no surge" blocks. Figure 3 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. Importantly, we find minimal differences between the industrial sub-classification of establishments (i.e. the kinds of goods and services) in evacuation zone A that saw high storm surges and those that did not.

[25] 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).

[26] 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 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.

As for spatial spillovers, since “low-surge” and “high-surge” blocks are naturally contiguous, the “low-surge” indicator could capture some 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, as shown in Figure 4. 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

To test for any changes in the probability of closure after Sandy, we estimate both a linear probability model and a survival model at the establishment level between 2010 and 2016. 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 for the cohort of establishments in existence as of 2010.[27] In order to ensure accurate tracking of establishment closures, every business in the InfoUSA universe is contacted at least once a year. Tracking establishment closures is one of the most important parts of Infogroup's database maintenance (Lavin, 2000).

For the linear probability model, the dependent variable takes on the value of 1 after the establishment closes, and 0 otherwise:

$$P_{it} = \lambda + \beta\, High_i * PostSandy_t + \gamma\, Low_i * PostSandy_t + \delta Chain_i + \theta \#Employees_i + \eta NAICS_i + \zeta N_n + \alpha D_{b,t} + e_{it} \qquad (1)$$

PostSandy takes on the value of 1 starting in 2013.[28] *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 block that saw some surge but more modest levels, as defined above. We are interested in β and γ, which capture the post-Sandy impacts relative to areas without any flooding, and we expect that β will have a larger magnitude than γ. Chain takes on the value of 1 if the establishment is part of a multi-establishment chain, $\#Employees_i$ captures the number of employees at establishment *i* in 2010 (baseline). *NAICS* includes three-digit NAICS dummies, controlling for the type of businesses. In addition, we include N_n, block fixed effects, and $D_{b,t}$, a vector of SBA-year dummies to control for broader neighborhood changes over time.[29] We also estimate models where the post-Sandy impact varies across time, by interacting the *High* and *Low* dummies with year-specific indicators.

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[27] Results are qualitatively the same when we look specifically at closures and exclude establishments that move to a different location, see Appendix G2 for details.

[28] 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.

[29] We also tried ZIP*Year dummies, and the results are consistent. In order to minimize the AIC, we present analyses with SBA*Year controls.

In addition, we estimate 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.[30]

$$h_{i,j}(t) = h_0(t) \exp(\lambda PostSandy_t + \beta High_j + \gamma Low_j + \eta High_i * PostSandy_t + \zeta Low_i * PostSandy_t + \delta Chain_i + \theta \#Employees_i + \alpha Cluster_j) \quad (2)$$

where the *PostSandy*, *High*, *Low, Chain, #Employees* are defined the same as in equation (1). $Cluster_j$ is the baseline number of retail/non-retail establishments on block j.[31] 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.[32]

3.4.2 Jobs

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

$$Jobs_{it} = \lambda + \beta\, High_i * PostSandy_t + \gamma\, Low_i * PostSandy_t + \delta N_n + \theta D_{b,t} + e_{it} \qquad (3)$$

[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.
[31] 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).
[32] We also ran models with census tract strata and results are measured with more error but qualitatively the same.
[33] We also run, and display, log-linear models and the results are substantially the same.

where the indicators, *PostSandy*, *High*, and *Low,* N_n, and $D_{b,t}$ are defined the same as in equation (1).[34] 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:

$$log(Sales_{j,q}) = \lambda+\beta High_j*PostSandy_t+\gamma Low_j*PostSandy_t+ \delta \boldsymbol{N}_j + \theta \boldsymbol{D}_{b,q} +e_{j,q} \quad (4)$$

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).[35] $\boldsymbol{D}_{b,q}$ 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.[36] We can estimate changes in sales over time within each ZIP-zone (i.e. evacuation and surge) and how they vary with surge intensities. All of the regressions are weighted by the

[34] We also tried ZIP*Year dummies, and the results are consistent. In order to minimize the AIC, we present analyses with SBA*Year controls.
[35] 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.
[36] The sample still excludes Sub-borough areas without any blocks inside evacuation zone A and without any blocks that saw flooding during the storm.

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.

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 linear probability model of the pre- and post-Sandy difference in closure rates between high-, low- and no-surge blocks within the evacuation zone. All of the estimates are conditioned on SBA*Year and three-digit NAICS code dummies, and borough-block fixed effects. The results show that the annual closure rate for 2010 retail businesses on high-surge blocks in the evacuation zone rises by 10 percentage points after the storm compared to retail establishments on blocks in the evacuation zone that did not see any surge. Note that this difference is substantial; the average closure rate for retail establishments on blocks without any surge was 13 percent after 2012. We also see elevated closure rates for non-retail businesses on blocks seeing high levels of flooding, but the magnitudes of the difference are only about half as large.

Figure 5 shows the time trends in closure rates for retail businesses inside the evacuation zone (by surge level). Notably, there is no pre-existing trend in relative closure rates among businesses on blocks seeing surge in the years immediately preceding Sandy. The figures suggest elevated rates of closure for retail businesses in both high- and low-surge areas starting in 2013 but growing and peaking in 2014. We see elevated closure rates for non-retail businesses in high-surge area only starting in 2014, but again, the estimated magnitude of the increase is about half as large.

These results focus exclusively on the businesses that were operating in 2010. As an alternative specification, we also compare two-year closure rates of businesses operating in 2010 to the two-year closure rates of businesses operating in 2012 (that is, for the establishments that were open right before Sandy hit). We find similar results, with significantly elevated closure rates after Sandy for retail businesses on blocks seeing storm surge, and more modestly elevated closure rates after Sandy for non-retail businesses on blocks seeing high storm surges (see Appendix C).

