Importance of Households in Business Disaster Recovery

Maria Watson[1]; Yu Xiao[2]; Jennifer Helgeson[3]; and Maria Dillard[4]

Abstract: The authors seek to contribute to the understanding of post-disaster community interdependencies by examining the recovery linkages between businesses and households. Specifically, this research looks to identify the household dimensions that affect recovery quality in businesses in Lumberton, North Carolina, after the 2016 Hurricane Matthew. Through an interdisciplinary field study 15 months after the hurricane, businesses were asked about the loss of customers and various labor disruptions they experienced. Logistic regression used to examine the impact of these variables on the likelihood of a business reporting being fully recovered, controlling for damage, accessibility issues, business characteristics, owner or manager demographics, and financial assistance. This research found that customer loss in particular had a higher effect magnitude than initial damage in terms of hindering recovery. Labor disruption caused by transportation issues and childcare or school closure issues had a smaller relative effect, but it also significantly lowered a business's odds of full recovery. Not all labor variables were significant—including employee personal household damage—stressing the importance of understanding the specific dimensions of households affecting business recovery. **DOI: 10.1061/(ASCE)NH.1527-6996.0000393.**

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Introduction

Planning for disaster recovery requires a holistic understanding of the linkages, dependencies, and relationships within a community. Rather than seeing the community as simply a sum of its individual parts, this acknowledges the complex interplay of the social, economic, political, natural, and physical systems that determine a community's capacity and function. Encouraging households to return to or remain in a community after a disaster, for example, requires more than simply providing a physical structure. It might also require utility connections, economic prospects, social inclusion, and educational opportunities as households depend on and are affected by the community in which they are embedded (Bolin 1993). The authors seek to contribute to this effort by examining post-disaster recovery linkages between businesses and households as jobs and housing have been cited as key components of recovery (Comerio 2014).

Businesses, like households, are intricately linked to the social, structural, and functional environment of a given community. They rely on the government for operational inputs such as utilities in order to physically conduct their business, and in turn, businesses provide tax revenue back to the government, which can be reinvested into infrastructure. Businesses also rely on each other. Businesses specialize and therefore rely on other businesses for supply chain components, such as material inputs, transportation, and technology. However, most importantly, it could be argued, is a business's reliance on households. The work by Bolin and Trainer (1978) identifies employment recovery as the main components of household recovery, and Green, Bates, and Smyth (2007) acknowledge that household access to recovery capital is critical for recovery speed; given income is an essential part of household recovery, the authors can expect a corresponding relationship with employees and customers as essential parts of business recovery. A business must be profitable to survive, and households provide the market for the goods and services provided by businesses.

Households are not simply a source of business demand, but are also components of the business' function and production itself. A business requires labor to function, and business owners, managers, and employees also belong to a household. The business provides wages in exchange for labor, which contributes to households' income. However, the relationship between businesses and households is not purely economic and cannot be captured through exchanges alone. Businesses have long been conceptualized as part of the social fabric of a community (Jacobs 1961), and business recovery decisions were found to be influenced by business owners' community ties and community attachments (Xiao et al. 2018). Although this role is less easily quantifiable, some research has begun to indicate the impact businesses have on the psychological well-being of residents after a disaster (Liu et al. 2012) and acknowledging their role in restoring a sense of normalcy (Comerio 2014).

In general, the embeddedness of businesses in these interconnected networks and exchange flows has been thoughtfully conceptualized in the literature in terms of community disaster recovery (Lindell et al. 2006; Xiao and Van Zandt 2012; Zhang et al. 2009). Although research has progressively improved the understanding of these linkages, few have quantified them empirically. From the housing side, Nejat and Ghosh (2016) include employment among their predictors of post-disaster housing recovery. Xiao and Van Zandt (2012) looked at the relationship between household

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and business return after 2008 Hurricane Ike and found that they are spatially linked—controlling for damage as well as business and household characteristics, businesses significantly influenced household reopening decisions and vice versa at the 3-month recovery period.

The research presented in this paper, therefore, attempts to extend the findings of Van Zandt et al. (2012) through exploration of the specific dimensions of households that affect business recovery and their importance compared to other factors. The authors use data from face-to-face surveys of businesses in Lumberton, North Carolina approximately 15 months after the October 2016 Hurricane Matthew to understand the effect of household variables on business manager- or owner-reported recovery.

Literature Review

Importance of Households to Business Recovery

The factors that influence business performance after disasters can change in their influence through time (Lam et al. 2012; Sydnor et al. 2017). Immediately after a disaster event, a business must deal with the physical nature of the disaster including damage to the business's storefront and contents, utility loss, and transportation disruptions. As time progresses, the business is more likely to have cleaned up its premises, made repairs to its structure, and utility inputs will have been restored. After a business reopens, it is forced to contend with the recovery process and trajectory of the community as a whole. In other words, a business may reinvest and reopen only to find that its customer base has gone or its employees are unable to work (Runyan 2006).

The authors argue that household variables as they relate to businesses only increase in importance with time post-event. Household loss and compositional change mean changing markets and labor pools for a business; the impacts these changes have for a business are qualitatively well-documented in the literature (Alesch et al. 2001; Graham 2007; Runyan 2006; Green et al. 2007). In general, there are three population forces a business might contend with after a disaster: changing demand in the resident population, new population influx from recovery workers, and more permanent population changes due to immigrants bringing different markets and population loss due to dislocation and displacement (Alesch et al. 2001; Scanlon 1988; Runyan 2006; Webb et al. 2000). Changing demand in the resident population can stem from their own disaster impact: households that are damaged from a disaster will have less discretionary funding, or purchasing power, as their priorities are focused on the rebuilding and repair of their homes and property (Alesch et al. 2001). This can have a disproportionate impact on businesses (Scanlon 1988). Retail businesses, for example, are more likely to supply luxury goods and might see a decline in business, whereas a construction or manufacturing business might see a boom in residents needing services, tools, and raw materials during recovery (Alesch et al. 2001; Revenue and Brunton 2013; Webb et al. 2000). There is also a spatial component to these demand shifts. After Hurricane Katrina, Xiao and Nilawar (2013) found that growth occurred at a faster rate along the edge of the impacted area, resulting in slower growth in the damaged core. This demonstrates a secondary market impact to the businesses recovering in the damaged core that, in the case of Hurricane Katrina, can last up to 3 years after the event (Xiao and Nilawar 2013).

There is also an influx of relief and recovery workers after a disaster event that can impact local demand for business' services/products. Accommodation businesses may be able to take advantage of the need for temporary housing for these workers, as well as residents looking for temporary accommodation while their homes are being repaired. Similarly, restaurants that are able to open quickly can serve relief workers and residents who are unable to cook their own meals (Runyan 2006). However, relief workers will eventually leave, and the resident population may or may not be able to provide the same level of support to these businesses. Accommodation hosts in particular will struggle in tourism economies that are negatively affected by the perception of the community and its recovery as a whole once the temporary workers have gone (Wilson 2016).

This leads to a discussion of the long-term or even permanent population changes that might occur in a community after a disaster. Alesch et al. (2001) detail several instances, across disaster events, of businesses trying to contend with these changes. The authors write of the area around Homestead Air Force Base after Hurricane Andrew: "it is an entirely different place than it was before the hurricane a decade ago. Community demographics have changed dramatically. Businesses that did not adapt to the new reality did not survive" (Alesch et al. 2001). This occurs across geographies, disaster events, and time. After the September 11th terrorist attacks, small businesses in Manhattan struggled to adapt to changing demographics and clientele (Graham 2007). Similar to Homestead and Hurricane Andrew, business representatives were quoted saying, "businesses are failing now because they are not keeping pace with the new economic environment" in Lower Manhattan (Graham 2007). Loss of customers, at least on a binary or categorical scale, has been shown to significantly affect recovery quality (Alesch et al. 2001; Corey and Deitch 2011; Dietch and Corey 2011).

