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Deciphering small business community disaster support using machine learning

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Abstract

With the increase in severity and frequency of natural hazards due to climate change, developing a holistic understanding of community resilience factors is critically important to disaster response and community support. Our investigation of small business survey responses about COVID-19 impacts finds that they are conduits of national support to their local communities. Small businesses that have demonstrated high levels of pre-disaster local involvement are more likely to take an active role in community resilience during a disaster, regardless of their own financial security. In addition, businesses with natural hazard experience before or during COVID-19 provided help to more community groups than hazard inexperienced businesses. While community resilience models often characterize small businesses as passive actors using variables such as employment or financial security, this research suggests that small businesses take an active role in community resilience by providing critical local support. The pandemic presented an opportunity to consider small business' role in community resilience nationally, which was utilized here to identify the multidimensional factors that predict small business operators' community disaster support. This study improves upon previous research by studying the small business-community resilience interface at both regional (n = 184) and national (n = 6,121) scales. We predict small business' active involvement in community resilience using random forest machine learning, and find that adding social capital predictors greatly increases model performance (F1 score of 0.88, Matthews Correlation Coefficient of 0.67).

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1. Introduction

Natural hazard impacts worsened by climate change are driving increased interest into contributors to community resilience. To this end, the importance of small businesses to communities is assumed; however, the relative significance of factors contributing to this positive relationship is largely unexplored. This study of small businesses and provision of community support during the COVID-19 pandemic sheds light on existing factors to support community resilience and provides insights into factors that increase horizontal support networks within communities. In this paper, we draw new insights into small businesses' active participation in, and contributions to, community resilience. Using Random Forest machine learning, we

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identify variables that predict small business' community disaster support during the COVID-19 pandemic. Community disaster support (CDS) is based upon previous literature on philanthropy and is measured as an empirical dependent binary variable [1–3]. Previous studies have focused on either in-depth case studies or broader models, this study blends the two to answer not just "what" but "how" the factors of the small business-community resilience interface manifest. These findings point to potential opportunities when planning for and 16 responding to future disasters.

We sought to understand the multi-dimensional nature of the relationships between small businesses and community resilience (i.e. the small business-community resilience interface). We chose independent variables that covered potential dimensions of this relationship. Variables were selected by drawing upon literature from social capital [4–6], economic resilience [7–9], social relationships [1, 3, 10, 11]), organizational competence [12–14], and place attachment [15, 16].

In community resilience models, small businesses are consistently subsumed within a general economic category [9, 17]. Studies have linked microeconomic disaster resilience at the individual enterprise level using financial capital, level of damage, age, and size [18–21], while mesoeconomic and macroeconomic resilience are often described in terms of price and supply adjustments and interdependencies between sectors [8, 20, 22].

While community resilience is acknowledged as multi-dimensional, small businesses' contribution to community resilience is often distilled to a single variable, such as local employment, number of businesses, or a combination of these variables [7, 23, 24]. These models treat small businesses as passive participants in, instead of active contributors to, community resilience. However, small business owners and operators are not simply economic actors, but also may choose to maintain social, infrastructural, and institutional roles [25]. By treating businesses as complex community actors, Adekola and Clelland's (2020) case study of small business owners in Scotland found that businesses contribute to each of the community resilience dimensions identified by Cutter, Burton, and Emrich (2010). Social and economic factors also created an interdependence between small businesses and household recovery in Lumberton, North Carolina [26].

Small businesses are able to facilitate and use the flows of social capital. Natural hazards literature identifies social capital as critical to community resilience [5, 6, 27]. Swinney (2008) found a correlation between business participation in and sponsorship of communities and the business' social capital. This finding demonstrates the horizontal flows of social capital between businesses and other community members [28]. Existing social capital pre-disaster facilitated community and business resilience and recovery [27]. Such contributions to community resilience pair vertical social capital (relationships with other levels of organizations or government) with horizontal social capital (relationships between community actors) [6].

