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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 11 percentage point higher closure rates and 9 percent 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.

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, economic diversification or cross-regional migration (Coulson et al., 2020; 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 customer-facing retail businesses, and especially those that serve a localized consumer base, will be most harmed by an extreme event like Sandy, which wrought both physical destruction *and* economic displacement. 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, even for retailers who serve a broader base, the closure of nearby establishments (and in the short-term, the disruption in transportation networks) may also reduce the number of visitors and workers in the neighborhood who might shop at local stores (Boarnet 1996). Some of these indirect impacts could be persistent. The reduction in local income and the contraction of clusters could result in a long-term reduction in demand for customer-facing retail establishments. 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.

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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. To be clear, the storm may have also had impacts beyond the surge area, which likely means our results understate overall impacts. Our results should be interpreted as the *localized* effect of storm damage on business outcomes relative to nearby areas.

Results indicate that neighborhood economic losses from Sandy are significant and, in certain cases, persistent. Consistent with theoretical expectations, losses are primarily concentrated among customer-facing 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, even those located on the same blocks as retail establishments. Further, establishment closures are concentrated among standalone establishments. Finally, we see no evidence that new establishment openings mitigate impacts in hard-hit areas, suggesting that the closures result in a net reduction in retail establishments in these areas.

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 et al., 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 their predisposition to risk and harm. Specifically, we distinguish between customer-facing 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.[1] 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. There also may be differences in the types and quality of goods and services across chain and independent retailers that could mediate post-storm resiliency.

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 and Mill 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).[2]

The literature considering micro-geographies yields a few common findings (whether the disasters are tornados, hurricanes, floods or earthquakes). First, business characteristics matter, supporting the notion of differential recovery (Cutter et al. 2000, 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 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

[1] The displacement of residents can be driven both by the involuntary relocation due to destruction of their homes and also the choice to relocate due to increased risk salience (this is modeled at the municipal level by Pan 2020).

[2] Basker and Miranda (2018) is an exception.

(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 et al. (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. While our findings are largely consistent with those of Indaco et al. (2019), our analysis takes a different approach 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).[3] We posit that the evacuation zones are more relevant for risk calculations on the part of businesses than the FEMA flood zones, which are largely pertinent for purchasers of residential properties. 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. As noted above, impacts on retailers serving local customers may be persistent if the storm leads to a more permanent reduction in population or income as areas are viewed to be more risky places to live, or if the contraction in local clusters reduces street traffic and overall demand.

[3] There are newer studies focusing on the impacts of Hurricane Sandy in New York City, primarily on residential prices (for example Barr, Cohen, and Kim 2017 and Ortega and Taspinar 2017). We do not focus on this literature as it looks at a distinct outcome, with different mechanisms.

3. Data and analytical strategy

In late 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 cost the city $19 billion; it was the second-costliest hurricane on record in the U.S., after Hurricane Katrina in 2005.[4]

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 Fig. 1). In the face of such warnings, however, only thirty to forty percent of residents actually left Evacuation Zone A.[5]

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 Fig. 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.[6] MOTF reports surge levels at a very

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

[5] Based on conversations with the NYC Mayor's Office of Resiliency.

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

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). Fig. 2 displays a map of surge levels for blocks across the city.[7] We exploit the variation in surge height for our identification strategy, discussed in the next section. 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.[8]

We obtain information on establishments from the Infogroup historical business database, a longitudinal panel of establishments constructed by Infogroup.[9] Infogroup identifies establishments using yellow pages, phone books and newspapers, and incorporates phone verification for the entire database (Lavin, 2000).[10] 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.[11] The dataset also reports on the number of employees at each establishment and distinguishes between chains and standalone businesses. Most importantly for this analysis, the data track both the closure of 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.[12] Our core sample includes 17, 320 establishments operating in 2010 in Evacuation Zone A.

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.[13] 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).[14] We use the variable that records jobs based on the location of employment. Our sample for the employment analyses includes 9995 block-year observations, covering 1679 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).[15] 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 subgroups, or zones: blocks outside the evacuation zone and without any surge; blocks in the evacuation area but without any post-storm surge; blocks with surge but not in the evacuation zone; and blocks in the evacuation and with surge; (ii) filers were then grouped first according to their ZIP code, then according to their designation into one of these four zones[16] 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.[17] 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 for establishments that operate inside and outside the evacuation zone A.[18] We have this information for 2012.

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

[8] We did replicate analyses using damage variable, and found qualitatively similar results.

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

[10] 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.

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

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

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

[14] 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).

[15] 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.

[16] 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.

[17] 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.

[18] 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.

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.

Fig. 1. NYC evacuation map.

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.

Fig. 2. Surge Levels by borough-block.

Table 1
Retail classification by NAICS.

Infogroup	LODES	Sales from DOF	Description	# of establishments
44–45	44–45	44–45	Retail Trade	2017
72	72	72	Accommodation and Food Services	910
311811, 812111, 812112, 812113, 812310, 812320			Neighborhood-based services, including beauty salons and laundry services	349
		61, 62, 71, 81	Educational, health care, entertainment, and other services	5701

Notes: The # of establishments are those located inside evacuation zone A as of 2012 (sourced from InfoGroup data).

3.2. Identifying commercial economic activity

We examine outcomes for all types of businesses but also conduct separate analyses for customer-facing 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.[19] See Table 1 for a list of NAICS codes included in the customer-facing "retail" classifications in our three different datasets. (Our core definition of retail is consistent with that used in other studies; see Meltzer and Capperis, 2017; Bingham and Zhang, 1997; Stanback, 1981.) In the InfoUSA dataset, our customer-facing "retail" category includes, in addition to the establishments classified as retail trade by NAICS (44–45), food services (722) and other personal services that tend to rely on neighborhood-based markets. Unfortunately we are not able to mimic the identical categorization in the other datasets, but we get as close as the data allow.[20]

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.[21] 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.

Table 2
Summary statistics commercial activities in evacuation zone A

Variable	Mean	Std. Dev.	Min	Max	# of observation
Probability of closure, 2010–2016	0.315	0.464	0	1	122,143
Probability of closure, 2010–2016 (retail)	0.299	0.458	0	1	22,862
Probability of closure, 2010–2016 (non-retail)	0.318	0.466	0	1	99,281
# of years until closure[a]	3.317	1.631	1	6	10,213
# of years until closure (retail)	3.162	1.699	1	6	1717
# of years until closure (non-retail)	3.349	1.65	1	6	8496
# of jobs per block	176.60	783.37	1	12226	9995
# of jobs per block (retail)	18.02	65.63	0	1274	9995
# of jobs per block (non-retail)	158.58	766.34	0	12168	9995
quarterly average sales per filer, $	$65,407	$36,647	$3044	$363,174	10,644
quarterly average sales per filer, $ (retail)	$69,795	$42,208	$6326	$430,205	8610
quarterly average sales per filer, $ (non-retail)	$48,964	$32,347	$1582	$265,601	8574

Notes: Business closure variables are from Infogroup, # of jobs are from LODES, and quarterly average sales are from the NYC Dept. of Finance.
[a] 17,320 establishments operated in 2010 in evacuation zone A. 3276 were retail, and 14,044 were non-retail. The number of years until closure is only reported for establishments that closed before 2016.

Table 2 shows summary statistics for these dependent variables: the probability of closure between 2010 and 2016 for establishments operating in 2010, 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 customer-facing 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 businesses, based on the reported status code.[22] Finally, in looking at closures, we separately consider a more conservative classification of the 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

[19] 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. We do approximate this difference with the building height of where the establishment resides and those results are described later in Section 4.

[20] 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 6-digit NAICS categories from NAICS 81. However, based on frequencies observed in the Infogroup data, the Correspondence between LODES and Infogroup should be around 70 percent. 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.