However, these issues are not simply a matter of a changing customer base, but a changing skills and labor pool as well. Community populations dictate both supply (in terms of labor and production) and demand. A report following the Canterbury earthquakes in New Zealand writes about migration and population concerns: "The first (concern) is that if a large enough number of people leave, regardless of age and skill level, the remaining population may not be sufficient to drive the general economy of Christchurch/Canterbury. The second concern is that people with the skills required for the rebuild leave, creating a skills shortage" (Stevenson et al. 2012). Businesses might struggle to find employees due to issues ranging from relocation, temporary housing decisions, and inequitable housing recoveries to rent increases and gentrification during disaster recovery (Pais and Elliott 2008; Peacock et al. 2014; Zhang et al. 2009). To the knowledge of the authors, very few studies have quantitatively looked at labor issues in depth. Regressions have found significant effects related to staffing issues and labor shortages in terms of recovery quality, but there is a gap in the literature with respect to the reason for these disruptions (Corey and Deitch 2011; Dietch and Corey 2011). Labor variables in general are not frequently utilized in business recovery analyses. This research, therefore, specifically focuses on labor as well as customers as dimensions of the interdependency of household recovery and business recovery.

Factors Influencing Business Recovery

Business recovery, however, is impacted by several other categories of variables that need to be controlled for in this research. Broadly speaking, businesses can be damaged directly by a hazard event, for example through the damage sustained to the business's physical capital, and indirectly such as the hazard's impact on its infrastructure needs, suppliers, and other functional inputs (Tierney and Nigg 1995; Zhang et al. 2009). For example, in a flooding event, a business can experience water damage to its storefront and machinery;

a business may also experience contents damage due to flooding-related loss of electricity, especially for food retailers whose contents are perishable or require refrigeration (Gissing and Blong 2004). Damage may also lead to issues regarding the accessibility of the business by employees and customers. Debris, standing water, and clusters of unassessed or potentially unsafe buildings—such as after an earthquake—may lead to road closures that can be particularly disruptive to a business in terms of access to necessary labor, customers, and suppliers (Boarnet 1998; Fitchett et al. 2016). If employees and suppliers cannot access the business and the business does not have remote access or stockpiled inventory, the business may be forced to close until the roads are cleared and it can receive necessary inputs; at minimum, delays due to detours can decrease productivity (Stevenson et al. 2012). Even if a business can function, transportation access issues can also mean customers cannot easily access the business or the business cannot deliver its goods or services, both of which result in a loss of profit (Runyan 2006).

In addition to damage, recovery can be affected by the characteristics of the business itself. This includes whether the business has multiple locations, the size of the business, and whether the business owns or rents its premises. A business that has multiple locations (i.e., a branch or franchise) may have additional resources to draw upon in the event of a disaster (Ergun et al. 2010; Xiao and Van Zandt 2012). To illustrate, if a business experiences transportation issues or damage to one location, it can relocate to an alternative location or rely on the revenue at other branches to provide the cash flow needed for recovery. Also related to resources is business size, which is commonly measured by the number of employees (Corey and Deitch 2011; Khan and Sayem 2013; McDonald et al. 2014; Webb et al. 2002). Like franchises or multi-branch firms, larger businesses are likely to have more capital, labor, and resources or staff dedicated to mitigation, preparedness, and recovery (Sadiq and Graham 2016; Webb et al. 2000). Capital availability allows a business to buffer the impacts of a disaster because it can be used in place of revenue streams during downturns and interruption to keep a business afloat or replace damaged infrastructure. Lastly, owning or renting the building out of which the business operates can make a difference in recovery (Brown et al. 2016; Sapountzaki 2005). Renting may mean the business is not financially responsible for repairs to the structure, but it also means a business is at the mercy of the owners' decision-making and timeline; a business may be stuck waiting for repairs or trapped in a lease and unable to adapt to the changing environment (Alesch et al. 2001).

Business recovery is also impacted by the management of the business and the demographics of the owner or manager. Because recovery requires decision-making in a high stakes environment where there is competition for resources and information, it makes some intuitive sense that having more managerial experience will better prepare a business owner or manager (Marshall et al. 2015; Olshansky et al. 2012). Similarly, the age of a business owner or manager may also capture this type of experience. However, age is also particularly important for business owners or managers because it relates to retirement—some business owners or managers may choose to retire early after a disaster event rather than dedicate resources toward reopening (Alesch et al. 2001). There has been much research on social vulnerability and disaster recovery, particularly in terms of disproportionate impacts and recoveries for minority populations (Cutter et al. 2003; Peacock et al. 1997; Van Zandt et al. 2012). Although not extensively studied in business populations, these types of issues may also affect minority-owned or managed businesses (Marshall et al. 2015). At the least, these issues impact the household recoveries of the business owners, managers, and employees, which in turn can impact the availability of labor and in some cases capital for business recovery.

Lastly, business recovery is impacted by the financial assistance made available by insurance companies, banks, or other recovery programs. The largest federal program that provides assistance to individual businesses is the US Small Business Administration Disaster Loan Program, which provides low-interest loans to businesses after a disaster. Businesses, however, may choose to pursue private bank loans or may receive other types of assistance such as insurance payouts or recovery aid from nonprofits or state and local governments. Looking at US disaster events specifically, Dahlhamer and Tierney (1998) found that post-disaster aid was significantly and negatively associated with recovery, McDonald et al. (2014) and Stafford et al. (2013) found a positive and significant relationship between federal assistance and business survival, and Webb et al. (2002) found no significant relationship between the number of aid sources and long-term recovery. Although access to additional capital may intuitively seem beneficial, the literature is mixed on the effectiveness of recovery programs for businesses.

Research Design

Hurricane Matthew and the Study Area

Our research uses the case of 2016 Hurricane Matthew and its effect on the business community in Lumberton, North Carolina. Hurricane Matthew impacted North Carolina in October 2016 after passing through Haiti, the Bahamas, and heading up the east coast of Florida (National Hurricane Center 2018). Heavy rains led to severe inland flooding in Lumberton; the Lumber River, which runs through Lumberton, experienced historic flood levels. It crested at approximately 6.7 m (22 ft), passing the previous maximum flood level of 5.5 m (18 ft) set in 2004 and flooding much of the area south of the river and some isolated areas to the north (North Carolina Emergency Management 2017; USGS 2018).

Exacerbating the impact of the hurricane was the fact that many of the hardest-hit counties in North Carolina were also some of the most economically disadvantaged counties in the state (Centers for Disease Control and Prevention 2018). Ahead of Hurricane Matthew, Lumberton, situated within Robeson county, had a poverty rate of 35.1% for individuals and an unemployment rate of 10% according to 2012–2016 American Community Survey 5-Year Estimates. Using Lumberton as the study area for this analysis is relevant due to the severity of Hurricane Matthew's impact in the area, but more importantly, the Lumberton case allows us to use the research findings to provide recommendations related to employee and business retention for future disasters where these issues are most salient. Understanding the relationships between housing and businesses, especially in terms of the barriers employees face in reporting to work, can help identify programs that address these issues for future disasters. Lastly, Lumberton is racially and ethnically diverse, with 36% of Lumberton identifying as nonhispanic White, 37% as nonhispanic Black, and 13% as nonhispanic American Indian or Alaska Native, allowing us to examine potential recovery disparities across demographic groups (2012–2016 American Community Survey 5-Year Estimates).

Sampling, Survey Instrument, and Data Collection

To generate the sample of businesses for this analysis, the authors used *ReferenceUSA* (InfoUSA, Inc.) to download all for-profit businesses operating in Lumberton, NC, in 2016 that had been verified by phone. The authors then used ArcGIS to select all businesses that were within the inundation area or a 100-m buffer.

The inundation shapefile was created at the University of Alabama through modeling that combined a digital elevation model and the hydrograph from the stream gauge in Lumberton (USGS 02134170). This selection process resulted in 218 businesses. Because response rates for business surveys are generally low, the authors also generated a random sample of businesses in the FEMA 100-year floodplain north of the Lumber River to reach a total sample size of 350. By including the northern floodplain, the research design captured two more major commercial corridors that would not have been captured with the southern inundation area plus buffer. The authors also wanted to include businesses in the sample that did not receive water damage, but rather might have experienced contents damage due to utility loss or customer loss due to accessibility issues. Medical professionals were under-sampled in that they were excluded from the northern floodplain sample selection process. This was done due to the low walk-in availability of medical professionals for survey work as time in the field was limited. In addition, the authors believe medical professionals, surgeons, and doctors behave differently than a typical business and therefore the survey questions would be less relevant in relation to the cost of interrupting their practice. However, the authors did not exclude this sector from the southern inundation area so that it would still be captured. Lastly, during data collection, the authors found several ineligible businesses due to errors in the ReferenceUSA database, so a decision was made to include approximately 100 previously randomly selected businesses from the northern floodplain as substitutes to be added to the sample. A map of the sample is illustrated by Fig. 1.