Small business motivations to contribute to community resilience are complex, though certain factors are shown to increase their contributions. In a study of non-disaster community support, Litz and Stewart (2000) found that family-owned businesses were more involved in their communities and in charitable giving. A sense of obligation to the community can also motivate small business owners and managers to donate time and money [29]. This perceived obligation depends on a diverse set of business and personal characteristics, shared experiences, and place attachments [6, 30, 31]. For example during COVID-19, minority-owned businesses were more likely to offer support to their local communities [32]. Miller and Besser (2000) categorized small businesses by their level of community value. They found businesses with high, medium, and low levels of community values had varying characteristics but similarities in terms of their success strategies [33]. Business operators' tendency toward collectivism and market orientation such as attention to customers and communication within the company are also related to community relations and may influence the community's social perceptions of that business [34].

Social and risk perceptions may result in small business owners adjusting their business-level decisions. In a study of accommodation managers, Wang and Ritchie (2012) found that subjective social norms, attitudes towards crisis preparation, and previous hazard experience significantly influenced business disaster planning [35]. These psychological constructs are adapted from the Theory of Planned Behavior [36]. These constructs, in addition to perceived control over the outcome of a hazard event, were significant in June studies of individual disaster preparedness [37, 38]. Although each of these studies hypothesize that planned behaviors impact post-event outcomes, they have only tested the Theory of Planned Behavior pre-event. Our study is the first to test this in the context of business decisions related to resilience planning and actualized behavior during and after an event.

This study advances previous research by investigating small business support of community resilience at both regional and national scales. The in-depth Coastal Carolinas survey and shorter National survey investigate the small business-community resilience interface. In contrast to previous studies, we treat small businesses as active participants in community resilience by predicting community disaster support by the business. We use random forest machine learning to identify the most important predictors for determining community disaster support during the COVID-19 pandemic. Principal component analysis (PCA) or categorical PCA have previously been used to study community resilience; however, we found that using random forest improved result interpretability by providing importance values for individual predictors in addition to model accuracy measurements. We then discuss the relationships between identified predictors and community disaster support, and conclude by identifying promising directions for future research on the small business-community resilience interface.

2. Materials and methods

2.1 Data collection and sample

We conducted a Coastal Carolinas and National Survey (August to October 2020 and November 2020, respectively). The Coastal Carolinas survey focused on small businesses in the coastal counties of North Carolina and South Carolina and included 60 questions sent via a direct email list of approximately 7,500 businesses and through local Chambers of Commerce. We received 275 responses and a full 184 responses.

Our second survey was conducted in partnership with Alignable (More information about Alignable can be found at www.alignable.com). Alignable is an online small business networking platform with over 4.5 million members across North America. Beginning with the COVID-19 pandemic, Alignable sent out monthly baseline polls (which they call "pulse" surveys) in addition to short topic-based surveys to their members [39]. Our Alignable survey was a 15-question poll on natural hazard experience, social networks, and COVID-19 impacts. We received 7,422 responses of which, after removing non-US businesses and nonprofits, 6,121 responses were usable. This is in line with the Bartik et al. (2020) response rate. It also represents 66% of the active respondents from the Alignable November 2020 pulse survey.

The survey questions used in this study covered variables previously linked to community and small business resilience. Both surveys obtained Institutional Review Board exempt status. By using data from these two surveys, we are able to validate small business responses between a locally-focused Coastal Carolinas sample and a broader national sample.

2.2 Coastal Carolinas survey

Businesses with under 200 employees in the coastal counties of North and South Carolina were contacted using a dataset from the U.S. Business Database (n = 14, 565). Twenty-seven local Chambers of Commerce were contacted within the coastal counties to deploy the survey, of whom eight sent it out to their members. Small businesses often have low response rates with accepted studies ranging from 4% to 40% [40]. To remunerate respondents for their time, we offered a $5 gift card for completing the survey with a follow up email offering a $10 gift card. After cleaning the email lists for hard bounces, a total of 7,500 businesses are estimated to have received the survey.