Table 4 shows hazard model estimates of the difference in time to closure across pre- and post-Sandy periods and across high-, low-, and no-surge blocks.[37] 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 surge levels 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 4.98 retail establishments on the typical "high-surge" block (compared to 4.36 establishments on a block without any inundation). The significant coefficient on *Low*PostSandy* suggests that establishments in less inundated areas were also threatened, albeit to a lesser degree than those hit directly by higher surges. In contrast, the hazard ratios for the

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

non-retail subsample (column 3) are far smaller in magnitude (less than one for *Low*PostSandy*) and statistically insignificant. Appendix D shows the survival curves for the retail and non-retail sub-samples and illustrates the divergence in survival estimates across 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 down our more inclusive retail category to confirm that the results appear to be driven by the neighborhood-based businesses, like grocery stores and drug stores.[38] These results are displayed in column 4 of Table 3 and Table 4. The coefficients for *High*SandyPost* are far larger in magnitude for this restricted set of retail businesses than those for the full set of retail businesses in Table 3. We do not see the same significant differences when we estimate the hazard model (although the rates still indicate higher rates of closure), but the estimates are very noisy given the small sample size.

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 Table 4, and while we see negative coefficients for three of the four coefficients, their magnitudes are small and none is statistically significant.

[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.

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 E.

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. For simplicity, we show these results for the hazard model only, in Table 5, but results are qualitatively the same when we estimate with the linear probability model.[39] Perhaps surprisingly, we see no difference in post-Sandy closure rates between smaller and larger establishments—those with fewer than 10 employees (which comprise 76 percent of retails inside the evacuation zone A). As for differences in impacts across chain and standalone establishments, our results 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.

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 6 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 was parallel to that for blocks without any surge until 2011. We do see a decline in retail employment between 2011 and 2012 on blocks seeing high surges during Sandy, however, which suggests a pre-existing trend (the pre-trend overall, however, is not statistically significant). We explored whether this one-year decline might have been due to flooding from Hurricane Irene, which hit the same areas in 2011, but when we omit census tracts seeing high storm surge from Irene, we still see a decline. After Hurricane Sandy, the number of retail employees in high-surge areas falls compared to no-surge areas, but some of this large decline could be an extension of the pre-existing trend. 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 6. 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.[40] 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

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

variable.[41] Again, the drop in employment in the year preceding Sandy, however, suggests some caution in interpreting these results.

4.3 Spillover effects

To examine whether Hurricane Sandy generated 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 7 shows the regression results for closures and for employment for retail and non-retail establishments. The coefficients on *High*PostSandy* are largely unchanged, and the coefficients on *Moderate*PostSandy* are similar to those on *Low*PostSandy* in earlier regressions. Meanwhile, 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 7 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 on retail sales in the low-surge area, which could reflect spillovers to these

[41] 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.

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 8 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.[42] 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.[43] The persistence of the "high-surge" effects displayed in column 3 is evident in Figure 7: retail sales do not recover and the null effect in "low-surge" areas is stable over time.

[42] 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.

[43] There are only 96 observations in the non-surge areas for retail analysis.

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 7, show an upward trend relative to no-surge areas leading up to the storm. Therefore, any positive effects after the storm are likely to be, at least partially, a continuation of that upward trajectory.[44]

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 F1 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 F2, 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.

[44] 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.

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.[45] 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 Appendix G1. The estimates are generally unchanged, suggesting that impacts are not driven by transit-related interruptions for local residents and potential consumers.

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, we re-estimate our preferred model excluding establishments operating in 2010 that relocated during 2011-2016. These results are displayed in Appendix G2 (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 (3.3% of establishments operating in 2010 that close in one location in the evacuation zone A relocated to another site in the city between 2011-2016).

[45] 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.

6.3 Replication using FEMA flood zones

Finally, we replicate the analysis replacing the evacuation zone boundaries with those designated by the FEMA flood zones. About half of the properties in evacuation zone A are located inside the FEMA designated flood zone (but nearly 70 percent of the FEMA zone properties are also inside evacuation zone A). Inside the FEMA flood zone, purchasers of home mortgages are required to also purchase flood insurance; however this should not directly impact the establishments locating in the flood zone as they rarely own the property where they operate. Nevertheless, it is possible that the flood zones generate some salience of risk, even for the establishments. Therefore, we run the same set of regressions restricting the sample to only blocks in the FEMA flood zone. Results for closures and employment are shown in Appendix H. The coefficients have the same signs, but they fall somewhat in magnitude and are not statistically significant. The establishment sample size does go down slightly, which could partially explain the loss of precision in the estimates.

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 establishments, which 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 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. In the case of the employment results, however, we caution that we observe a drop in retail employment in hard-hit areas during the year immediately *prior to* the storm. So some of the large post-storm decline in employment we witness could be an extension of this pre-existing trend.

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, sales revenues had not recovered and we did not observe increased establishment openings. 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 independent establishments.

Third, and not surprisingly, the most significant impacts are caused by extreme flooding. However, in the case of closures, establishments exposed to less dramatic flooding were also vulnerable. Finally, regardless of the outcome observed, hurricane-induced damages appear to be larger for retail enterprises than for other types of businesses. 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. Our research suggests that resiliency and recovery strategies need to give particular consideration to the physical and economic disruption that can vary neighborhood by neighborhood, which in turn disproportionately threatens the viability of the retail activity tied to those local conditions.