[21] 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.

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

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.

We find some evidence of such differences. Specifically, we see some systematic differences between establishments located in evacuation zone A and those located outside the evacuation zone A but still in neighborhoods, or Sub-Borough Areas, with at least one block experiencing storm surge. (Sub-Borough Areas (SBAs) are a collection of census tracts with aggregated population around 100,000.)[23] 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.[24] The retail share of establishments is 4.5 percentage points lower in the evacuation zone.[25] 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.[26]

Further, 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.[27] Establishments in the evacuation zone are also 8 percentage points more likely to be located in industrial buildings than their counterparts outside the zone and are located in newer structures (though the overwhelming majority of all establishments in both areas were built before 1990, when new resiliency 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.[28]

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 (as well as blocks and ZIP-zones) located in the pre-determined evacuation zone A, and therefore similarly subject to evacuation warnings. This restriction addresses 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 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."[29] 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."[30] (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. 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. Fig. 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. The effects we identify will be localized, or will capture the wedge in outcomes between establishments in areas hit more or less hard by the storm but equally exposed to flooding risk. We recognize that this wedge is not a full quantification of the total impact of the storm on business outcomes and likely understates the extent of harm. We return to this implication in the concluding discussion.

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. 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), or if commercial activity in less affected areas is hurt by the attenuation in retail clustering nearby, we will be able to directly estimate these effects by examining what happens to businesses on the spillover blocks relative to those on the no-surge blocks. Again, we note that our localized spillover estimates will understate any broader impacts covering areas without any inundation in other parts of the city (i.e. not adjacent to the hardest hit blocks).

3.4. Estimation

We estimate a series of regression models in which the dependent

[23] 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..

[24] All differences significant at the 99% level.

[25] 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.

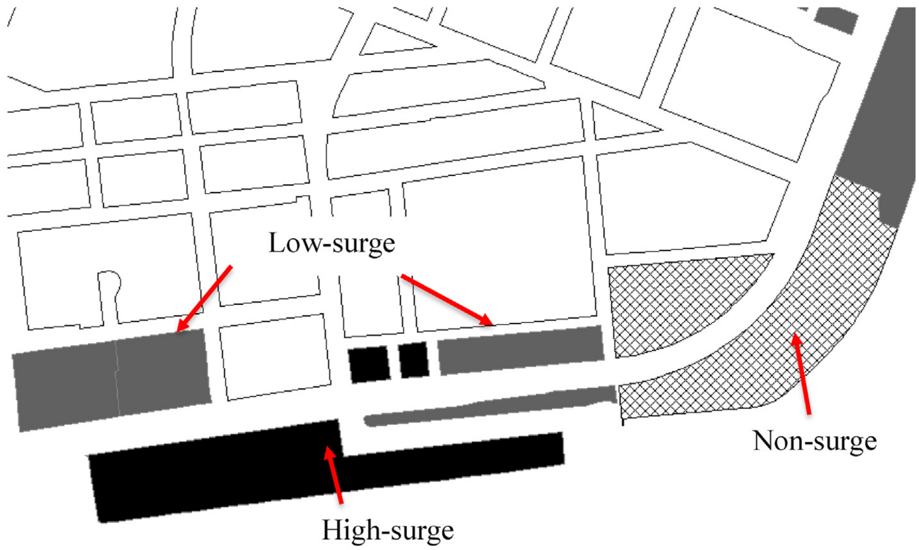
[26] Outside Evacuation Zone A, 17% of retail establishments sell clothing, shoes, or jewelry while 15% offer personal care services. By contrast, among retail establishments inside Evacuation Zone A, 10% sell clothing, shoes, or jewelry, while 9% offer personal care services.

[27] All reported differences significant at the 99% level.

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

[29] 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).

[30] 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.



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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Fig. 3. Evacuation and surge zones.

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.[31] 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:

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

PostSandy takes on the value of 1 starting in 2013.[32] *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.[33] We also estimate models where the post-Sandy impact varies across time, by interacting the *High* and *Low* dummies with year-specific indicators (similar to the estimation strategy employed by Coulson et al., 2020).

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.[34]

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

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 (this variation was absorbed by block fixed effects in the LPMN regressions)*.[35] 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.[36]

[31] Results are qualitatively the same when we look specifically at closures and exclude establishments that move to a different location, see Appendix I2 for details.

[32] 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.

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

[34] 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.

[35] 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).

[36] We also ran models with census tract strata and results are measured with more error but qualitatively the same.

3.4.2. Jobs

For the employment model the unit of analysis is the census block. The regression takes the following form[37]:

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

where the indicators, *PostSandy*, *High*, and *Low*, N_n, and $D_{b,t}$ are defined the same as in equation (1).[38] 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:

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

Our dependent variable is the log of average sales in quarter-year q in ZIP-zone j. We use log of average sales to account for differences in sales volume across retail and non-retail filers. The indicators, *PostSandy*, *High*, and *Low* are defined as they are in equation (1).[39] $\boldsymbol{D}_{b,q}$ 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.[40] 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 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 subsamples.

4. Effects on business closures and employment

In this section we summarize the results of our regression models for 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 retail businesses operating as of 2010 on high-surge blocks in the evacuation zone rises by 11 percentage points after the storm compared to retail establishments on blocks in the evacuation zone that did not see any surge. The magnitude of effect is very similar for those establishments exposed to low levels of surge, suggesting that any degree of inundation disrupted those businesses.[41] 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 less than half as large. And unlike retail businesses, there is no effect on non-retail establishments that were exposed to lower surge levels.

Fig. 4 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 areas only starting in 2014, but again, the estimated magnitude of the increase is about half as large. The persistence in establishment closures over time suggests that while initial exits might be due to the direct impacts of physical property destruction, over time the exits are likely due to indirect effects. For example, businesses may suffer in hard-hit neighborhoods if residents and other businesses are permanently displaced.[42]

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.[43] 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).[44] 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 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 subsamples 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. For the remaining set of results, we focus on the LPM results; the hazard model results are largely consistent with the LPM ones presented.

We validate these findings in several ways. First, to confirm that the different results across retail and non-retail establishments are not driven by discrete location choices or localized conditions, we replicate the non-retail regression retaining only those blocks that have both retail and

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

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

[39] 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. In addition, unlike the previous estimations, the *High* and *Low* indicators are specified for each group of tax filers that have already been aggregated by surge height within each ZIP.

[40] The sample still excludes Sub-borough areas without any blocks inside evacuation zone A and without any blocks that saw flooding during the storm.

[41] The *High*Sandy* and *Low*Sandy* coefficients are not significantly different for the retail sample, but significantly different for the non-retail sample at the 1 percent level.

[42] Businesses may also reassess their exposure to risk and choose to locate in safer sites in the city (although the number of within-city relocations is very small compared to permanent closures).

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

[44] The *High*Sandy* and *Low*Sandy* coefficients are not significantly different for the retail sample, but significantly different for the non-retail sample at the 5 percent level.

Table 3
Linear probability model, establishments.