The survey instrument itself was two pages front and back and asked businesses questions related to their damage and interruption, business characteristics, recovery status, financial assistance, and owner or manager demographics. The business survey effort was part of a larger interdisciplinary effort and longitudinal field study (van de Lindt et al. 2018), and physical damage assessments for the businesses were completed using a tool developed by a team of engineers on the project. Damage states ranged from DS0 to DS4 for building structural damage, content and inventory damage, and machinery/equipment damage. Descriptions of each damage state were printed on a separate laminated page to be given to the surveyed business to review. One engineer was present on each survey team to assist businesses in categorizing their damage in the field.

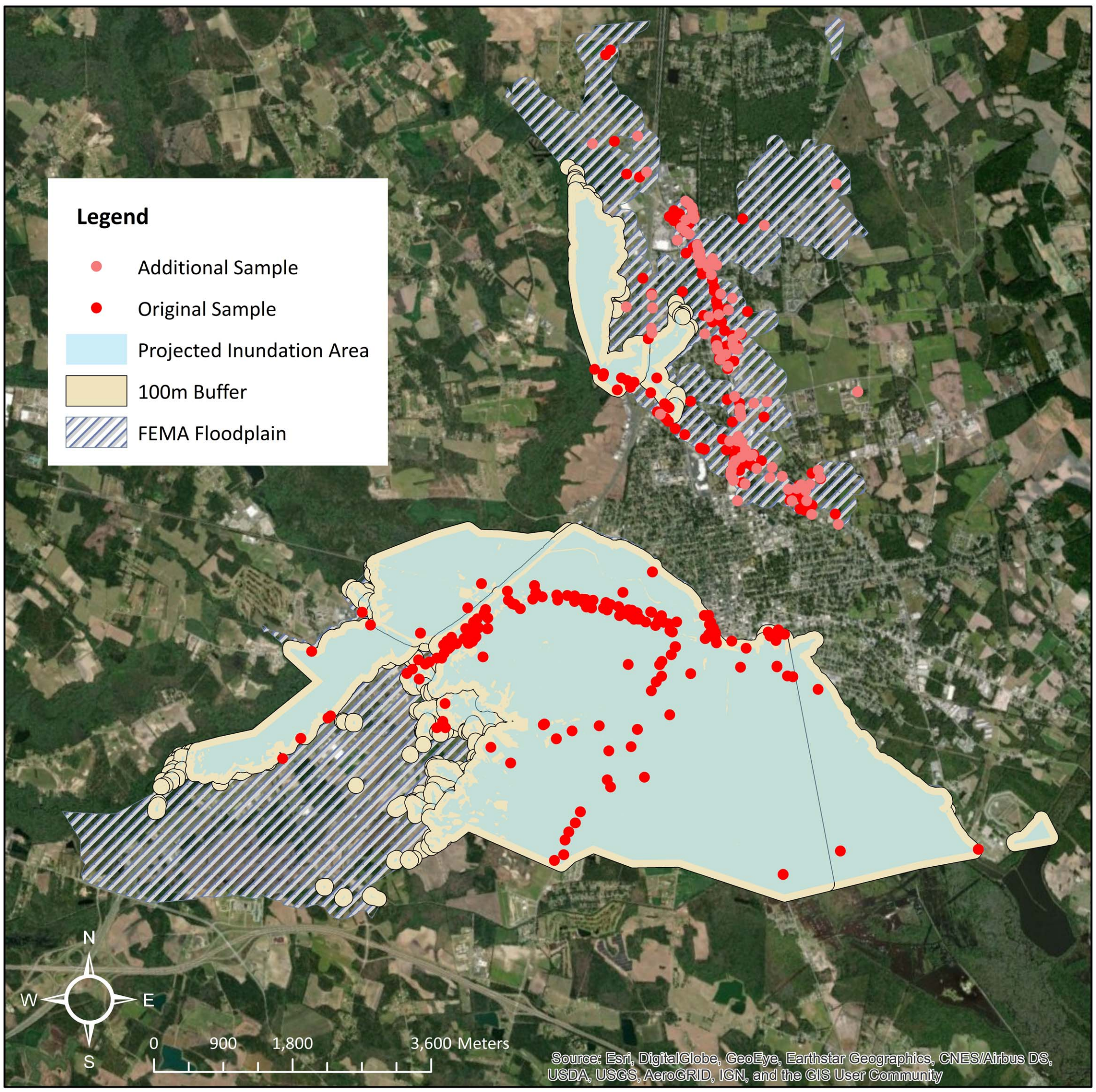

Fig. 1. Map of business sample. [Source: Esri, Digital Globle, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, USGS, AeroGRID, IGN, and the GIS User Community.]

In addition, the business survey was conducted concurrently with a housing survey, so there was feedback and collaboration through the survey design and deployment stages with respect to household-related questions.

Data collection was done using face-to-face surveys in January 2018, approximately 15 months after Hurricane Matthew made landfall. Surveys were only administered to owners or managers of the businesses. If an owner or manager was not available, follow-up visits were scheduled and/or a survey was left at the business for the owner or manager to fill out at their convenience. Phone calls were made to businesses that were not able to complete the survey while the researchers were in the field. The final sample, excluding the ineligible businesses, was 380. Of the 380 businesses, the authors received 164 survey responses, yielding a response rate of 43%. This data is a result of human subjects research and is therefore protected by the Common Rule and Institutional Review Board guidelines. Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g., anonymized data).

Analytical Methods

As identified in the literature review, the authors focus on customers and labor as the two dimensions of household influence impacting business recovery. The authors control for damage, accessibility issues, business characteristics, owner or manager demographics, and financial assistance. Descriptive statistics of the variables used in this analysis are presented in Table 1.

All variables that are used in this analysis were generated from the survey responses, except for branch and sector information, which the authors generated from the ReferenceUSA database information. ReferenceUSA also has employment information for the businesses—to preserve sample size, businesses that did not report employment information had the ReferenceUSA employment data substituted in its place. This was done for nine observations. Additionally, businesses were included in the count of employee issues if they responded to at least four of the five labor dimensions. Otherwise, the authors took no other action on missing values; those businesses without responses for all variables in the model were excluded from the analysis.

The authors utilize logistic regression for the primary analyses. The authors first establish a baseline model of business recovery based on damage, business characteristics, and owner/manager characteristics. The authors present the model below using the Variable Name field from Table 1:

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access + \beta_5 Branch \\ &\quad + \beta_6 Man\_const + \beta_7 Retail + \beta_8 Emp\_pre\_total + \beta_9 Rent \\ &\quad + \beta_{10} Age + \beta_{11} Nonwhite + \beta_{12} Experience + \beta_{13} Assistan \end{aligned} \tag{1}$$

Our measure of recovery, as indicated by the model, is whether or not the business has fully recovered since the impact of Hurricane Matthew based on owner or manager perception, similar to the dependent variable used by Dahlhamer and Tierney (1998). This research hopes to extend the findings of Xiao and Van Zandt (2012) by moving the scope of households' influence from reopening probabilities after 3 months to owner- or manager-perceived recovery at 15 months.