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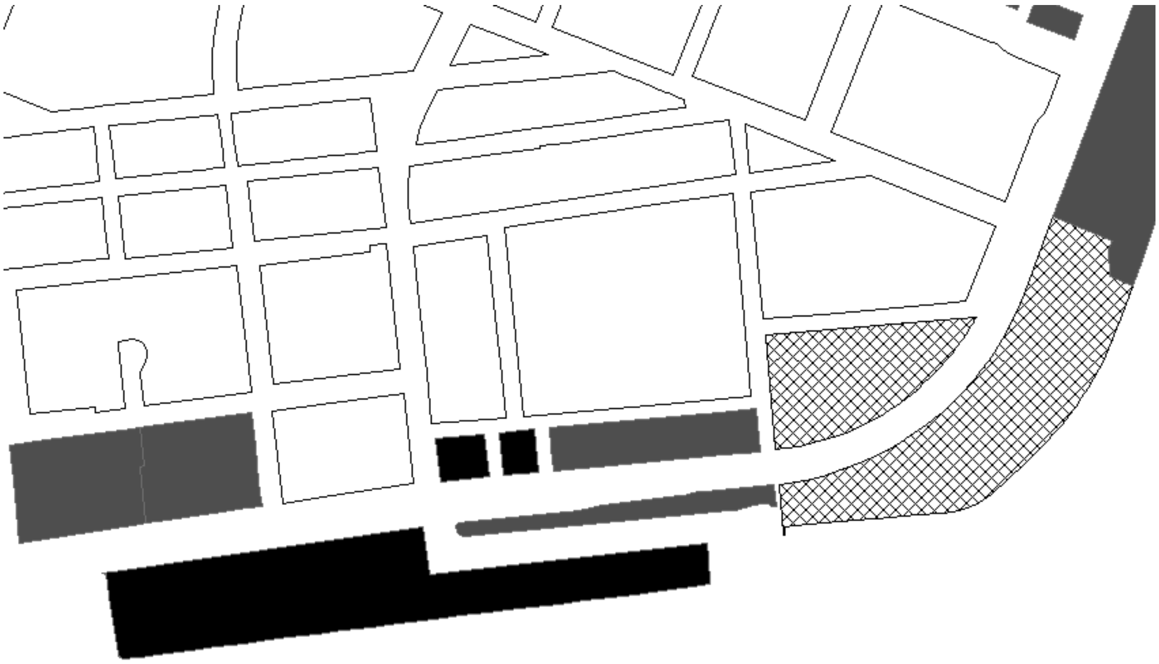
Figure 1: NYC Evacuation Map

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: 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.

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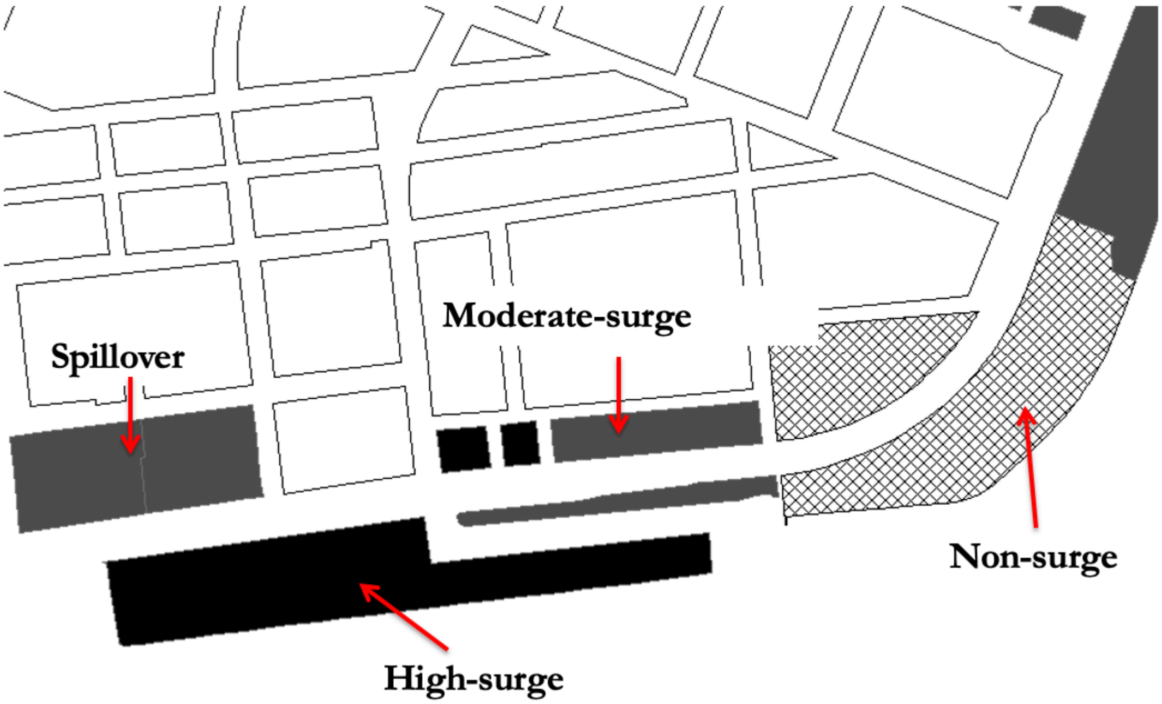
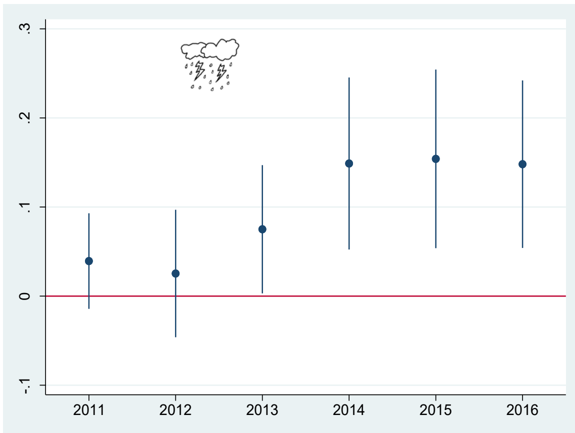
Figure 4: High-surge, Moderate-surge, and Spillover Areas.