Prob (closure)	(1)	(2)	(3)	(4)	(5)
	Total	Retail	Non-retail	Neighborhood-based Retail	Non-neighborhood-based Retail
*High*SandyPost*	0.0629***	0.111***	0.0481***	0.156***	0.0965***
	(0.0149)	(0.0313)	(0.0159)	(0.0422)	(0.0334)
*Low*SandyPost*	0.0217	0.0968***	0.00115	0.134***	0.0873***
	(0.0144)	(0.0294)	(0.0158)	(0.0404)	(0.0312)
Chain	−0.0712***	−0.0975***	−0.0621***	−0.0733	−0.102***
	(0.0134)	(0.0256)	(0.0147)	(0.0520)	(0.0310)
Number of Employees	−5.70e-05***	−0.000304**	−5.15e-05***	−0.00103*	−0.000125
	(2.06e-05)	(0.000146)	(1.98e-05)	(0.000528)	(0.000287)
Constant	−0.207	0.237	−0.258	−0.0389	−0.156
	(0.230)	(1.048)	(0.227)	(0.0517)	(0.459)
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	122,143	22,862	99,281	5873	16,989
R-squared	0.214	0.182	0.226	0.206	0.186
Number of blocks	1162	639	1100	334	577

Standard errors are clustered by block.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.
Notes: This table presents the estimates of equation (1), showing the impact of Hurricane Sandy on the probability of closure for establishments in high-surge and low-surge areas, by retail and non-retail sectors.

non-retail establishments. These results are displayed in Appendix E. We see that the coefficients on *High*PostSandy* and *Low*PostSandy* are similar for this sample as for full sample.

Second, we consider that the larger impacts on retail establishments (as compared to other businesses) could be at least partially driven by broader declines in the retail sector, which were accelerating during our study period. We find some support for this expectation in the regressions shown in Appendix F, which separate out those establishments classified as Retail Trade (44–45) from those classified as Accommodation and Food Services (72) and Other Services (81). Closure rates are significantly higher only for those establishments classified as Retail Trade. That said, the difference may be due to the fact that Retail Trade (44–45) establishments also constitute the largest share in our full retail sample (62 percent), whereas Accommodation and Food Services (72) constitute 28 percent and Other Services (81) the remaining 10 percent. The coefficient estimates for the Other Services sample are not significantly different from those for the retail trade sample, and they are nearly statistically significant.

Further, we see larger impacts for retailers with local customer bases. Specifically, we use the rich industry detail in the Infogroup data to isolate neighborhood-based businesses that are more likely tied to the fortunes of the local community rather than solely national retail trends.[45] We disaggregate our broader consumer-facing retail category (NAICS 44–45, 72 and 81) into neighborhood-based (26 percent) and non-neighborhood based (74 percent). These results are displayed in column 4 and 5 of Table 3. We see that while non-neighborhood retailers do experience elevated closure rates, the magnitude of response is significantly smaller than that for the other retailers more tied to the localized economy.[46]

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 G.

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 linear probability model only, in Table 5, but results are qualitatively the same when we estimate with the hazard model. Perhaps surprisingly, we see no significant difference in post-Sandy closure rates between smaller and larger establishments—those with fewer than 5 employees (which comprise 66 percent of customer-facing retail establishments inside the evacuation zone A). Although, the very small retail establishments are more likely to close under both *High* and *Low* surge conditions, whereas the bigger establishments only under more severe flooding. 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.[47] The same coefficients for the models run on chain businesses are smaller in magnitude and statistically insignificant (although they are statistically different than those produced for stand-alone establishments).[48]

4.2. Jobs

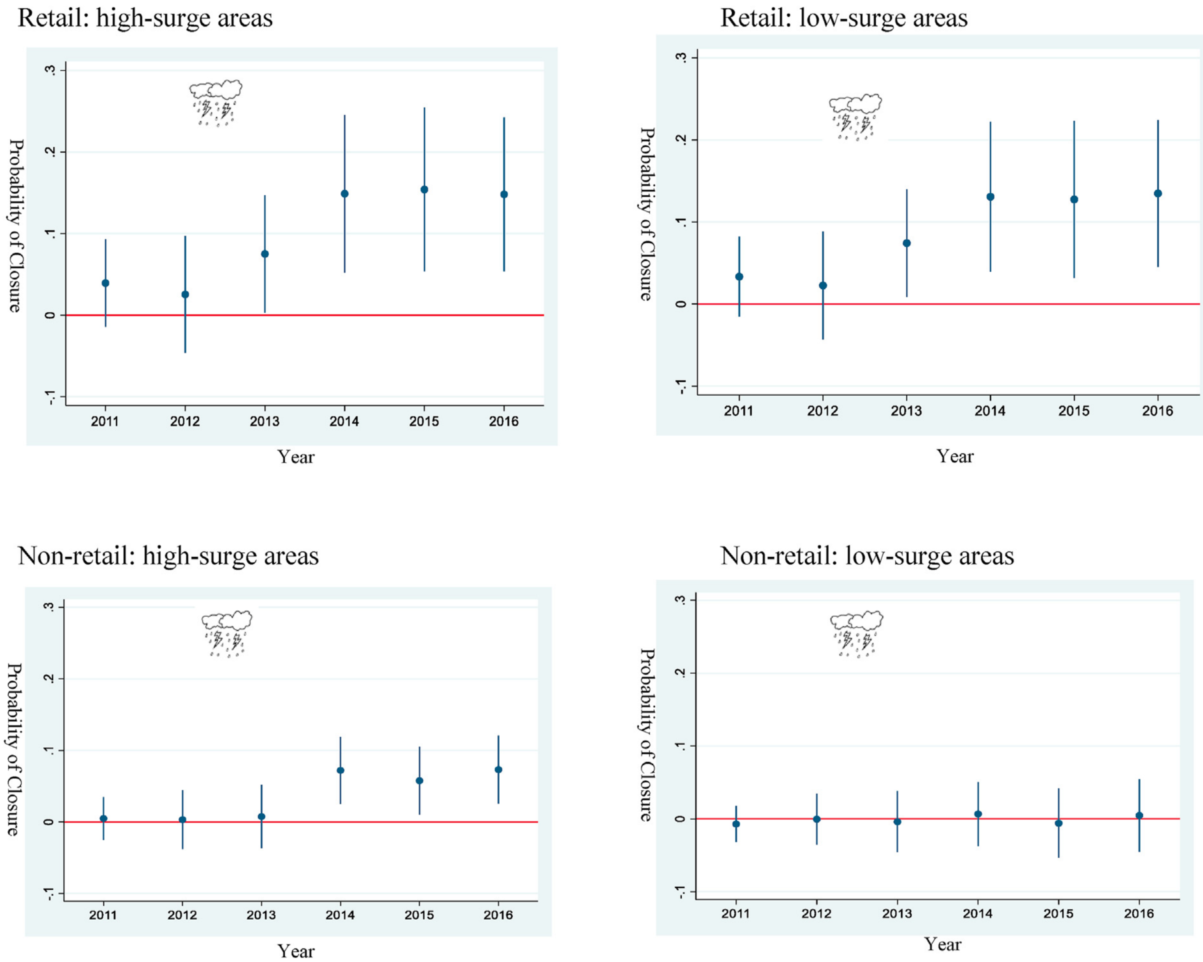
As for employment, Fig. 5 shows that for both retail and non-retail establishments leading up to Sandy, the trend in the number of

[45] 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.

[46] We also explore heterogeneity within the non-retail category, and 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 find no evidence that the results for non-retail are obscuring significant outcomes for establishments that might benefit, economically, from storm recovery. The results are not displayed here, but available upon request.

[47] The difference is significant at the 1 percent level.

[48] We also test for different closure rates across buildings of different ages and scales (to proxy for vulnerability to damage due to less resilient or ground level infrastructure). We find no meaningful differences in closure rates for retail establishments. We also tested for heterogeneity by size and structure for non-retail establishments 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 are not presented here but are available upon request.



Notes: Plotted points show time trends for probability of closure for establishments in high-surge and low-surge areas, relative to non-surge areas, controlling for borough-block fixed effects, three-digit NAICS, SBA-year dummies, chain, and employee. Vertical lines represent 95 percent confidence intervals.

Fig. 4. Retail and non-retail probability of closure by year.