The Carolinas survey included 63 multiple choice questions with written response options and took respondents an average of ten minutes to complete. From these questions, we determined 15 independent variables to be used in the random forest algorithm based conceptually on previous literature studying small businesses, natural hazards, and community resilience (Table 1). We received 275 responses of which 184 were usable for the final model analysis. This represents a 3.6% response rate [41].

2.3 National survey

The National Survey was an abbreviated version of the Coastal Carolinas Survey. Due to the smaller n (184) for the Coastal Carolinas Survey, we chose to use the National Survey to validate the findings from the Carolinas. The National Survey did not include all of the variables and so is not a perfect reflection; however, the similarities in findings for the variables that do overlap allows for validation from the regional to national levels. It also indicates that further work should be completed to test the additional Carolinas variables at the National scale.

The survey was conducted in partnership with Alignable. Alignable is an online small business referral network with over 4.5 million small business members based in 30,000 communities and every country in North America. During the COVID-19 pandemic, they conducted monthly pulse surveys [36]. We partnered with Alignable to conduct a topic-based survey two weeks after their November pulse survey. The survey included 15 multiple choice questions on natural hazards experience and community disaster support. Respondents had the opportunity to write in responses to questions using the "Other" category. We received 7,422 responses of which 6,121 were US-based for-profit businesses. This represents 66% of the respondents from the Alignable November 2020 pulse survey, a reasonable conversion rate [42].

2.4 Statistical analysis

Machine learning has contributed to a revolution in social science statistical analysis allowing for the analysis of many predictors and their interactions. This dataset was analyzed using Random Forest, a machine learning classifier that grows many decision trees from bootstrapped samples to minimize the overfitting issues that exist with single decision trees. Random forest allows for categorical data and datasets with many weak inputs [43]. It has been previously applied to independent social capital investigations and to disaster studies employing survey data [44, 45]. We chose Random Forest over other classifiers as it is generally recognized to be one of the best classification methods [46].

In the random forest classification, the dependent variable was a binary measurement of small business' community disaster support, an indicator of active community resilience support (0 = Did not give to the community, 1 = Gave to at least one community organization) for both the Carolinas and National datasets. McKnight and Linnenluecke (2016) identified donations of cash, cash-like resources, and in-kind materials as potential pathways for corporate giving. We expanded on this to include donation of time and expertise, as written responses

Table 1. Variables used in the final random forest model. Additional discussion of the variables can be found in the S1 Text.