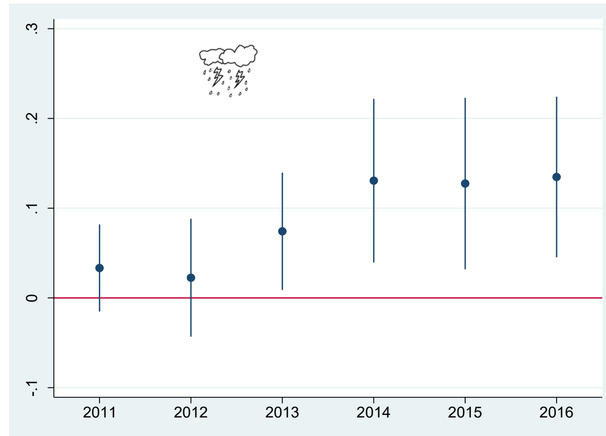
Notes: This is a part of Lower East Side. The unshaded blocks are outside the evacuation zone A.

Figure 5: Retail and Non-Retail Probability of Closure by Year

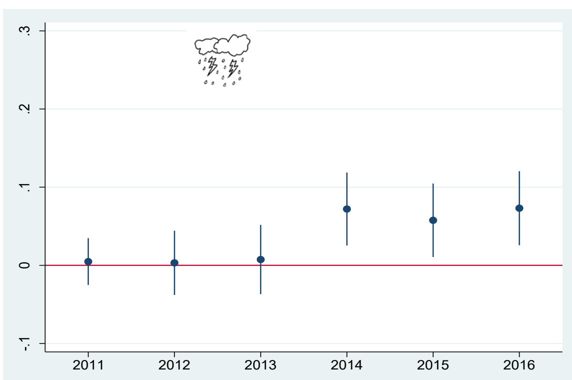
Retail: high-surge areas



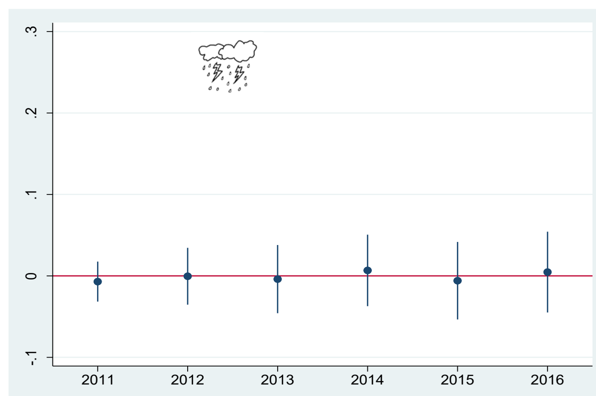
Retail: low-surge areas



Non-retail: high-surge areas



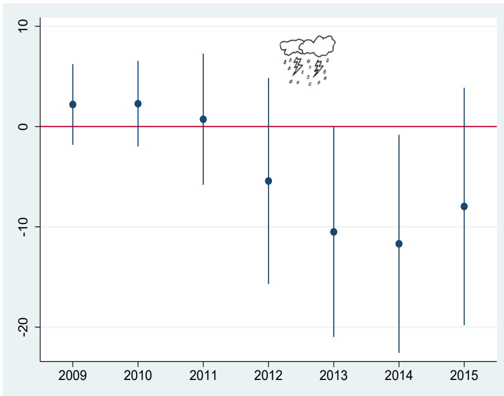
Non-retail: low-surge areas



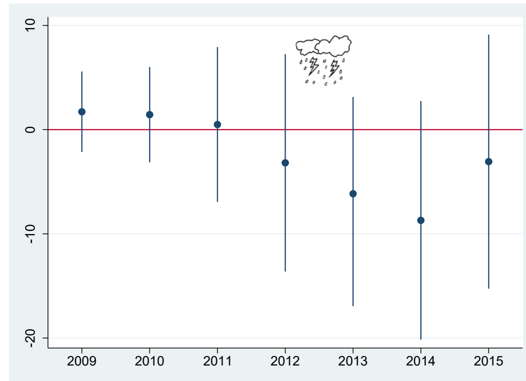
Notes: Plotted points are adjusted values, controlling for borough-block fixed effects, three-digit NAICS, SBA-year dummies, chain, and employee.