Once the baseline model is established, customer variables and employee variables are included one at a time. This helps

Table 1. Descriptive statistics

Variable	Variable name	Observations	Mean	Standard deviation	Minimum	Maximum
Dependent variable						
Fully recovered: Yes = 1; No = 0	Fully_recov	162	0.44	0.5	0	1
Damage						
Building damage: none, minor, moderate, severe, complete	Dmg_bldg	162	1.93	1.4	1	5
Content damage: none, minor, moderate, severe, complete	Dmg_con	162	2.40	1.6	1	5
Accessibility issues						
Accessibility problem (i.e., street or sidewalk closure): Yes = 1; No = 0	Access	153	0.59	0.5	0	1
Customer issues						
Customer loss: Yes = 1; No = 0	Customers	162	0.64	0.5	0	1
Percent loss of customers	Cus_per	147	21.33	25.2	0	100
Employee issues						
Employee transportation problems: Yes = 1; No = 0	Em_trans	159	0.48	0.5	0	1
Employee home repair problem: Yes = 1; No = 0	Em_dmg	154	0.48	0.5	0	1
Employee children/school problems: Yes = 1; No = 0	Em_sch	157	0.24	0.4	0	1
Employee physical health problems: Yes = 1; No = 0	Em_phys	154	0.06	0.2	0	1
Employee mental health problems: Yes = 1; No = 0	Em_mental	156	0.03	0.2	0	1
Number of employee issues reported	Em_number	156	1.45	1.3	0	5
Business characteristics						
Branch: Yes = 1; No = 0	Branch	164	0.35	0.5	0	1
Manufacturing or construction sector: Yes = 1; No = 0	Man_const	164	0.10	0.3	0	1
Retail or wholesale sector: Yes = 1; No = 0	Retail	164	0.36	0.5	0	1
Number of part- and full-time employees before Hurricane Matthew	Emp_pre_total	163	16.70	29.6	1	250
Rents premises: Yes = 1; No = 0	Rent	161	0.47	0.5	0	1
Business owner/manager profile						
Age: years	Age	159	48.21	14.3	21	81
Race: non-white = 1; white = 0	Nonwhite	159	0.45	0.5	0	1
Years of experience	Experience	158	16.43	12.9	0.02	70
Financial assistance						
Received assistance (insurance/bank/recovery program): Yes = 1; No = 0	Assistance	164	0.15	0.4	0	1

to understand their individual influence as well as avoid issues of multicollinearity in the different measures. The subsequent models of household influence as customers then become as follows, with variables different from the baseline model [Eq. (1)] bolded for convenience:

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \beta_6 Branch + \beta_7 Man\_const + \beta_8 Retail \\ &\quad + \beta_9 Emp\_pre\_total + \beta_{10} Rent + \beta_{11} Age + \beta_{12} Nonwhite \\ &\quad + \beta_{13} Experience + \beta_{14} Assistance \end{aligned} \tag{2}$$

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_2} + \beta_6 Branch + \beta_7 Man\_const + \beta_8 Retail \\ &\quad + \beta_9 Emp\_pre\_total + \beta_{10} Rent + \beta_{11} Age + \beta_{12} Nonwhite \\ &\quad + \beta_{13} Experience + \beta_{14} Assistance \end{aligned} \tag{3}$$

where $Customers_1$ = Customers; and $Customers_2$ = Cus_per.

In addition, the models of household influence as labor become as follows, with variables different from the baseline model [Eq. (1)] bolded for convenience:

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \boldsymbol{\beta_6 Employees_1} + \beta_7 Branch \\ &\quad + \beta_8 Man\_const + \beta_9 Retail + \beta_{10} Emp\_pre\_total \\ &\quad + \beta_{11} Rent + \beta_{12} Age + \beta_{13} Nonwhite + \beta_{14} Experience \\ &\quad + \beta_{14} Assistance \end{aligned} \tag{4}$$

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \boldsymbol{\beta_6 Employees_2} + \beta_7 Branch \\ &\quad + \beta_8 Man\_const + \beta_9 Retail + \beta_{10} Emp\_pre\_total \\ &\quad + \beta_{11} Rent + \beta_{12} Age + \beta_{13} Nonwhite + \beta_{14} Experience \\ &\quad + \beta_{14} Assistance \end{aligned} \tag{5}$$

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \boldsymbol{\beta_6 Employees_3} + \beta_7 Branch \\ &\quad + \beta_8 Man\_const + \beta_9 Retail + \beta_{10} Emp\_pre\_total \\ &\quad + \beta_{11} Rent + \beta_{12} Age + \beta_{13} Nonwhite + \beta_{14} Experience \\ &\quad + \beta_{14} Assistance \end{aligned} \tag{6}$$

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \boldsymbol{\beta_6 Employees_4} + \beta_7 Branch \\ &\quad + \beta_8 Man\_const + \beta_9 Retail + \beta_{10} Emp\_pre\_total \\ &\quad + \beta_{11} Rent + \beta_{12} Age + \beta_{13} Nonwhite + \beta_{14} Experience \\ &\quad + \beta_{14} Assistance \end{aligned} \tag{7}$$

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \boldsymbol{\beta_6 Employees_5} + \beta_7 Branch \\ &\quad + \beta_8 Man\_const + \beta_9 Retail + \beta_{10} Emp\_pre\_total \\ &\quad + \beta_{11} Rent + \beta_{12} Age + \beta_{13} Nonwhite + \beta_{14} Experience \\ &\quad + \beta_{14} Assistance \end{aligned} \tag{8}$$

where $Employees_1$ = Em_trans; $Employees_2$ = Em_dmg; $Employees_3$ = Em_sch; $Employees_4$ = Em_phys; and $Employees_5$ = Em_mental.

As shown in Eqs. (2)–(8), the authors include two measures of customer loss and five measures of labor disruption. It is unlikely that a business knows the exact reason why individual customers are no longer coming to the business, but they do have information related to why an employee is not reporting for work, for example when the employee calls in to miss work or returns after an absence.

The authors then conclude with a full model that incorporates labor issues as a count variable. This is a way to incorporate all of the labor variables in a single model as well as understand the magnitude of their combined effect. The full model becomes as follows, with variables different from the baseline model [Eq. (1)] bolded for convenience:

$$\begin{aligned} logit(Fully\_recov) &= \beta_1 + \beta_2 Dmg\_bldg + \beta_3 Dmg\_con + \beta_4 Access \\ &\quad + \boldsymbol{\beta_5 Customers_1} + \boldsymbol{\beta_6 Em\_number} + \beta_7 Branch \\ &\quad + \beta_8 Man\_const + \beta_9 Retail + \beta_{10} Emp\_pre\_total \\ &\quad + \beta_{11} Rent + \beta_{12} Age + \beta_{13} Nonwhite + \beta_{14} Experience \\ &\quad + \beta_{14} Assistance \end{aligned} \tag{9}$$

The authors note that the later models [Eqs. (4)–(9)] include at least one variable representing hazard characteristics, capital, labor, suppliers, customers, sector, business management, owner/manager demographics, external disruption (e.g., utilities and transportation), and assistance. The authors believe this is important for model specification, although the outcome events per variable (EPV) drops below ten for some of the models. The EPV at its lowest, however, never drops below nine, which research suggests still has a similar risk of bias to the ten EPV rule of thumb (Vittinghoff and McCulloch 2007).

The study also makes use of two measures of model fit in reporting because there is not an R^2 for logistic regression equivalent to that of an ordinary least squares (OLS) regression. The first is McFadden's R^2, which is arguably comparable to the relationship between the total sum of squares and the residual sum of squares in OLS (McFadden 1974). However, because this is still a pseudo R^2 and there is not a consensus on the most ideal fit statistic for logistic regression, the authors also include the percentage of observations whose outcome was correctly classified by the model using 0.5 as the cutoff for the predicted probability.

The equation numbers are consistent with the model numbers when presenting the results of the analysis.

Results

Descriptive Statistics

The authors first discuss the descriptive statistics presented in Table 1 to provide an overview of the recovery of businesses in the sample, the impacts of Hurricane Matthew experienced by these businesses, and their characteristics. At the time of the survey, 44% of businesses reported being fully recovered. Damage-wise, businesses reported experiencing more content damage than building damage, with the average content damage ranging from minor to moderate and building damage averaging closer to the minor category. Most businesses reported DS0 (no damage) for both building (56%) and contents (49%), but the second most frequent damage category for contents was DS4 (complete damage, 21% of respondents), whereas the second most frequent category for building damage was DS2 (minor damage, 23% of respondents). Close to 60% of businesses experienced accessibility issues (e.g., street and sidewalk closure) related to the disaster. As discussed in the literature review, this type of indirect impact can still be very disruptive to business operation and can prevent customers from accessing the business location. Approximately 64% of businesses reported a loss of customers with an average percent customer loss of around 21% and a maximum of 100%.