Variable	Survey Question(s) Carolinas	Survey Question (s) National[1]	Related Literature
Community Disaster Support (CDS)	Who has your business supported/donated to during COVID-19?	Who has your business supported/donated to during COVID-19?	
Hurricane Preparation Attitude (HA)	"I see preparing for hurricanes at this business as. . . very negative/very positive, very useless/very useful, very harmful/very beneficial, very difficult/very easy"		Theory of Planned Behavior (Ajzen, 2012 [47]; Daellenbach et al., 2018 [37])
Hurricane Preparation Social Norms (HSN)	"My close friends, family, and colleagues think that my business should prepare for hurricanes", "It is expected that my business prepares for hurricanes", "I feel under social pressure as a business operator to prepare for hurricanes"		Theory of Planned Behavior (Ajzen, 2012 [47]; Daellenbach et al., 2018 [37])
Hurricane Preparation Perceived Control (HPC)	"I am confident that my business is prepared for hurricanes", "The effectiveness of my business' hurricane preparations is beyond my control", and "Whether or not my business takes any hurricane preparations is completely up to me"	Respondent who had experienced a hurricane indicated "I feel there is nothing I can do" under natural hazards	Theory of Planned Behavior (Ajzen, 2012 [47]; Daellenbach et al., 2018 [37])
Pre-Disaster Community Involvement (CI)	Involvement from "Not involved to "Very involved (e.g. provide leadership, serve on boards, act as community representative)" in Business associations, community service organizations, and disaster relief organizations pre-COVID-19	Respondents indicated that before COVID-19 they had a "Strong business community", "Maintained relationships with law enforcement and local government", or "Help others that are in worse shape"	Litz and Stewart, 2000 [1]
Business Age (BA)	2020 minus Reported year of establishment		Sydnor et al., 2017 [20]
Employee Total (ET)	Reported employment as of Fall 2020		Sydnor et al., 2017 [20]
Ownership Type (OT)	Reported demographics of the business owner(s) 3		Dua et al., 2020 [32]; Litz and Stewart, 2000 [1]
Customer Location (CL)	Three options: the majority of customers came from either the same city, the same state, or out of state		Zwiers, 2016 [16]
Location Ownership (LO)	Owned or rented/leased (entirely remote answers were excluded)		Zwiers, 2016 [16]
Essential Business (EB)	Essential and partially essential were coded together or non-essential		Kong and Prinz, 2020 [60]; Storr et al., 2021 [61]
Community Support Received (CSR)	Received any support from one of the following groups: Local government, customer support, support from other businesses, rent or mortgage relief, no support received, or other. "Other" responses were not included in the binary variable and any respondents who answered "No support received" were coded as not receiving support	"Who has provided this support for your business during COVID-19?" Only the following options were included: local government, non-profit organizations, local businesses, landlord(s), and customers	Murphy, 2007 [6]
Financial Security (FS)	Currently had excess funds to cover less than six months of expenses or seven months to over one year	Level of financial impact of COVID-19 on their business. If they indicated a negative impact, they were coded as a zero. If they indicated a positive impact or no change, they were coded as a one.	Alesch et al., 2001 [18]; Chang and Rose; 2012 [17]; Kroll et al., 1990 [62]
Government Support Received (GSR)	Received or did not receive federal, state, or local government assistance	"Who has provided this support for your business during COVID-19?" Answers used: federal, state, or local government	Alesch et al., 2001 [18]; Chang and Rose 2012 [17]; Kroll et al., 1990 [62]
Disaster Planning (DP)	Business had (or did not have) a hurricane plan, pandemic plan, or business continuity plan before March 2020	Indicated they "create detailed crisis plans."	Fink, 1986 [63]; Quarantelli, 1998 [64]; Spillan and Hough, 2003 [65]
Rural Location (RL)	Rural or suburban/urban based on the Federal Office of Rural Health Policy's rural Zip Code Designation	Rural or suburban/urban based on the Federal Office of Rural Health Policy's rural Zip Code Designation	Adekola and Clelland, 2020 [25]; FORHP, 2021 [54]; Manzoor et al, 2021 [23]

[1] If a question is not included in the National Survey column, it was not tested in the abbreviated survey.

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from small businesses indicated that the corporate giving definition was too narrow. Examples of non-monetary or disaster-specific in-kind materials include, "We added a holiday shopping page to our website for the sole benefit of our vendors, hoping to help them make money into the holiday season", "[We helped] anyone seeking information", and "Just offered support to my networking groups in terms of encouragement and planning." Those who did not donate wrote about financial difficulties, lack of awareness of giving opportunities, or not receiving support themselves. Representative quotes from both surveys include, "We can't support ourselves, let alone any other businesses," "Help is not wanted or we are unknown," and "We didn't get support."

The selected predictors fit within five constructs related to previous research 1) Institutional Resilience (Hurricane Experience, Disaster Planning, and Business Age, 2) Economic Resilience (Financial Security, Location Ownership, Government Financial Support Received, and Employee Total), 3) Organizational Resilience (Ownership Type, Essential Business, and Rural Location), 4) Social Capital (Pre-Disaster Community Involvement, Customer Location, and Community Support Received), and 5) Hurricane Planned Behavior (Preparation Social Norms, Preparation Attitude, and Preparation Control). Disaster preparation attitudes, subjective social norms, and perceived behavioral control variables were derived from the Theory of Planned Behavior [47] and have been proven to successfully predict disaster preparation in individuals [37, 38] and business managers [35]. To understand the flow of vertical and horizontal support provided during the COVID-19 pandemic, we asked both the Carolinas and National respondent groups a series of questions on support sources where they could select multiple options. The respondents were also asked about the type of support received including federal financial assistance (e.g., loans, grants, delayed payments, etc.) and in-kind support (e.g., personal protection equipment, food, signage, information sharing, etc.).