Figure 6: Retail and Non-Retail Jobs by Year

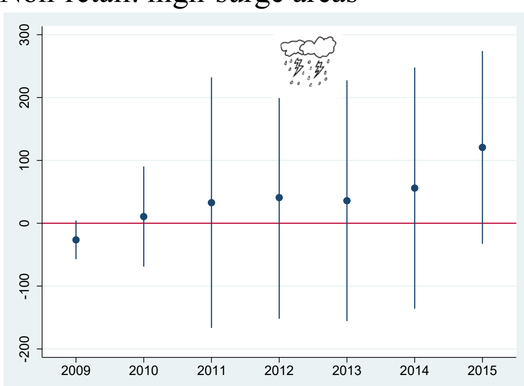
Retail: high-surge areas



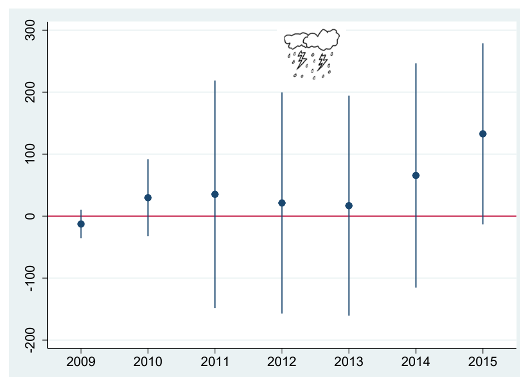
Retail: low-surge areas



Non-retail: high-surge areas



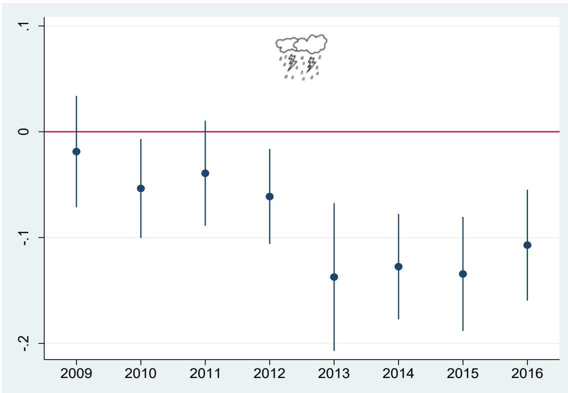
Non-retail: low-surge areas



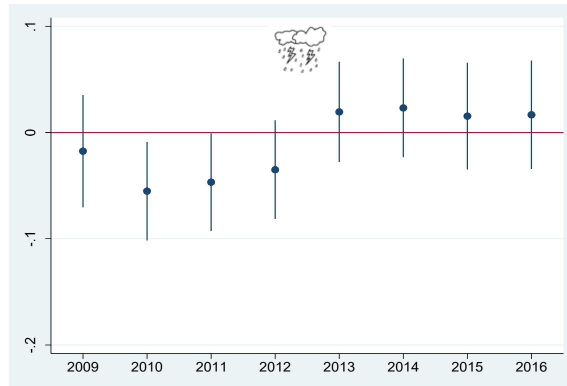
Notes: Plotted points are adjusted values, controlling for census-block fixed effects, and SBA-year dummies.

Figure 7: Retail and Non-Retail log(Average Sales)

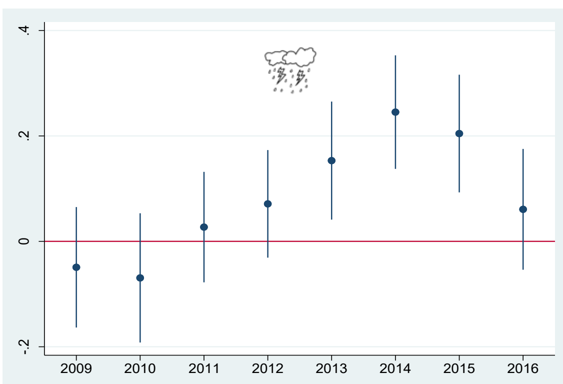
Retail: high-surge areas



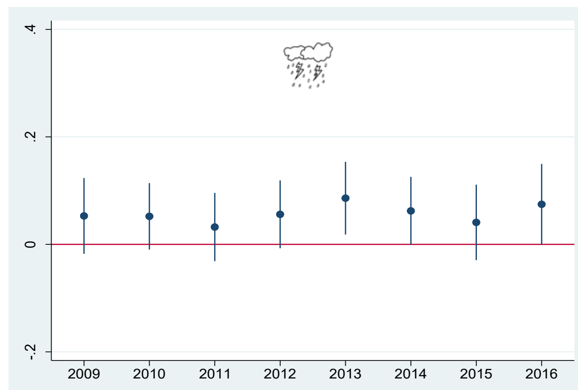
Retail: high-surge areas



Non-retail: high-surge areas



Non-retail: high-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: 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[46]		
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

[46] 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: Summary Statistics Commercial Activities in Evacuation Zone A

Variable	# of Obs	Mean	Std. Dev.	Min	Max
Probability of closure, 2010-2016	124,810	0.315	0.464	0	1
Probability of closure, 2010-2016 (retail)	22,960	0.299	0.458	0	1
Probability of closure, 2010-2016 (non-retail)	101,850	0.318	0.466	0	1
# of years until closure[47]	10,213	3.317	1.631	1	6
# of years until closure (retail)	1,717	3.162	1.699	1	6
# of years until closure (non-retail)	8,496	3.349	1.65	1	6
# of jobs per block	9,995	176.60	783.37	1	12226
# of jobs per block (retail)	9,995	18.02	65.63	0	1274
# of jobs per block (non-retail)	9,995	158.58	766.34	0	12168
quarterly average sales per filer, $	10,644	65407.32	36646.89	3044.32	363173.8
quarterly average sales per filer, $ (retail)	8,610	69794.58	42208.05	6326.21	430204.8
quarterly average sales per filer, $ (non-retail)	8,574	48963.95	32346.64	1582.13	265601.4

[47] 17,320 establishments operated in 2010 in evacuation zone A. 3,276 were retail, and 14,044 were non-retail. The number of years until closure is only reported for establishments that closed before 2016.

Table 3: Linear Probability Model, Establishments

Prob (closure)	(1) Total	(2) Retail	(3) Non-retail	(4) Neighborhood-based Retail	(5) Recovery-related Non-retail
*High*SandyPost*	0.0633***	0.104***	0.0501***	0.156***	0.00172
	(0.0147)	(0.0305)	(0.0162)	(0.0422)	(0.0338)
*Low*SandyPost*	0.0216	0.0932***	0.00198	0.134***	-0.00436
	(0.0143)	(0.0288)	(0.0160)	(0.0404)	(0.0294)
Chain	-0.0667***	-0.0928***	-0.0556***	-0.0733	-0.0147
	(0.0128)	(0.0274)	(0.0137)	(0.0520)	(0.0530)
Number of Employees	-5.92e-05***	-0.000249	-5.65e-05**	-0.00103*	-0.00198***
	(2.28e-05)	(0.000286)	(2.26e-05)	(0.000528)	(0.000365)
Constant	-0.0792	-0.0807	-0.147	-0.0389	0.0699
	(0.224)	(0.0567)	(0.243)	(0.0517)	(0.0680)
boro-block fixed effects	Y	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y	Y
Three-digit NAICS	Y	Y	Y	Y	Y
Observations	122,248	22,883	99,365	5,873	9,212
R-squared	0.214	0.182	0.226	0.206	0.204
Number of blocks	1,163	636	1,102	334	552