In addition to customer loss, several businesses reported issues related to labor. The two most common sources of labor disruption were transportation issues and damage to an employee's personal goods. There were 48% of businesses that reported employees could not come to work due to transportation issues, and 48% of businesses reported that employees could not come to work due to their own personal damage or repairs going on at home. Fewer businesses reported issues related to school closure or childcare issues, with only 24% of the surveyed businesses indicating that employees were unable to come to work due to having children at home. Lastly, 6% of businesses reported that employees could not come to work due to physical health issues and 3% reported that they had employees not come into work due to mental health issues. Businesses usually reported more than one labor issue, with an average of 1.4 labor issues out of five reported by each business.

When it comes to the make-up of the sample, businesses were primarily single-location businesses, with only 35% of businesses being listed as a branch in the ReferenceUSA database. There were 36% of businesses considered retail or wholesale businesses, which are considered vulnerable to disaster; by contrast, only 10% of businesses were in the manufacturing or construction sector, which is considered a more resilient sector (Alesch et al. 2001; Revenue and Brunton 2013; Webb et al. 2000). Almost half (47%) of the businesses in the sample rented their premises. In terms of size, businesses in the sample ranged from 1 employee to 250 employees with an average number of employees of 17. When it comes to the respondents, the average age of the owner or manager of the business was around 48 years. Approximately 45% of owners or managers responding to the survey identified as a race other than White and had an average of 16 years of experience.

Lastly, the number of businesses reporting that they had received any type of financial assistance, be it an insurance payout, bank loan, or recovery program, was quite low. Only around 15% of businesses reported receiving any of these types of assistance programs.

Baseline Model

Next, the authors present the results of the baseline model of business recovery, as shown in Table 2, which does not consider household variables. Coefficients have been converted to odds ratios for easier interpretation.

In the baseline model [Eq. (1), Model 1], the authors account for damage, accessibility of the business, business characteristics, business owner or manager characteristics, and financial assistance. Of these variables, contents damage, accessibility issues, and minority ownership or management were significant, negative predictors of full recovery. For every increase in content damage category (e.g., DS2 "minor" to DS3 "moderate"), the odds of being fully recovered decrease by 37%. Businesses that experienced accessibility issues saw a 72% decrease in odds of full recovery compared to businesses that did not have accessibility issues. Similarly, businesses owned or managed by an individual whose race was other than White also saw a 72% decrease in odds of full recovery. Being a branch was the only significant, positive predictor. Businesses that were branches had odds of full recovery that were 4.46 times (346%) higher than businesses that were single-location businesses.

Table 2. Baseline model of business recovery in Lumberton, North Carolina

	Model 1		
Variable	O.R.	S.E.	p-value
Constant	2.109	2.298	0.247
Damage			
Building damage	1.012	0.217	0.477
Content damage	0.635	0.112	0.005**
Accessibility issues			
Accessibility problems	0.277	0.121	0.002**
Business characteristics			
Branch	4.461	2.376	0.003**
Manufacturing/construction sector	0.741	0.544	0.342
Retail/wholesale sector	1.229	0.564	0.327
Number of employees	1.006	0.009	0.271
Rents premises	1.122	0.535	0.405
Business owner/manager profile			
Age	1.006	0.020	0.374
Race (minority-owned/managed)	0.276	0.128	0.003**
Years of experience	1.009	0.022	0.335
Financial assistance			
Received assistance	1.305	0.839	0.678
Likelihood ratio chi-square (G^2)	49.73	—	—
G^2 p-value	0.000	—	—
-2 log (L_1)	143.70	—	—
Correctly classified	75.35%	—	—
Pseudo R^2	0.257	—	—
N	142	—	—

Note: O.R. = odds ratio; S.E. = standard error; and p = value represents 1-tailed test. **$p \leq 0.05$.

When controlling for content damage, building damage was not significant; surprisingly, business size and financial assistance were also insignificant predictors of full recovery in the baseline model. The results of the full baseline model are fairly consistent with what might be expected based on the sample and the literature with a few surprises. In the context of the sample, the insignificance of content damage is unsurprising as both inundated and noninundated businesses were sampled. Businesses in the sample might have lost contents due to utility outages rather than the flooding itself. If the inventory was perishable or temperature-sensitive, this could result in large losses for the business even if the building was unharmed. As indicated previously, fewer businesses in the sample reported building damage, while more experienced content damage. The two damage variables alone had a McFadden's R^2 of 0.11 and could correctly classify almost 70% of the observations. Although building damage was insignificant, it still contributed a good amount of explanatory power in the model when combined with contents damage.

Accessibility issues and branch status are also fairly unsurprising. Accessibility issues, like content damage, have the potential to affect businesses that were not directly flooded. Businesses that are location-dependent may be forced to close until the business is accessible, also resulting in loss. Branches, in this scenario, might

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Table 3. Customer loss

Variable	Model 2 O.R.	Model 2 S.E.	Model 2 p-value	Model 2 bStdXY	Model 3 O.R.	Model 3 S.E.	Model 3 p-value	Model 3 bStdXY
Constant	5.919	7.236	0.073*	—	6.438	8.577	0.081*	—
Damage								
Building damage	0.921	0.246	0.379	−0.039	1.067	0.308	0.411	0.032
Content damage	0.621	0.124	0.009**	−0.266	0.611	0.133	0.012**	−0.288
Accessibility issues								
Accessibility problems	0.216	0.113	0.002**	−0.252	0.180	0.097	0.001**	−0.298
Customer issues								
Customer loss (binary indicator)	0.063	0.038	0.000***	−0.433	—	—	—	—
Customer loss (%)	—	—	—	—	0.952	0.013	0.000***	−0.423
Business characteristics								
Branch	5.390	3.364	0.004**	0.267	4.444	2.750	0.008**	0.248
Manufacturing/construction sector	0.369	0.333	0.135	−0.100	0.721	0.610	0.350	−0.035
Retail/wholesale sector	1.996	1.099	0.105	0.112	1.807	1.029	0.150	0.101
Number of employees	1.016	0.012	0.092*	0.127	0.998	0.015	0.440	−0.018
Rents premises	1.911	1.068	0.124	0.108	1.268	0.712	0.337	0.042
Business owner/manager profile								
Age	1.012	0.022	0.286	0.056	0.996	0.022	0.427	−0.021
Race (Minority-owned/managed)	0.284	0.151	0.009**	−0.211	0.344	0.187	0.025**	−0.188
Years of experience	1.024	0.024	0.160	0.103	1.026	0.025	0.146	0.119
Financial assistance								
Received assistance	1.303	0.979	0.363	0.032	2.822	2.186	0.091**	0.131
Likelihood ratio chi-square (G^2)	77.88	—	—	—	65.59	—	—	—
G^2 p-value	0.000	—	—	—	0.000	—	—	—
$-2 \log (L_1)$	114.45	—	—	—	109.32	—	—	—
Correctly classified	81.56%	—	—	—	82.81%	—	—	—
Pseudo R^2	0.405	—	—	—	0.375	—	—	—
N	141	—	—	—	128	—	—	—

Note: O.R. = odds ratio; S.E. = standard error; bStdX = log odds standardized on X and Y; and p = value represents 1-tailed test. *p ≤ 0.1; **p ≤ 0.05; and ***p ≤ 0.001.

be able to operate out of an alternative location in the meantime. They also might have access to additional resources that contribute to their recovery. Owner or manager race, while not often significant in business studies, makes sense in the context of social vulnerability and inequitable recoveries across demographic groups (Cutter et al. 2003; Peacock et al. 1997; Van Zandt et al. 2012).

The insignificance of receiving post-event assistance in explaining business' full recovery mirrors the conflicting literature on disaster assistance programs for businesses and must be understood in the context of the lack of assistance to businesses in the sample (Webb et al. 2002). The size of a business is surprising in its insignificance, considering businesses with more resources to be usually in a better position to recover. This may become more important as the authors add household variables. The model fit remains acceptable. McFadden's R^2 is approximately 0.26, and looking at it in terms of classification error, overall, the model correctly classified 75.35% of the observations.