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. This suggests that much of the drop was due to establishment closures (which did not return); any slight resurgence in jobs is likely due to a (re)expansion of surviving establishments (since we do not observe any meaningful change in new establishment openings). 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.[49] This represents a 14 percent net loss for the typical block with non-zero employment prior to Sandy. This loss could be due to both establishment closures and reduction in employment for surviving establishments; unfortunately, we are unable to disentangle this in the jobs data. 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

[49] The *High*Sandy* and *Low*Sandy* coefficients are significantly different at the 5 percent level for the retail sample, but not significantly different for the non-retail sample.

Table 4
Hazard model regression Result, establishments.

	(1)		(2)		(3)	
	All		Retail		Non-retail	
	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio	Coefficient	Hazard Ratio
PostSandy	−38.90	0	−36.62	0	−35.30	0
	(0)		(1.185e+06)		(0)	
High	−0.0517	0.950	−0.0885	0.915	−0.0443	0.957
	(0.111)		(0.306)		(0.120)	
Low	−0.0662	0.936	−0.0321	0.968	−0.0745	0.928
	(0.107)		(0.300)		(0.115)	
*High*PostSandy*	0.283**	1.327**	0.816**	2.261**	0.169	1.184
	(0.138)		(0.369)		(0.149)	
*Low*PostSandy*	0.151	1.163	0.724**	2.062**	0.0262	1.027
	(0.134)		(0.363)		(0.145)	
Chain	−0.173***	0.841***	−0.167	0.846	−0.166**	0.847**
	(0.0558)		(0.113)		(0.0647)	
Number of Employees	−0.000194	1.000	−0.00128	0.999	−0.000159	1.000
	(0.000167)		(0.00107)		(0.000166)	
Cluster	0.000264	1.000	−5.63e-05	1.000	0.000169*	1.000*
	(0.00126)		(0.00269)		(8.66e-05)	
Stratified by Zip and three-digit NAICS	Y	Y	Y	Y	Y	Y
Observations	17,320	17,320	3276	3276	14,044	14,044

Notes: This table presents the estimates of equation (2), showing the impact of Hurricane Sandy on the hazard ratio for establishments in high-surge and low-surge areas, by retail and non-retail sectors. *Cluster* is calculated as the # of retails/non-retails by block.

Table 5
Retail establishments, heterogeneity analysis.

Prob (closure)	(1)	(2)	(3)	(4)
	Employee ≤ 5	Employee>5	Standalone	Chain
*High*SandyPost*	0.106***	0.0992**	0.114***	0.00625
	(0.0364)	(0.0484)	(0.0331)	(0.0617)
*Low*SandyPost*	0.114***	0.0396	0.0958***	0.0287
	(0.0340)	(0.0453)	(0.0312)	(0.0585)
Chain	−0.0817**	−0.108***		
	(0.0399)	(0.0329)		
Number of Employees	−0.00207	−0.000189	−0.000203	−0.000907***
	(0.00720)	(0.000179)	(0.000189)	(0.000260)
Constant	0.553	−0.850	0.256	2.459
	(1.263)	(0.921)	(1.164)	(1.598)
boro-block fixed effects	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y
Three-digit NAICS	Y	Y	Y	Y
Observations	15,176	7686	20,342	2520
R-squared	0.196	0.195	0.189	0.205
Number of blocks	552	372	620	154

Standard errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Notes: This table presents the estimates of equation (1), showing the impact of Hurricane Sandy on the probability of closures for retail establishments in high-surge and low-surge areas, by establishment features.

4–6 show that results are consistent when we use log-transformed employment counts as the dependent variable.[50] 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 spillovers on areas proximate 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.[51] For retail establishments, the coefficient on *Spillover*PostSandy* is also statistically significant and of a similar magnitude to that for the *Moderate*PostSandy* coefficient in the establishment closure regressions.[52] This suggests that at least some of the closure impacts could be driven by interruptions in agglomeration benefits—-even the establishments that were not directly hit were hurt. These findings are qualified by the fact that our spillover sub-sample for retail establishments is quite small—just under 400 establishments (100 census blocks for the jobs analysis) or about one-third the size of the *High* and *Moderate* sub-samples. Therefore, in addition to missing the spillovers that might extend beyond the adjacent blocks in our sample, the observed effects are likely imprecisely estimated compared to those for the directly flooded areas.[53]

5. Sales revenues

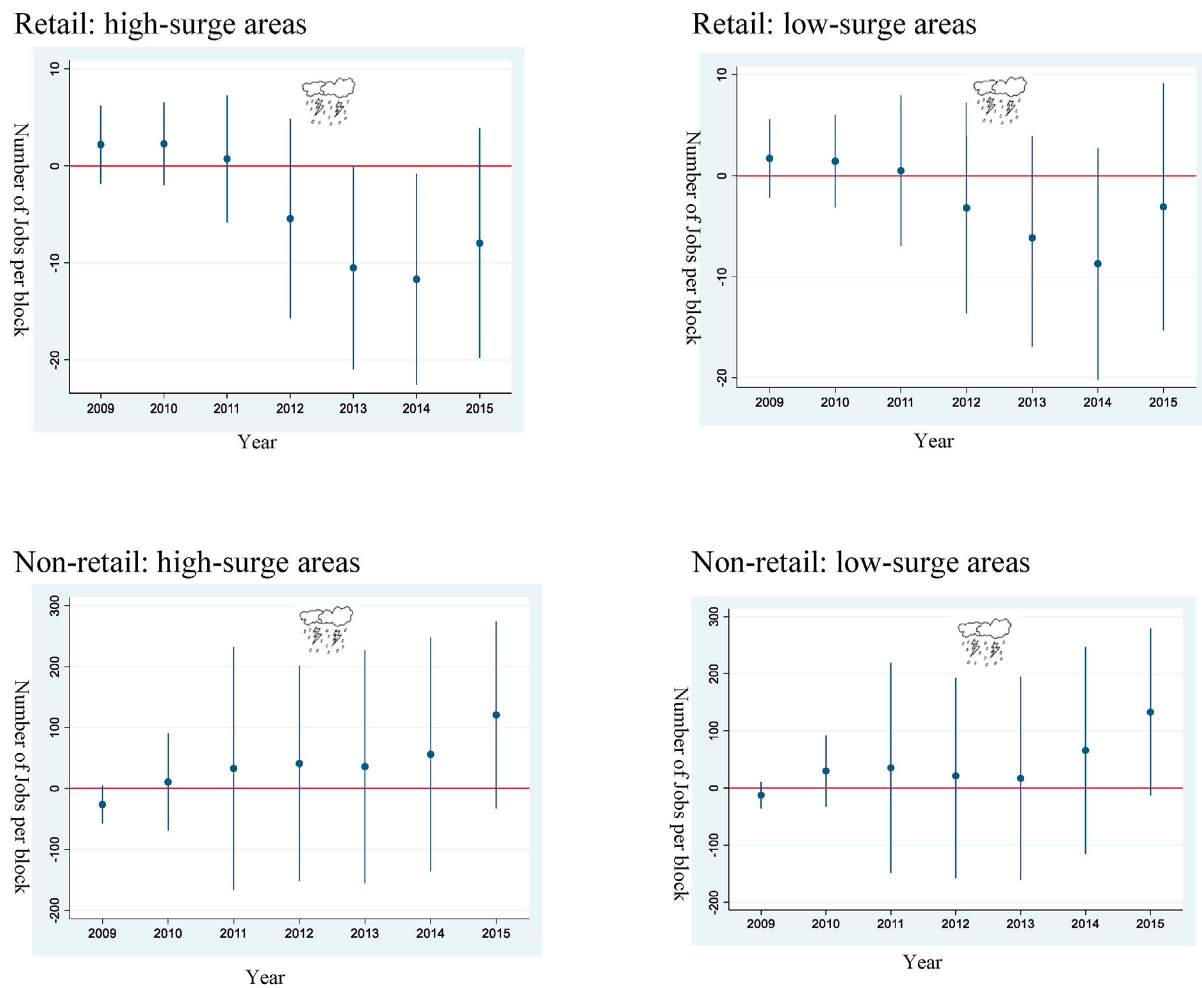
Fig. 6 confirms parallel trends in sales revenues between surge areas and the comparison area without any surge for retail businesses. The figures also suggest a sharp and persistent decline in sales for retail businesses in high-surge areas after the storm. The sustained drop in sales could be due to both the persistence in establishment closures as well as

[50] 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. The results are consistent when we use log(1+# of jobs) as the dependent variable.