Standard errors are clustered by block

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

Table 4: 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	-38.90	0	-36.62	0	-35.30	0	-36.44	0	-36.11	0
	(0)		(1.185e+06)		(0)		(2.713e+06)		(2.251e+06)	
High	-0.0517	0.950	-0.0885	0.915	-0.0443	0.957	0.752	2.122	0.246	1.278
	(0.111)		(0.306)		(0.120)		(1.210)		(0.288)	
Low	-0.0662	0.936	-0.0321	0.968	-0.0745	0.928	0.595	1.814	0.0539	1.055
	(0.107)		(0.300)		(0.115)		(1.178)		(0.243)	
*High*PostSandy*	0.283**	1.327**	0.816**	2.261**	0.169	1.184	0.387	1.473	-0.154	0.857
	(0.138)		(0.369)		(0.149)		(1.283)		(0.387)	
*Low*PostSandy*	0.151	1.163	0.724**	2.062**	0.0262	1.027	0.246	1.279	-0.0460	0.955
	(0.134)		(0.363)		(0.145)		(1.252)		(0.342)	
Chain	-0.173***	0.841***	-0.167	0.846	-0.166**	0.847**	-0.296	0.744	0.0828	1.086
	(0.0558)		(0.113)		(0.0647)		(0.328)		(0.260)	
Number of Employees	-0.000194	1.000	-0.00128	0.999	-0.000159	1.000	-0.00109	0.999	-0.00300	0.997
	(0.000167)		(0.00107)		(0.000166)		(0.00441)		(0.00238)	
Cluster	0.000264	1.000	-5.63e-05	1.000	0.000169*	1.000*	0.00766	1.008	0.000378	1.000
	(0.00126)		(0.00269)		(8.66e-05)		(0.00621)		(0.000599)	
Stratified by Zip and three-digit NAICS	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	17,320	17,320	3,276	3,276	14,044	14,044	829	829	1,206	1,206

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.

Table 5: Hazard Model Regression Result, Retail Establishments, Heterogeneity Analysis

	(1) <10 employees Coefficient	Hazard Ratio	(2) >=10 employees Coefficient	Hazard Ratio	(3) Standalone Coefficient	Hazard Ratio	(4) Chain Coefficient	Hazard Ratio
PostSandy	-41.41	0	-40.82	0	-38.57	0	-46.74	0
	(0)		(0)		(3.771e+06)		(0)	
High	-0.00310	0.997	-0.0711	0.931	-0.135	0.874	0.652	1.919
	(0.412)		(0.840)		(0.368)		(1.237)	
Low	0.0273	1.028	-0.0797	0.923	-0.0911	0.913	0.499	1.647
	(0.407)		(0.845)		(0.362)		(1.460)	
*High*PostSandy*	0.656	1.927	0.577	1.781	0.873**	2.393**	-0.582	0.559
	(0.478)		(0.989)		(0.434)		(1.560)	
*Low*PostSandy*	0.587	1.799	0.402	1.495	0.772*	2.163*	0.157	1.170
	(0.473)		(0.990)		(0.427)		(1.741)	
Chain	-0.104	0.901	-0.347	0.707				
	(0.154)		(0.232)					
Number of Employees	0.0103	1.010	-0.00482*	0.995*	-0.000932	0.999	-0.00140	0.999
	(0.0209)		(0.00249)		(0.00112)		(0.00361)	
Cluster	0.000550	1.001	-0.00351	0.996	0.000443	1.000	-0.00193	0.998
	(0.00313)		(0.00719)		(0.00282)		(0.0120)	
Stratified by Zip and three-digit NAICS	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,490	2,490	786	786	2,902	2,902	374	374

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

Note: Cluster is calculated as the # of retail/non-retail establishments by block.

Table 6: Regression Results, Jobs

	# of jobs			ln(# of jobs)		
	(1)	(2)	(3)	(4)	(5)	(6)
	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 7: Regression Results, Spillover Effects

	(1) Hazard-Retail		(2) Hazard-Non-retail		(3) Jobs-Retail	(4) Jobs-Non-retail
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio		
PostSandy	-38.09	0	-34.76	0		
	(2.296e+06)		(0)			
High	-0.0985	0.906	-0.0483	0.953		
	(0.305)		(0.120)			
Moderate	-0.0655	0.937	-0.0830	0.920		
	(0.302)		(0.117)			
Spillover	0.155	1.167	-0.0464	0.955		
	(0.382)		(0.141)			
*High*PostSandy*	0.821**	2.272**	0.157	1.169	-9.678**	55.72
	(0.370)		(0.149)		(3.758)	(42.61)
*Moderate*PostSandy*	0.748**	2.113**	-0.00442	0.996	-5.336	47.71
	(0.367)		(0.148)		(4.168)	(42.98)
*Spillover*PostSandy*	-0.181	0.835	0.104	1.109	-6.734	66.23
	(0.337)		(0.129)		(4.227)	(51.00)
Constant					166.2	3,431
					(743.0)	(6,347)
Observations	3,276	3,276	14,044	14,044	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, number of employees, and cluster are controlled. In Column (3) and (4), block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block.

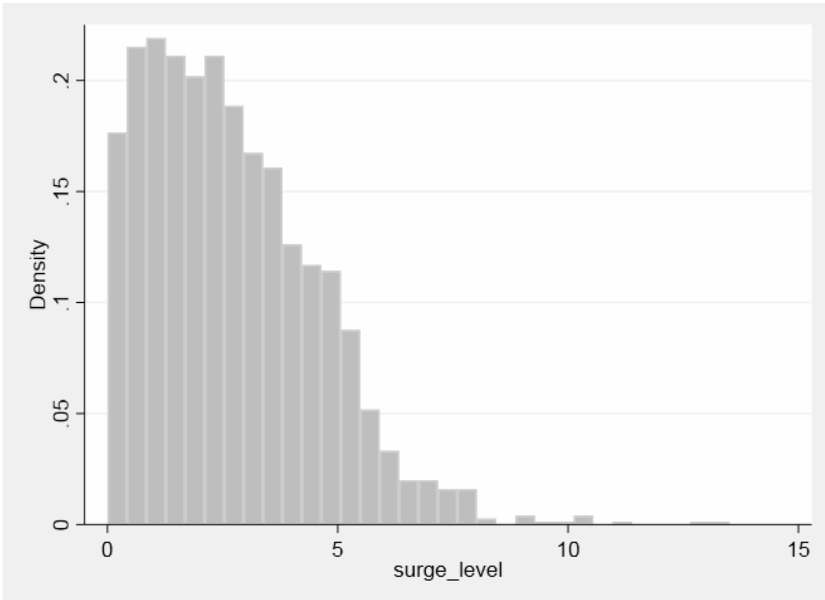
Table 8: Regression Results, Sales Revenues