We conducted exploratory analysis on the predictor variables and independent variable using Spearman Rank Choice Correlations (ρ) for both the Coastal Carolinas and National survey data to check for multicollinearity. To avoid the Accuracy Paradox caused by imbalanced datasets and to better compare the two surveys that had different ratios of the binary dependent variable options, we use oversampling to bring both ratios to 50% [48]. We then use the final dataset to run a random forest classification analysis, employing the SciKit Learn RandomForestClassifer Python implementation with default settings using gini to measure the quality of the split with the RandomSearchCV function for hyperparameter optimization [45]. We made 40 random selections with replacement for a 25%/75% training and testing data split to reduce the risk of a training bias [44]. The RandomForestClassifer class allows for variables of varying scale and number of categories which could otherwise cause bias in a more classical statistical analysis such as PCA [49]. RandomSearchCV performs a randomized search with cross-validation of the hyperparameter space (trees grown, tree depth, minimum samples required for split and leaf nodes, etc.) in order to optimize the F_1 score and MCC. We used the package's default values except to increase the iterations and cross validation folds to 100 and 10, respectively, to avoid overfitting. The F_1 score is the harmonic mean of the model's precision and recall and varies between a score of 0 and 1 (Eq 1). It is known to be biased by unbalanced datasets that favor positive predictions; however, it is widely used within the machine learning literature [50]. Precision is a measurement of false positives (FP) compared to true positives (TP), when the model places a business in "Giving" when they did not give support. Recall is a measurement of false negatives (FN) in comparison to true negatives (TN), when the model incorrectly places a business in "Did not give" when they did give support (Eq 2). MCC varies between -1 and 1 and is a more reliable measure as it requires a model to predict well in all four quadrants of the confusion matrix and is not biased by unbalanced datasets (Eq 190 3) [51]. MCC can be interpreted similar to other correlation coefficients where a strong relationship is greater than |0.6| [52].

$$F_1 = \frac{2}{recall^{-1} + precision^{-1}} = 2 \times \frac{precision \times recall}{precision + recall} \tag{1}$$

$$precision = \frac{TP}{TP + FP}, recall = \frac{TP}{TP + FN} \tag{2}$$

$$\frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{3}$$

3. Ethics statement

Both surveys obtained University of South Carolina Institutional Review Board exempt status. The data from the surveys were kept separate due to differences in measurement; however, their parallel analysis allows for validation between the findings and suggests areas for future work.

4. Results

4.1 Respondent characteristics

Respondents to the Coastal Carolinas survey are broken down into South Carolina (56%) and North Carolina (36%). Respondents represented 16 out of 23 coastal counties in the region. The national survey responses were normalized by state and compared with the US Small Business Administration's 2020 state profiles [53]. There was an oversampling of Arizona, Colorado, and the Pacific Northwest (2%) and an undersampling of Texas (3%) (Fig 1). Using the