Customer Issues

The authors now add household variables as dimensions of recovery, beginning with the role households play as consumers. The authors look at two measures of customer loss: a dichotomous measure and a continuous measure. The results of the model including the customer loss variables are presented in Table 3.

Model 2 shows the results of including a dichotomous measure of whether or not a business experienced customer loss. According to the model, the odds of being fully recovered decrease by 94% for businesses that lost customers compared to businesses that did not, controlling for the baseline variables. When the authors look at the standardized coefficients to examine the magnitude of effect across variables, customer loss resulted in the second-highest standard deviation change in log odds per standard deviation increase in X. This is a higher magnitude of effect than both of the damage variables. Although standardized coefficients are difficult to interpret for dummy variables, they still represent the relative magnitude of effect in relation to the other covariates (Poston 2002; Scott Long 1997). In addition, the McFadden's R^2 increased from 0.26 to 0.40 when the authors included the dichotomous customer variable. The model now correctly classifies 81.56% of the cases.

Model 3 looks at the loss of customers as a continuous measure, where businesses reported an estimation of the percent loss of customers they experienced. As illustrated by Model 3, for each additional percentage point increase in customer loss, the odds of being fully recovered decrease by 5%. This model had more missing values, and the number of observations decreased from 141 to 128. However, the McFadden's R^2 is still 0.38, with an 82.81% correct classification rate. Like Model 2, customer loss still has the second-highest magnitude of effect compared to the other variables.

The continuous measure is more informative when looking at business sensitivity to customer loss. Specifically, the authors can predict the odds of full recovery at various levels of customer loss. For example, Fig. 2 presents the predicted probability of being fully recovered at 5% intervals of customer loss, holding the other covariates at their means. This further illustrates the sensitivity of businesses to customer loss.

Contents damage, accessibility issues, minority ownership or management, and branch status remain significant predictors of full recovery even when adding customer loss measures in Models 2 and 3. Each increase in contents damage category decreased odds of full recovery by 38% and 39% in Models 2 and 3, respectively; businesses with accessibility issues had a 78% and 82% decrease in odds; minority-owned or managed businesses had a 72% and 66% decrease in odds, and branches had an odds increase of 439% and

Cus_per=	Prob.	S.E.[1]	p-value	
0%	0.615	0.079	0.000	***
5%	0.556	0.073	0.000	***
10%	0.494	0.067	0.000	***
15%	0.433	0.062	0.000	***
20%	0.374	0.060	0.000	***
25%	0.318	0.061	0.000	***
30%	0.268	0.061	0.000	***
35%	0.222	0.062	0.000	***
40%	0.183	0.061	0.002	**
45%	0.149	0.058	0.006	**
50%	0.120	0.055	0.015	**
55%	0.096	0.051	0.028	**
60%	0.077	0.046	0.046	**
65%	0.061	0.040	0.065	*
70%	0.048	0.035	0.086	*
75%	0.038	0.031	0.106	
80%	0.030	0.026	0.125	
85%	0.024	0.022	0.143	
90%	0.019	0.019	0.160	
95%	0.015	0.016	0.176	
100%	0.011	0.013	0.191	

[1] Calculated using the delta method

* = p ≤ 0.1; ** = p ≤ 0.05; *** = p ≤ 0.001

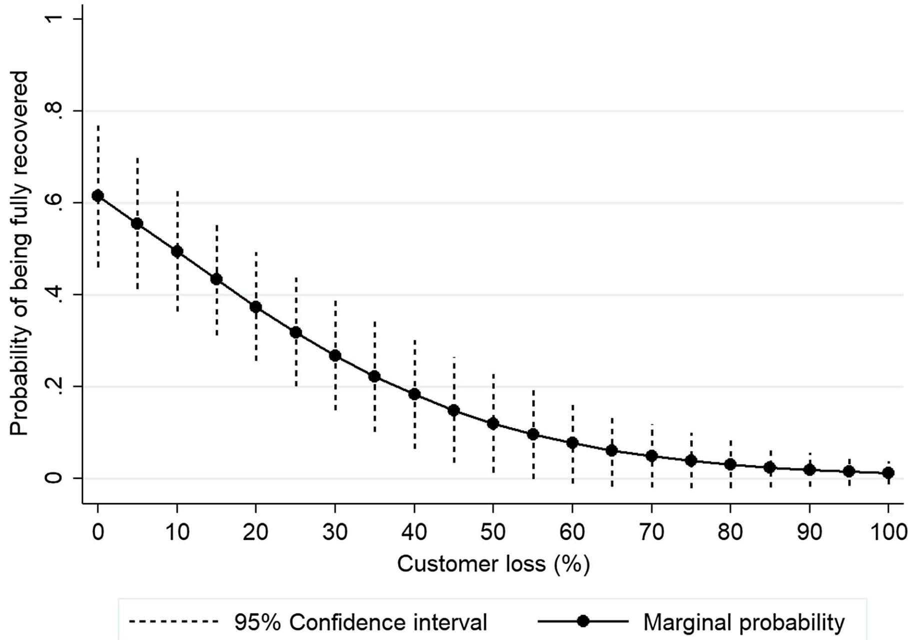

Fig. 2. Probabilities of recovery by customer loss.

Table 4. Labor issues correlation matrix

Variables	Employee transportation problems	Employee home repair problems	Employee children/ school problems	Employee physical health problems	Employee mental health problems	Customer loss
Employee transportation problems	1.000	—	—	—	—	—
Employee home repair problems	0.514***	1.000	—	—	—	—
Employee children/school problems	0.342***	0.452***	1.000	—	—	—
Employee physical health problems	0.179*	0.264**	0.386***	1.000	—	—
Employee mental health problems	0.132	0.192*	0.326***	0.735***	1.000	—
Customer loss	0.080	0.108	−0.088	0.073	0.060	1.000

Note: *p ≤ 0.1; **p ≤ 0.05; and ***p ≤ 0.001.

344%, respectively. Once adding customer variables, however, the number of employees (a proxy for business size) becomes significant in Model 2. Each additional employee increases the odds of full recovery by 1.6%. Businesses with more employees are more likely to be fully recovered when controlling for customer issues, perhaps indicating that businesses with more resources can withstand customer loss better than those with fewer resources. Additionally, recovery assistance became a significant, positive predictor of full recovery when the authors control for the continuous measurement of customer loss in Model 2. Businesses that received some form of financial assistance had full recovery odds 2.8 times (182%) higher than businesses that did not.

Labor Issues

The authors now add the role of households as a source of labor. The survey asked businesses about five sources of labor disruption and whether they prevented employees from reporting to work after Hurricane Matthew. These disruptions were transportation issues, personal home damage, childcare issues or school closure issues, and physical and mental health issues resulting from the disaster. The relationship between these variables is presented in Table 4.

Almost all of the labor issues are significantly correlated with the exceptions of employee transportation problems and employee mental health problems. In addition, the authors cannot separate how much overlap there is between categories (e.g., individual employees suffering from multiple issues). Therefore, the authors decided to add each variable individually into the model rather than add them in a nested or stepwise fashion. The labor issues were not significantly correlated with customer issues so the authors kept the dichotomous customer loss variable in the model. This was preferable to the continuous customer loss measure since it preserved the most observations. The results of the separate models are presented in Table 5.