[51] The significance test results between *Moderate*PostSandy* and *High*PostSandy* are also the same as the significance test results between *Low*PostSandy* and *High*PostSandy* in previous regressions.

[52] The coefficients for *Moderate*PostSandy* and *Spillover*PostSandy* are not significantly different in any columns.

[53] The coefficient on *Spillover*PostSandy* is not statistically significant from zero in any of the regressions using hazard model, which are different from linear probability model results.



Notes: Plotted points show time trends for number of job for census blocks in high-surge and low-surge areas relative to non-surge areas, controlling for census-block fixed effects and SBA-year dummies. Vertical lines represent 95 percent confidence intervals.

Fig. 5. Retail and non-retail jobs by year.

reductions in spending power in the area. We also see some weak evidence of a positive effect on retail sales in the low-surge area, which could reflect spillovers to these areas. Also, we see some evidence of an upward trend in sales for non-retail firms, prior to the storm, which clouds our interpretation of the results for non-retail businesses.

Table 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.[54] Columns 1, 3, and 5 shows results when we retain the full sample and include ZIP-zone dummies, which

[54] 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.

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	2776	451.7	2325	3.003***	2.198***	2.866***
	(9370)	(753.3)	(9149)	(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	9995	9995	9995	9995	4842	9396
R-squared	0.039	0.085	0.035	0.046	0.080	0.042
Number of blocks	1679	1679	1679	1679	1000	1622

Standard errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Notes: This table presents the estimates of equation (3), showing the impact of Hurricane Sandy on the number of jobs per census block in high-surge and low-surge areas, by retail and non-retail sectors.

Table 7
Regression results, spillover effects.

	(1)	(2)	(3)	(4)
	Prob(closure) Retail	Prob(closure) Non-retail	Jobs-Retail	Jobs-Non-retail
*High*PostSandy*	0.111***	0.0490***	−9.678**	55.72
	(0.0315)	(0.0158)	(3.758)	(42.61)
*Moderate*PostSandy*	0.0969***	0.00360	−5.336	47.71
	(0.0313)	(0.0187)	(4.168)	(42.98)
*Spillover*PostSandy*	0.0968***	−0.00317	−6.734	66.23
	(0.0296)	(0.0170)	(4.227)	(51.00)
Constant			166.2	3431
			(743.0)	(6347)
block fixed effects	Y	Y	Y	Y
SBA*Year dummies	Y	Y	Y	Y
Three-digit NAICS	Y	Y	N	N
Observations	22,862	99,281	9995	9995
R-squared	0.182	0.226	0.085	0.035
Number of blocks	639	1100	1679	1679

Notes: This table shows the impact of Hurricane Sandy on the probability of closure for establishments and the number of jobs per census block in high-surge (>3 feet), moderate-surge (0.5–3 feet), and spillover (0–0.5 feet) areas, by retail and non-retail sectors. Chain and number of employees are controlled in Column (1) and (2).

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.[55] Again, this reduction in sales could be due to both establishment closures and changes in consumption behavior at surviving establishments—we are unable to disentangle this in the sales data. 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*PostSandy*. 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.[56] The persistence of the "high-surge" effects displayed in column 3 is evident in Fig. 6: retail sales do not recover and the null effect in "low-surge" areas is stable over time.

As for non-retail filers, the coefficient on *High*PostSandy* is significant and positive in the broader sample, while the coefficient on *Low*PostSandy* is not significant. We think the apparent positive effect on non-retail sales is explained by the fact that pre-Sandy sales trends, displayed in Fig. 6, 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.[57]

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 H1 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 H2, show that they are robust to adjustments in to surge height. Our findings are clearly not driven by our selection of a three-foot cutoff, and as expected, the magnitude of the *High*PostSandy* coefficient generally increases as the threshold gets higher.

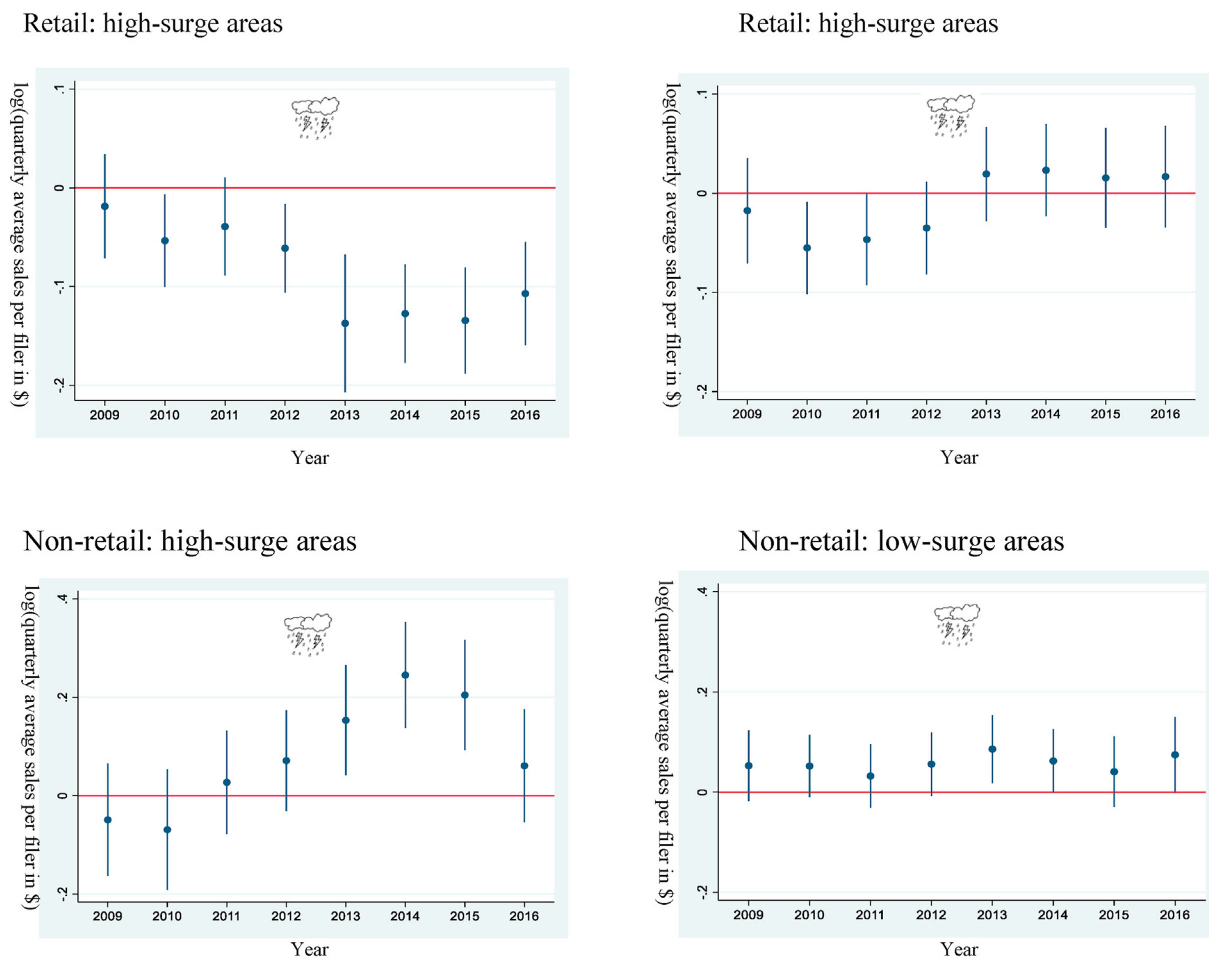
6.2. Controlling for transit interruptions and relocations

While transportation networks, like the subway, were interrupted

[55] The *High*Sandy* and *Low*Sandy* coefficients are significantly different at the 1 percent level for the retail sample, but not significantly different for the non-retail sample.