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

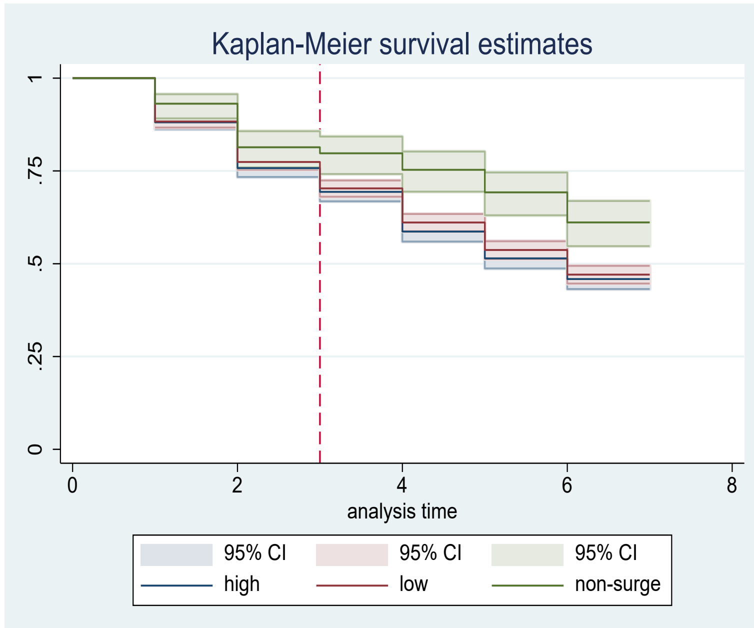
Appendix C: Two-year Closure Rate Comparison

Prob (closure)	(1) Total	(2) Retail	(3) Non-retail
*High*SandyPost*	0.0788***	0.114**	0.0643**
	(0.0280)	(0.0451)	(0.0312)
*Low*SandyPost*	0.0293	0.106**	0.00303
	(0.0236)	(0.0433)	(0.0255)
Chain	-0.0697***	-0.118***	-0.0527***
	(0.0150)	(0.0258)	(0.0156)
Number of Employees	-1.96e-05	-0.000178	-1.91e-05
	(2.26e-05)	(0.000138)	(2.31e-05)
Constant	0.0543	0.203	0.00431
	(0.109)	(0.129)	(0.117)
boro-block fixed effects	Y	Y	Y
SBA*Year dummies	Y	Y	Y
Three-digit NAICS	Y	Y	Y
Observations	35,698	6,646	29,052
R-squared	0.039	0.019	0.046
Number of blocks	1,233	712	1,176

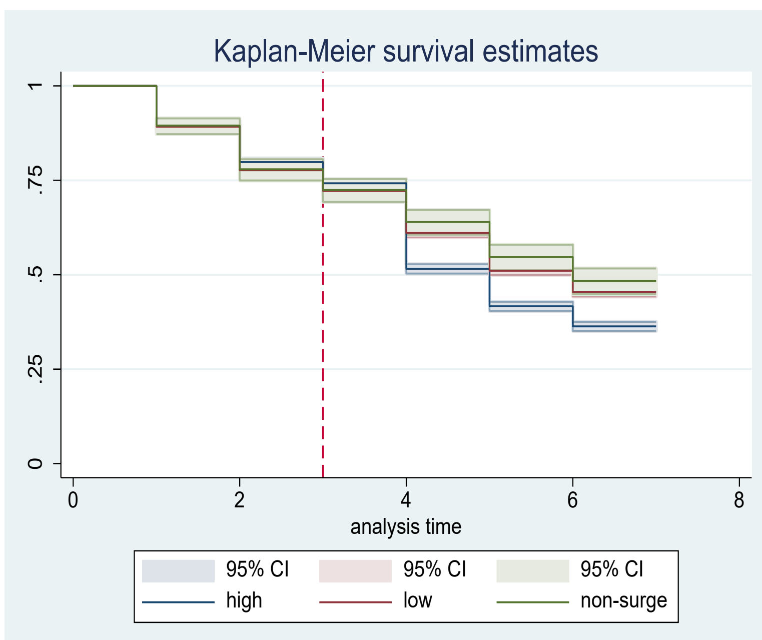
Standard errors are clustered by block
*** p<0.01, ** p<0.05, * p<0.1

Appendix D: Retail vs. Non-Retail Survival Curves, Before and After Sandy

Retail



Non-retail



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

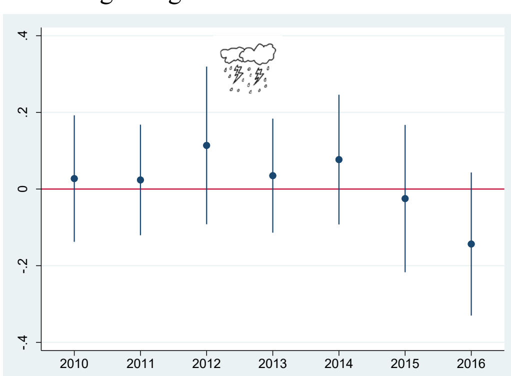
Appendix E: Establishments openings by block