Two of the labor issues were negatively significant at the 0.1 level, specifically, transportation problems and issues related to children or school disruption in Model 4 and Model 6, respectively. Businesses whose employees did not report to work because transportation issues saw a 56% decrease in odds of being fully recovered compared to those who did not have employees with these issues; businesses whose employees did not report to work due to issues related to children and schools saw a 60% decrease in odds of being fully recovered compared to businesses whose employees did not report issues with children or schools. Employees not

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Table 5. Labor issues

Variable	Model 4			Model 5			Model 6			Model 7			Model 8		
	O.R.	S.E.	p-value	O.R.	S.E.	p-value	O.R.	S.E.	p-value	O.R.	S.E.	p-value	O.R.	S.E.	p-value
Constant	10.264	13.911	0.043**	6.021	7.688	0.080*	8.122	10.488	0.053*	5.657	7.142	0.085*	5.826	7.411	0.083*
Damage															
Building Damage	0.887	0.238	0.328	0.847	0.237	0.277	0.810	0.231	0.230	0.818	0.245	0.252	0.804	0.238	0.230
Content Damage	0.630	0.128	0.012**	0.643	0.130	0.015**	0.677	0.141	0.030**	0.625	0.131	0.013**	0.624	0.130	0.012**
Accessibility issues															
Accessibility problems	0.206	0.109	0.002**	0.227	0.118	0.002**	0.215	0.113	0.002**	0.240	0.128	0.004**	0.229	0.122	0.003**
Customer issues															
Customer loss (binary indicator)	0.064	0.040	0.000***	0.066	0.041	0.000***	0.056	0.036	0.000***	0.054	0.036	0.000***	0.052	0.034	0.000***
Employee issues															
Employee transportation problems	0.441	0.251	0.075*	—	—	—	—	—	—	—	—	—	—	—	—
Employee home repair problem	—	—	—	0.968	0.522	0.476	—	—	—	—	—	—	—	—	—
Employee children/school problems	—	—	—	—	—	—	0.402	0.268	0.086*	—	—	—	—	—	—
Employee physical health problems	—	—	—	—	—	—	—	—	—	0.452	0.516	0.244	—	—	—
Employee mental health problems	—	—	—	—	—	—	—	—	—	—	—	—	1.349	1.861	0.414
Business characteristics															
Branch	6.060	3.899	0.003**	5.005	3.157	0.006**	5.352	3.438	0.005**	6.128	4.027	0.003**	5.956	3.874	0.003**
Manufacturing/construction sector	0.340	0.331	0.134	0.385	0.349	0.146	0.303	0.296	0.111	0.339	0.315	0.123	0.357	0.334	0.135
Retail/wholesale sector	2.064	1.157	0.098*	2.093	1.147	0.089*	1.823	1.016	0.141	2.301	1.306	0.071*	2.352	1.333	0.066*
Number of employees	1.019	0.013	0.063*	1.015	0.013	0.114	1.020	0.013	0.060*	1.018	0.013	0.070*	1.017	0.013	0.093*
Rents premises	1.923	1.100	0.127	1.901	1.090	0.132	2.130	1.213	0.092*	2.007	1.154	0.113	1.927	1.104	0.126
Business owner/manager profile															
Age	1.010	0.023	0.336	1.012	0.022	0.296	1.011	0.023	0.318	1.011	0.023	0.310	1.012	0.022	0.299
Race (Minority-owned/managed)	0.302	0.162	0.013**	0.303	0.164	0.014**	0.275	0.153	0.011**	0.260	0.147	0.009**	0.267	0.150	0.010**
Years of experience	1.027	0.025	0.139	1.024	0.024	0.155	1.023	0.024	0.168	1.033	0.025	0.093	1.034	0.026	0.086
Financial assistance															
Received assistance	1.095	0.851	0.454	1.340	1.012	0.350	1.473	1.155	0.311	1.467	1.151	0.313	1.306	1.032	0.368
Likelihood ratio chi-square (G^2)	78.62	—	—	75.98	—	—	78.44	—	—	77.94	—	—	79.61	—	—
G^2 p-value	0.000	—	—	0.000	—	—	0.000	—	—	0.000	—	—	0.000	—	—
$-2 \log (L_1)$	110.89	—	—	112.42	—	—	111.07	—	—	107.64	—	—	108.17	—	—
Correctly classified	77.70%	—	—	81.16%	—	—	81.29%	—	—	83.09%	—	—	81.88%	—	—
Pseudo R^2	0.415	—	—	0.403	—	—	0.414	—	—	0.420	—	—	0.424	—	—
N	139	—	—	138	—	—	139	—	—	136	—	—	138	—	—

Note: O.R. = odds ratio; S.E. = standard error; and p = value represents 1-tailed test. $^*p \le 0.1$; $^{**}p \le 0.05$; and $^{***}p \le 0.001$.

reporting to work due to personal home damage and/or health issues were not significant predictors of full recovery for the businesses in the sample.

Like the customer loss models, the number of employees is again a positive, significant predictor when the authors begin to include household variables. Each employee increases the odds of full recovery by around 1%–2% in Model 4 and Models 6–8. It makes intuitive sense that businesses with more employees are better able to withstand employee issues. However, retail or wholesale sector became a significant, positive predictor in almost all of the models when an employee variable is included. Retail or wholesale businesses had odds that were between 82% and 135% higher than other sectors for Models 4–5 and 7–8. Since the authors control for business size, this may be due to the high substitutability of retail or wholesale employees compared to other sectors (Zhang et al. 2009). Businesses that have less labor specialization likely have fewer barriers in hiring, helping them buffer against post-disaster labor shortages.

Although the labor variables provide meaningful information, they are marginal in their impact on the model as a whole. The average correct classification for models with a labor variable is 81.02%, and McFadden's R^2 increased slightly in each of the models with the exception of Model 5.

Full Model

Lastly, because the authors cannot include all the labor issues in the model, the authors use a count variable to see whether the number of labor issues a business faces is significant in predicting whether or not they were fully recovered at the time of the survey. The authors present this model in Table 6.

Table 6. Full model of business recovery in Lumberton

	Model 9		
Variable	O.R.	S.E.	p-value
Constant	9.066	12.109	0.050**
Damage			
Building damage	0.786	0.234	0.209
Content damage	0.641	0.134	0.017**
Accessibility issues			
Accessibility problems	0.225	0.120	0.003**
Customer issues			
Customer loss (binary indicator)	0.053	0.035	0.000***
Employee issues			
Number of employee issues reported	0.774	0.171	0.123
Business characteristics			
Branch	6.648	4.465	0.003**
Manufacturing/construction sector	0.328	0.314	0.123
Retail sector	2.250	1.287	0.078*
Number of employees	1.022	0.014	0.048**
Rents premises	1.976	1.133	0.118
Business owner/manager profile			
Age	1.008	0.023	0.361
Race (minority-owned/managed)	0.255	0.146	0.009**
Years of experience	1.034	0.026	0.092*
Financial assistance			
Received assistance	1.398	1.105	0.336
Likelihood ratio chi-square (G^2)	81.28	—	—
G^2 p-value	0.000	—	—
$-2\log(L_1)$	106.51	—	—
Correctly classified	81.16%	—	—
Pseudo R^2	0.433	—	—
N	138	—	—

Note: O.R. = odds ratio; S.E. = standard error; and p = value represents 1-tailed test. *$p \leq 0.1$; **$p \leq 0.05$; and ***$p \leq 0.001$.

As shown in Table 6, the number of labor issues a business faced was insignificant. This illustrates the importance of understanding the dimensions of labor disruption as opposed to aggregating into a singular measure. However, McFadden's R^2 is the highest in this model compared to the individual labor variable models. In terms of variable significance, the variables from the baseline model are still important—contents damage, building access, whether or not the business is a branch, and minority ownership or management—as well as the dichotomous customer variable. Like the other household variable models, the number of employees is a significant, positive predictor of full recovery. Retail or wholesale sector remained a significant, positive predictor, with the specific addition of a labor variable. One divergence from the previous models is the significance of the managerial experience variable. When the authors include labor issues as a count variable, each additional year of experience increases the odds of being fully recovered by 3%. Managerial experience was also significant in Model 7 and 8, providing some additional evidence toward the notion that business management is important in managing labor disruptions.

Discussions and Conclusions

The authors began this research with the intention of understanding the specific dimensions of households that affect business recovery and their importance compared to other factors. This research has provided further evidence on the importance of households in business recovery, building off the work of Xiao and Van Zandt (2012). Household return affected the reopening decisions of businesses 3 months after a disaster (Xiao and Van Zandt 2012), which the present research suggests is wise decision-making on the part of the business: household variables significantly affected business outcomes even over a year post-event. The authors found that households, through roles of customers and labor, significantly affect whether a business was more or less likely to be fully recovered at the time of the survey controlling for damage, business characteristics, owner or manager characteristics, and financial assistance. Customer loss in particular had a higher effect magnitude than initial damage in terms of hindering recovery. Labor disruption caused by transportation issues and childcare or school closure issues had a smaller relative effect, but also significantly lowered a business's odds of full recovery. Not all labor variables were significant, and the number of disruptions was also insignificant, stressing the importance of understanding the dimensions of household disruption on business recovery.