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

[57] 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.



Notes: Plotted points show time trends for log(average sales) in high-surge and low-surge areas relative to non-surge areas, controlling for ZIP-zone fixed effects, borough-quarter-year dummies. The OLS regression is weighted by the number of filers per ZIP-zone. Vertical lines represent 95 percent confidence intervals.

Fig. 6. Retail and Non-Retail log(Average Sales).

Table 8
Regression results, sales revenues.

log(average sales)	(1)	(2)	(3)	(4)	(5)	(6)
	Total	Total	Retail	Retail	Non-retail	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	1965	8610	1154	8574	1150
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.
Notes: This table presents the estimates of equation (4), showing the impact of Hurricane Sandy on log (average sales per filer) in high-surge and low-surge areas, by retail and non-retail sectors. OLS regressions are weighted by the number of filers by industry and ZIP-zone.

following the storm, they were not disabled for long.[58] 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 I1. 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 I2 (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 and 2016).[59]

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 J. 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. The imprecision could also be driven by the ambiguous nexus between FEMA designation and salience of risk for commercial establishments.

7. 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 customer-facing 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. We also cannot distinguish between jobs and sales losses due to establishment closures and reductions in surviving establishments—we presume both responses are playing a role.

Our findings have three 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. While any immediate decline in retail activity is likely due to the physical destruction form the storm, the persistence over time could also be due to the indirect effects of permanently displaced residents (and income) and the attenuation of localized retail agglomeration benefits. 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.

Finally, business interruptions could generate meaningful fiscal losses, in the form of reduced sales and payroll tax revenues. Notably, our findings capture the localized impacts from the storm, on business activity relatively more damaged than those nearby and similarly exposed to flooding risk. However, these differences likely understate the total economic impact from the storm for businesses across the municipality. Notwithstanding the citywide fiscal implications, 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. This might also mean that certain, higher risk areas, should not host the level of commercial activity that preceded the storm. While some services may be deemed essential even in high-risk areas, it may be safer and more cost effective to encourage the development of other non-critical retail in less risky, but accessible, areas of the city.

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CRediT authorship contribution statement

Rachel Meltzer: Conceptualization, Methodology, Writing - original draft, Supervision, Project administration, Funding acquisition. **Ingrid Gould Ellen:** Conceptualization, Methodology, Writing - original draft, Supervision, Project administration, Funding acquisition. **Xiaodi Li:** Methodology, Formal analysis, Data curation, Writing - original draft, Project administration.

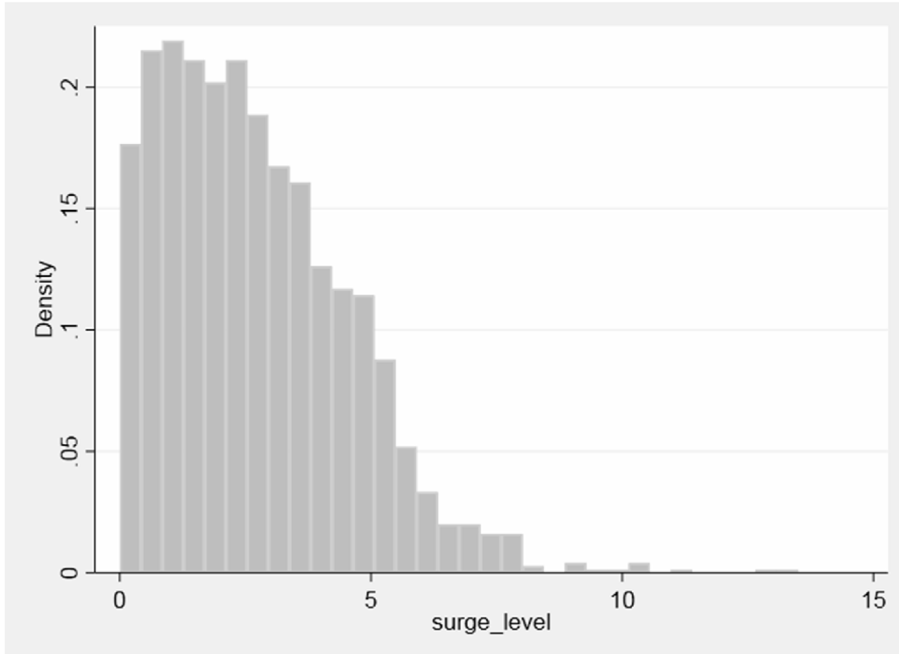
Declaration of competing interest

None.

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

[59] We conducted analyses separately by borough, and the results do vary. Retail establishments in Manhattan, Bronx, and Staten Island experienced significantly higher probabilities of closure and losses in employees. There were no significant closure or job effects for retail in Brooklyn and Queens. Retail sales in the Bronx, Brooklyn, and Queens significantly decreased (although the *High*PostSandy* coefficients are negative across the board, if not significant). In general, the citywide results do not appear to be driven by any single borough, and the borough-level sub-samples are much smaller, demanding a lot from our fine-grained identification strategy.

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. Neighborhood-based retail classification

NAICS	Description	# Estab.	Percent
311811	Retail Bakery	32	3.76%
445110	Groceries	155	18.24%
445210	Meat markets	10	1.18%
445220	Seafood markets	16	1.88%
445230	Fruit markets	30	3.53%
445292	Candy stores, packaged, retailing only	17	2.00%
446110	Pharmacies	101	11.88%
446130	Optical goods stores (except offices of optometrists)	25	2.94%
446191	Nutrition (i.e., food supplement) stores	8	0.94%
446199	All Other Health and Personal Care Stores	10	1.18%
451120	Hobby, toy, and game stores	23	2.71%
451211	Book stores	18	2.12%
451212	Newsstands (i.e., permanent)	28	3.29%
453110	Flower shops, fresh	47	5.53%
453910	Pet shops	15	1.76%
453991	Tobacco stores	5	0.59%
812111	Barber Shops	22	2.59%
812112	Beauty Salons	147	17.29%
812113	Nail Salons	42	4.94%
812310	Coin-Operated Laundries and Drycleaners	12	1.41%
812320	Dry cleaning and Laundry Services (except Coin-Operated)	87	10.24%

Notes: The # of establishments are those located inside evacuation zone A as of 2012 (sourced from InfoGroup data).