	(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

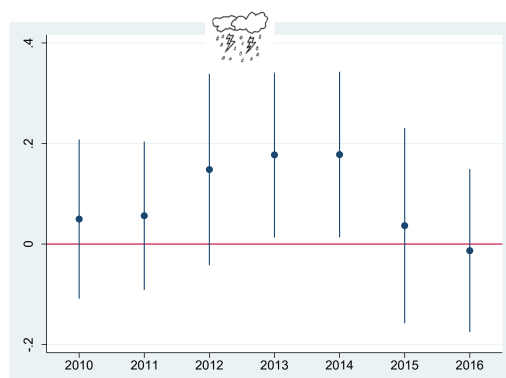
Clustered errors are clustered by block

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

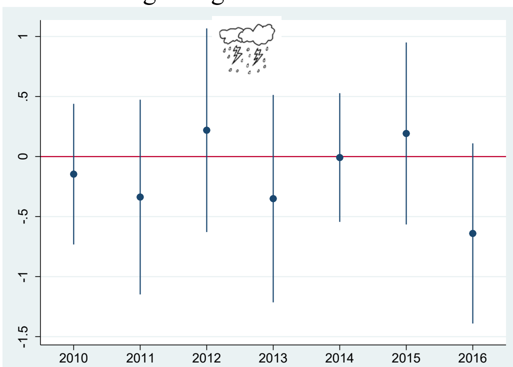
Retail: high-surge areas



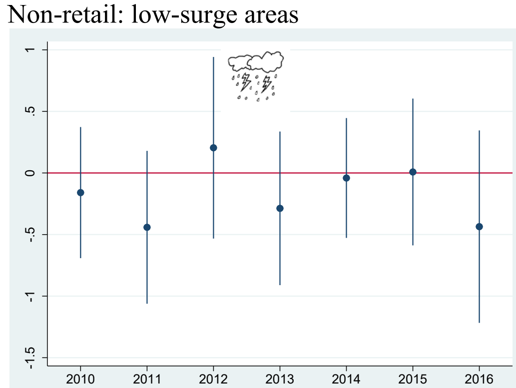
Retail: low-surge areas



Non-retail: high-surge areas



Non-retail: low-surge areas



Appendix F1: 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	-0.0175	0.983	0.00458	1.005				
	(0.0329)		(0.0161)					
*Surge Level*PostSandy*	0.0810*	1.084*	0.0170	1.017	-1.02***	4.323	-0.00784	0.0167
	(0.0417)		(0.0200)		(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	3,276	3,276	14,044	14,044	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 F2: Key Coefficients using Different Threshold, Evacuation Zone Sample

Threshold	Coefficients	(1) Hazard - Retail Coefficient	(1) Hazard Ratio	(2) Hazard - Non-retail Coefficient	(2) Hazard Ratio	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retail	(6) Sales - Non-retail
2 feet	*High*PostSandy*	0.766**	2.152**	0.0825	1.086	-8.787**	56.58	-0.0190	0.0601
		(0.362)		(0.145)		(3.766)	(43.03)	(0.0313)	(0.0444)
	*Low*PostSandy*	0.724*	2.063*	0.0938	1.098	-5.952	57.15	0.000543	0.0762
		(0.374)		(0.150)		(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*	0.866**	2.377**	0.134	1.143	-11.3***	73.27*	-0.0944**	0.0384
		(0.380)		(0.156)		(3.805)	(40.07)	(0.0436)	(0.140)
	*Low*PostSandy*	0.722**	2.058**	0.0702	1.073	-5.931	50.65	-0.00823	0.0651
		(0.361)		(0.143)		(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 G1: Regression Results, Excluding Transit-Interrupted Areas

	(1) Hazard - Retail		(2) Hazard - Non-retail		(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retails	(6) Sales - Non-retails
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio				
*High*PostSandy*	0.874**	2.397**	0.174	1.190	-10.02***	57.92	-0.095**	0.183**
	(0.373)		(0.149)		(3.788)	(42.88)	(0.0369)	(0.0781)
*Low*PostSandy*	0.798**	2.221**	0.0270	1.027	-5.895	56.78	0.0395	0.0252
	(0.367)		(0.145)		(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	3,206	3,206	13,807	13,807	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 G2: Hazard Model Regression Results, Close only

	(1)		(2)		(3)	
	All		Retail		Non-retail	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
PostSandy	-37.07	0	-37.55	0	-41.92	0
	(0)		(1.843e+06)		(0)	
High	-0.0781	0.925	-0.0753	0.927	-0.0751	0.928
	(0.116)		(0.320)		(0.125)	
Low	-0.0832	0.920	-0.0273	0.973	-0.0943	0.910
	(0.112)		(0.312)		(0.121)	
*High*PostSandy*	0.316**	1.372**	0.843**	2.323**	0.201	1.223
	(0.144)		(0.388)		(0.155)	
*Low*PostSandy*	0.188	1.207	0.809**	2.245**	0.0507	1.052
	(0.139)		(0.379)		(0.151)	
Chain	-0.185***	0.831***	-0.154	0.857	-0.185***	0.831***
	(0.0585)		(0.119)		(0.0678)	
Employee	-0.000328*	1.000*	-0.00126	0.999	-0.000283	1.000
	(0.000199)		(0.00106)		(0.000199)	
Cluster	-0.000277	1.000	-0.000663	0.999	0.000181**	1.000**
	(0.00133)		(0.00299)		(9.10e-05)	
Stratified by Zip and three-digit NAICS	Y	Y	Y	Y	Y	Y
Observations	16,732	16,732	3,170	3,170	13,562	13,562

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.

Appendix H: Regression Results, Restricted to FEMA Flooding Zone

	(1)		(2)		(3)	(4)
	Hazard - Retail		Hazard - Non-retail		Jobs - Retail	Jobs - Non-retail
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio		
*High*PostSandy*	0.875	2.400	0.391	1.479	-4.534	23.27
	(0.908)		(0.461)		(3.537)	(46.59)
*Low*PostSandy*	0.654	1.924	0.359	1.431	0.551	24.22
	(0.896)		(0.457)		(3.089)	(34.27)
Constant					664.6	2,849
					(830.0)	(6,688)
Observations	2,119	2,119	9,801	9,801	9,488	9,488
R-squared					0.063	0.034

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.