In addition, household variables influenced the effects of other variables within the models. The number of employees was also almost always significant when controlling for customer loss and labor disruptions, indicating the ability of larger businesses to absorb, address, or withstand these issues. Retail or wholesale businesses were also almost always significantly more likely to be fully recovered when controlling for labor in particular; this finding is perhaps due to the substitutability or ease of employee replacement in this sector (Zhang et al. 2009). Years of experience was also positively associated with full recovery in Model 7 and 8, and particularly in Model 9 looking at the number of labor disruptions a business experiences, highlighting the importance of management in dealing with business operational issues such as scheduling, hiring, and other issues of employee disruption. Control variables that were significant in the recovery of businesses in Lumberton included contents damage, difficulty in accessing the business, whether or not a business was a branch, and whether or not the business was minority-owned or managed. Contents damage, accessibility issues, and minority ownership or management all negatively impacted the odds of a business being fully recovered at the time of the survey. Businesses that were branches had higher odds of full recovery compared to single-location businesses. These variables were consistent throughout all the models the authors presented in the paper.

Research Contributions

This study contributes to the literature in a few ways. Research on business recovery at the individual business level tends to be more long-term, especially literature focusing on businesses in the United States (Marshall et al. 2015; McDonald et al. 2014; Webb et al. 2002). Recovery is complex; therefore, surveys are a useful tool to capture the wide range of factors affecting business performance after disasters. However, there are methodological challenges in conducting business disaster research (Schrank et al. 2013). The literature on more short-term recovery is sparser, with fewer studies utilizing surveys in timescales under 2 years after the event (Dahlhamer and Tierney 1996; Xiao and Van Zandt 2012). Short-term business outcomes, rather, have been examined using primarily observational data or convenience sampling (Corey and Deitch 2011; Lam et al. 2012; Lesage et al. 2011). The baseline model and subsequent analyses add to the business disaster literature that looks at shorter-term recovery outcomes.

In addition, previous research has been fairly one-dimensional in terms of labor disruption, and very few studies have included labor variables in their business recovery models. Corey and Deitch (2011) had businesses estimate the percentage of staff loss they experienced that was significant in their model of organization performance 6–8 months after Hurricane Katrina. Labor shortages remained a significant predictor of business performance even 3.5 years after Hurricane Katrina (Dietch and Corey 2011). However, to the knowledge of the authors, there has not been research that quantitatively models or even systematically documents the reasons for labor disruption or why employees are not reporting for work. Interestingly, the authors identified a report in the literature review that had some survey results that include reasons for labor disruption—an annual business continuity survey done in the United Kingdom looking at extreme winter weather events—which found that the most common effects of extreme weather events were staff unable to come to work due to travel disruption and staff unable to come to work due to school closure/childcare issues (Musgrave and Woodman 2013). This mirrors the particular significance of transportation issues and child or school issues compared to other causes of disruption in the present analysis.

Lastly, while this research was primarily focused on business-side outcomes of the business-household interdependency, the findings of this research bear relevance to housing studies given the importance of household income in recovery (Bolin and Trainer 1978).

Implications for Policy

Because the authors looked specifically at the dimensions of labor disruption that affected business recovery, the authors can identify more precise policy recommendations. This research indicates that transportation issues and school closures and/or childcare issues significantly affected business recovery. Improvements to the transportation network could be prioritized, which would also benefit the recovery of schools and childcare facilities. Additionally, accessibility issues were also significant and negatively related to the odds of full recovery in all models, further reinforcing the importance of transportation infrastructure in the operational performance of businesses.

Second, access to recovery resources was insignificant in all the fitted models except for Model 2 in the section "Customer Issues." Although this may be affected by the fact that few businesses reported that they received assistance in Lumberton, it also only took into consideration financial resources. This research suggests that alternative forms of assistance in the form of labor retention may have been helpful to businesses. Childcare assistance and bussing services can have dual roles of individual assistance as well as business assistance. This research also points to inequitable recoveries for minority-owned or managed businesses. Programs and initiatives to reach out to these business and household populations specifically will encourage a more equitable recovery as Lumberton moves forward.

In addition, encouraging businesses to set up an online presence (e.g., website) may help them retain customers after a disaster event. As Fig. 2 shows, even a 10% loss of customers drops a business to below a 50–50 chance of full recovery a little over a year after the event. Although the authors focus on the business side of the households and business linkage, this research suggests that policies aimed at households would improve business outcomes and have an economic effect.

Limitations and Considerations for Future Research

The authors conclude with some considerations for future research and acknowledge limitations to this study. Perhaps most importantly, the authors wish to re-emphasize the fact that the business-household interdependency goes both ways. Although this paper has focused on the role of household variables on business recovery, so too do businesses play a role in household recovery. Research has increasingly acknowledged the role of businesses as embedded entrepreneurs in the recovery process (Storr et al. 2015; Grube and Storr 2018). Businesses encourage customer and labor return by helping households navigate rebuilding uncertainty through social capital and opportunity recognition, and Xiao and Van Zandt (2012) show that businesses significantly affect household reoccupancy. This research shows the consequences of a reduced customer base on business recovery, but businesses themselves play a role in that recovery. Businesses that can recognize the needs of the recovering community and adapt accordingly will attract more customers; in turn, businesses will have better served recovering households thereby affecting the community's recovery overall (Alesch et al. 2001; Runyan 2006; Grube and Storr 2018). To some extent, this research emphasizes the consequences businesses face when they cannot respond to household needs accordingly. Because this research is part of a larger study on Lumberton, which includes household surveys as well as longitudinal observations, future research from the household side can help refine our understanding of the business-household relationship.

Household surveys may also shed some light on *why* some labor disruption variables are more important than others. There may be particular labor disruptions that last longer than others, and this research did not include a time dimension. In addition, the nature of the disruption may also make an employee more or less likely to miss work and for different lengths of time. For example, employees missing work due to household damage was not significant in the model. It is possible that an employee may still come to work even if (s)he is faced with home repair issues because (s)he needs the wages, making the disruption from home damage shorter and thereby dampening the negative impact to the business. Research that looks more specifically at employee behavior, or even more business research that includes labor variables, will help further our understanding. Many limitations of the current research revolve around the measure of the labor variables. For example, each employee likely faced multiple disruptions, and nuanced counts were not fully captured by the survey. Future research can better identify these co-relationships. Similarly, it is possible that there is under-reporting of health issues to an employer with employees choosing to cite one of the other labor disruption variables instead when they reported to their employer. The authors did not survey employees directly, but rather the manager or owner under the assumption that they are involved with the scheduling and operation of the business.

Lastly, the authors note that the results of this research contradict existing research that characterizes retail or wholesale as a vulnerable sector due to changing demand after a disaster event (Alesch et al. 2001; Revenue and Brunton 2013; Dahlhamer and Tierney 1996; Webb et al. 1999). When controlling for loss of customers and labor issues, however, retail or wholesale sector was a significant and positive predictor of full recovery in the model. The authors speculate that it may be due to the ease of employee replacement in that sector (Zhang et al. 2009). More evidence is needed to see whether including more labor variables in future models can replicate this effect or whether the finding is just a particular characteristic of the Lumberton case. The generalizability of this study is somewhat limited due to the nature of it being a singular case; this was done in order to direct resources toward a depth of study rather than breadth, with the intention of conducting yearly observation of the business and household communities in Lumberton. Nonetheless, Lumberton represents a community facing both social and economic vulnerability issues in the face of natural hazards, as highlighted by the findings presented in this research, making it a meaningful case for analysis in the effort for more equitable and just recoveries.

Data Availability Statement

Some or all data, models, or code generated or used during the study are proprietary or confidential in nature and may only be provided with restrictions (e.g., anonymized data). This includes:

1. All business survey data at a level of detail in which individuals and their responses to any survey/interview questions can be identified.
2. All ReferenceUSA data at a level of detail in which individuals can be identified as part of the sample.

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