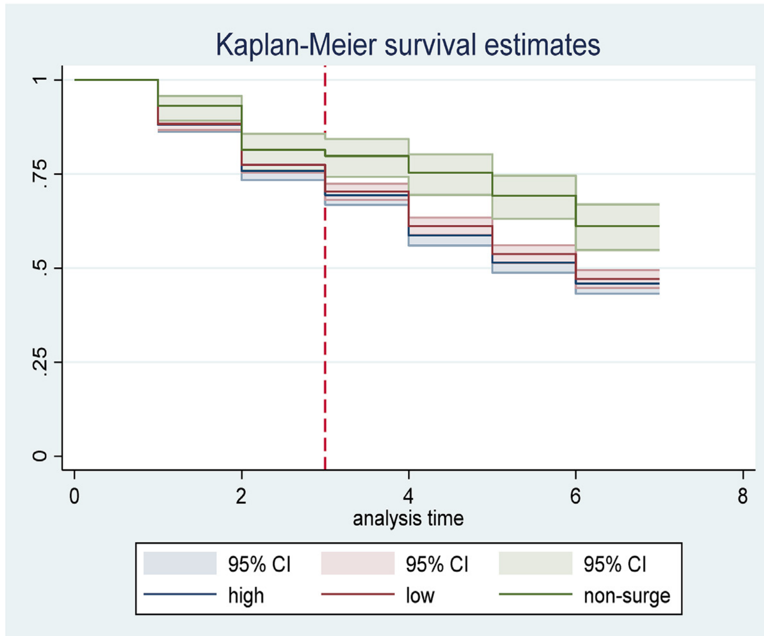
Appendix C. Two-year Closure Rate Comparison

Prob (closure)	(1)	(2)	(3)
	Total	Retail	Non-retail
*High*SandyPost*	0.0789***	0.114**	0.0644**
	(0.0280)	(0.0451)	(0.0312)
*Low*SandyPost*	0.0294	0.106**	0.00316
	(0.0236)	(0.0433)	(0.0254)
Chain	−0.0697***	−0.118***	−0.0529***
	(0.0150)	(0.0255)	(0.0156)
Number of Employees	−1.93e-05	−0.000176	−1.88e-05
	(2.25e-05)	(0.000136)	(2.30e-05)
Constant	−0.222	1.052	−0.288*
	(0.182)	(1.150)	(0.158)
boro-block fixed effects	Y	Y	Y
SBA*Year dummies	Y	Y	Y
Three-digit NAICS	Y	Y	Y
Observations	35,614	6632	28,982
R-squared	0.039	0.019	0.046
Number of blocks	1162	639	1100

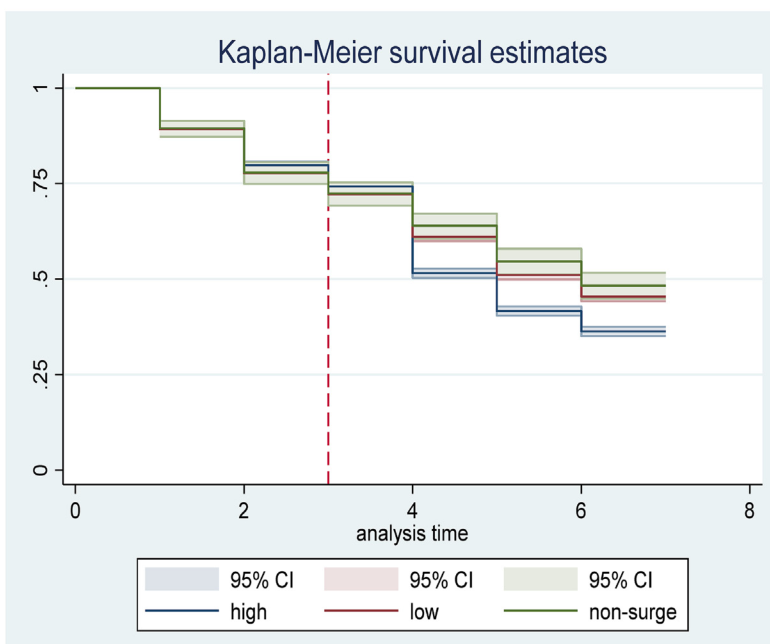
Standard errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Note: This table shows estimates comparing two-year closure rates of establishments operating in 2010 to the two-year closure rates of establishments operating in 2012.

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

Retail



Non-retail



Note: Figures show the survival curves for establishments inside evacuation zone A, by high-surge, low-surge, and non-surge groups. Kaplan-Meier survival estimates are not controlled by any establishment characteristic or stratified by any group.

Appendix E. Non-retail analysis using only blocks with retail establishments

	(1)	(2)
	Prob(closure)	# of jobs
*High*SandyPost*	0.0500**	79.50
	(0.0194)	(57.99)
*Low*SandyPost*	0.00541	78.36
	(0.0198)	(58.58)
Chain	−0.0538***	
	(0.0164)	
Number of Employees	−4.71e-05**	
	(2.14e-05)	
Constant	0.0627	8350
	(0.176)	(10,462)
block fixed effects	Y	Y
SBA*Year dummies	Y	Y
Three-digit NAICS	Y	N
Observations	86,723	6871
R-squared	0.227	0.037
Number of blocks	575	1000

Notes: This table shows the impact of Hurricane Sandy on the probability of closure for non-retail establishments and the number of non-retail jobs for census blocks in high-surge and low-surge areas using a sample of only blocks with retail establishments.

Appendix F. Subsector retail establishment analysis

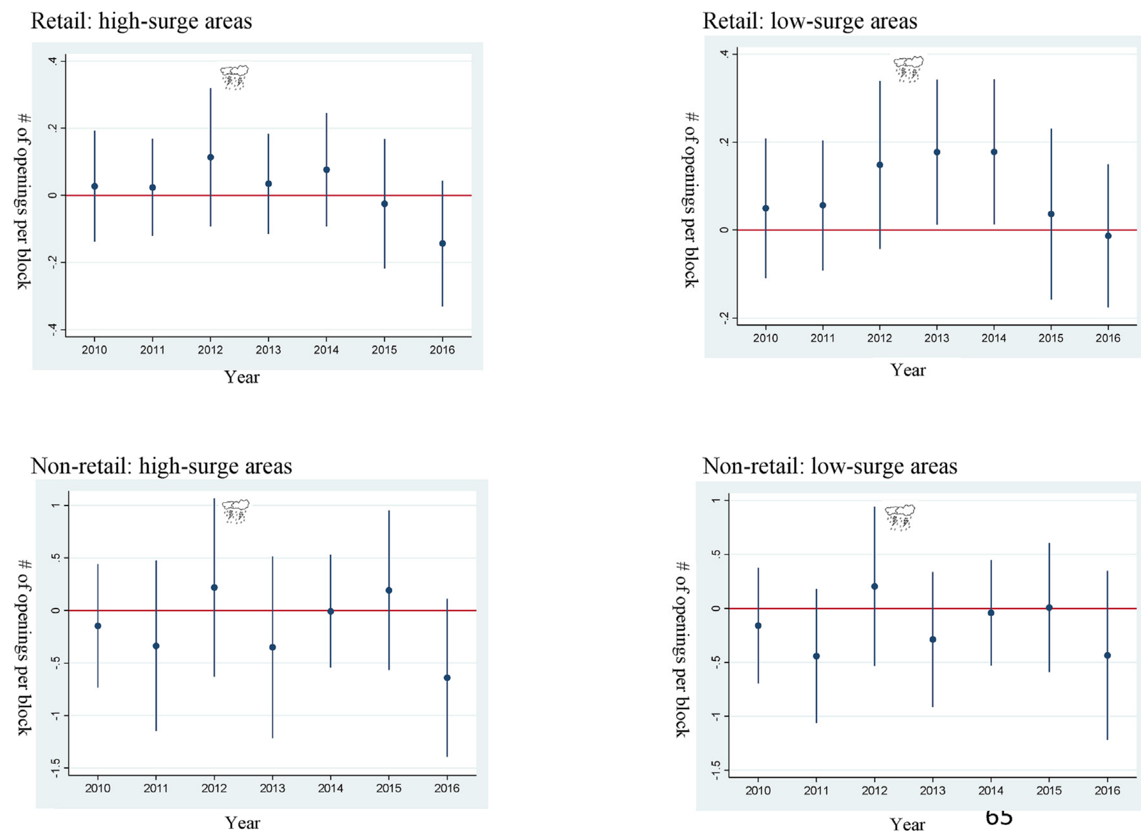
Prob (closure)	(1)	(2)	(3)
	Retail Trade	Accommodation and food	Other Services
*High*SandyPost*	0.127***	0.0572	0.0945
	(0.0369)	(0.0478)	(0.0689)
*Low*SandyPost*	0.110***	0.0494	0.102
	(0.0341)	(0.0452)	(0.0618)
Chain	−0.106***	−0.0641	0.127*
	(0.0321)	(0.0428)	(0.0697)
Number of Employees	−0.000125	−0.000610**	−0.00223***
	(0.000283)	(0.000294)	(0.00049)
Constant	0.200	0.688	−0.0209
	(0.625)	(0.462)	(0.0808)
boro-block fixed effects	Y	Y	Y
SBA*Year dummies	Y	Y	Y
Three-digit NAICS	Y	Y	Y
Observations	14,076	6351	2436
R-squared	0.191	0.192	0.225
Number of blocks	537	343	194

Standard errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Notes: This table presents the estimates of equation (1), showing the impact of Hurricane Sandy on the probability of closure for retail establishments in high-surge and low-surge areas, by subsectors.

Appendix G. Establishments openings by block

# of openings by block	(1)	(2)	(3)
	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	9832	9832	9832
R-squared	0.136	0.071	0.136
Number of blocks	1229	1229	1229

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



Appendix H1. Regression Results, Continuous Surge Level

	(1) Prob(closure) - Retail	(2) Prob(closure) - Retail	(3) Jobs - Retail	(4) Jobs -Non-retail	(5) Sales -Retail	(6) Sales -Non-retail
*Surge Level*PostSandy*	0.0113**	0.00965***	−1.02***	4.323	−0.00784	0.0167
	(0.00474)	(0.00278)	(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	22,862	99,281	9995	9995	8581	8545
R-squared	0.183	0.226	0.084	0.035	0.968	0.897

Clustered errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Note: The table shows the impact of Hurricane Sandy on all three commercial outcomes using the continuous variable "surge level" rather than high-surge/low-surge dummy variables. Column (1) and (2) control for borough-block and three-digit NAICS code fixed effects, SBA-year dummies, and chain and employee variables. 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 H2. Key Coefficients using Different Threshold, Evacuation Zone Sample

Threshold	Coefficients	(1) Prob(closure) - Retail	(2) Prob(closure) - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retail	(6) Sales - Non-retail
2 feet	*High*PostSandy*	0.107***	0.0265	−8.787**	56.58	−0.0190	0.0601
		(0.0306)	(0.0167)	(3.766)	(43.03)	(0.0313)	(0.0444)
	*Low*PostSandy*	0.0956***	0.00178	−5.952	57.15	0.000543	0.0762
		(0.0303)	(0.0153)	(3.955)	(42.75)	(0.0995)	(0.102)
3 feet	*High*PostSandy*	0.111***	0.0481***	−9.79***	57.65	−0.095***	0.156**
		(0.0313)	(0.0159)	(3.73)	(42.47)	(0.0345)	(0.0781)
	*Low*PostSandy*	0.0968***	0.00115	−5.931	56.25	0.0379	0.0250

(continued on next column)

(*continued*)

Threshold	Coefficients	(1) Prob(closure) - Retail	(2) Prob(closure) - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales - Retail	(6) Sales - Non-retail
		(0.0294)	(0.0158)	(3.809)	(42.27)	(0.0374)	(0.0447)
4 feet	*High*PostSandy*	0.125***	0.0437**	−11.3***	73.27*	−0.0944**	0.0384
		(0.0322)	(0.0178)	(3.805)	(40.07)	(0.0436)	(0.140)
	*Low*PostSandy*	0.0939***	0.00860	−5.931	50.65	−0.00823	0.0651
		(0.0292)	(0.0150)	(3.718)	(42.61)	(0.0343)	(0.0432)

Clustered errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Note: The table shows the impact of Hurricane Sandy on all three commercial outcomes using different cutoffs for high-surge/low-surge dummy variables. Column (1) and (2) control for borough-block and three-digit NAICS code fixed effects, SBA-year dummies, and chain and employee variables. 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 I1. Regression Results, Excluding Transit-Interrupted Areas

	(1) Prob(closure) - Retail	(2) Prob(closure) - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail	(5) Sales -Retails	(6) Sales -Non-retails
*High*PostSandy*	0.112***	0.0484***	−10.02***	57.92	−0.095**	0.183**
	(0.0315)	(0.0160)	(3.788)	(42.88)	(0.0369)	(0.0781)
*Low*PostSandy*	0.0993***	4.24e-05	−5.895	56.78	0.0395	0.0252
	(0.0296)	(0.0158)	(3.856)	(42.76)	(0.0380)	(0.0452)
Constant	0.486	−0.101	20.78***	158.0***	11.24***	10.89***
	(1.033)	(0.239)	(3.751)	(57.27)	(0.0212)	(0.0299)
Observations	22,372	97,636	9296	9296	8458	8422
R-squared	0.183	0.227	0.086	0.035	0.969	0.897

Clustered errors are clustered by block.
***p < 0.01, **p < 0.05, *p < 0.1.
Note: The table shows the impact of Hurricane Sandy on all three commercial outcomes for areas in NYC excluding the Rockaway neighborhoods (where major transit interruptions persisted). Column (1) and (2) control for borough-block and three-digit NAICS code fixed effects, SBA-year dummies, and chain and employee variables. 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 I2. Linear Probability Model, Close only

Prob (closure)	(1) Retail	(2) Non-retail
*High*SandyPost*	0.104***	0.0505***
	(0.0306)	(0.0161)
*Low*SandyPost*	0.0973***	0.00479
	(0.0286)	(0.0158)
Chain	−0.0974***	−0.0735***
	(0.0265)	(0.0160)
Number of Employees	−0.000271*	−5.87e-05***
	(0.000152)	(1.93e-05)
Constant	−0.514*	−0.0627
	(0.262)	(0.153)
boro-block fixed effects	Y	Y
SBA*Year dummies	Y	Y
Three-digit NAICS	Y	Y
Observations	22,036	96,075
R-squared	0.175	0.224
Number of blocks	629	1096

Notes: This table presents the estimates of equation (1), showing the impact of Hurricane Sandy on the probability of closure for establishments in high-surge and low-surge areas, excluding establishments that moved between 2010 and 2016.

Appendix J. Regression Results, Restricted to FEMA Flooding Zone

	(1) Prob(closure) - Retail	(2) Prob(closure) - Non-retail	(3) Jobs - Retail	(4) Jobs - Non-retail
*High*PostSandy*	0.0888	0.0604	−4.534	23.27
	(0.0615)	(0.0518)	(3.537)	(46.59)

(*continued on next column*)

(*continued*)

	(1)	(2)	(3)	(4)
	Prob(closure) - Retail	Prob(closure) - Non-retail	Jobs - Retail	Jobs - Non-retail
*Low*PostSandy*	0.0803	−0.00942	0.551	24.22
	(0.0614)	(0.0433)	(3.089)	(34.27)
Constant			664.6	2849
			(830.0)	(6688)
Observations	16,261	75,740	9488	9488
R-squared	0.134	0.150	0.063	0.034

Clustered errors are clustered by block.

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

Note: The table shows the impact of Hurricane Sandy on all three commercial outcomes using FEMA flood zone designations (instead of evacuation zone A) to proxy for pre-strom risk exposure. Column (1) and (2) control for borough-block and three-digit NAICS code fixed effects, SBA-year dummies, and chain and employee variables. In Column (3) and (4), block fixed effects and SBA-year dummies are controlled, standard errors are clustered by block.

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