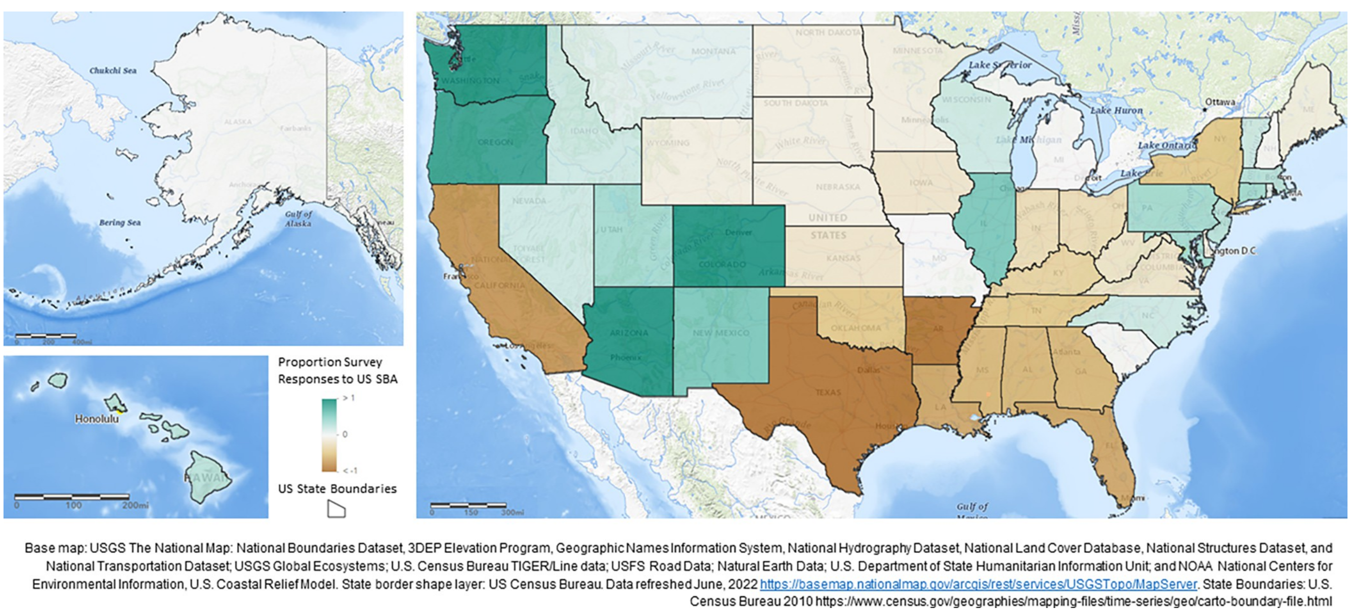

Fig 1. Proportion of business respondents in the National survey compared to SBA's 2020 state profiles. Green (1) indicates oversampling while brown (-1) indicates undersampling. The state shape file and base map layers come from the U.S. Census Bureau (https://www.census.gov/geographies/mapping-files/time-series/geo/carto-boundary-file.html) and U.S. Geological Survey (USGS https://basemap.nationalmap.gov/arcgis/rest/services/USGSTopo/MapServer), respectively.

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Federal Office of Rural Health Policy's definition of rural ZIP codes [54], we assigned each respondent who provided a ZIP code a rural or urban/suburban designation. Nationally there were 11% rural small business respondents, and in the Carolinas there were 15% rural respondents.

The Coastal Carolinas survey included more questions about the characteristics of small businesses and demographics of the owners, which were compared with the US Census 2018 Annual Economics Survey [55]. Definitions of small business size range from under 200 to under 500 employees [56–58]. This research used a threshold of 200 though very few of the final sample (n = 10) businesses were above 100 employees. When considering respondents from the Carolinas survey (U.S. Census values in parentheses), 9% (13%) identified as minority-owned, and 27% (24%) identified as woman-owned. There was an over representation of businesses with 20 to 49 employees, and businesses functioning for over 16 years. Both ownership by gender and minority status are relatively representative (Fig 2). Overall, the samples provided acceptable population representation.

4.2 Community disaster support

The Coastal Carolinas and National surveys both asked about types of support businesses provided to their communities in times of a disaster. The Coastal Carolinas survey included more inquiry into factors previously identified as being related to the small business-community resilience interface (see supplemental material for survey questions). Many small businesses demonstrated community disaster support to at least one group. Both the Coastal Carolinas (67%) and National (91%) respondents reported high levels of disaster-giving to local recipient groups. Within their communities, small businesses reported providing support to a variety of

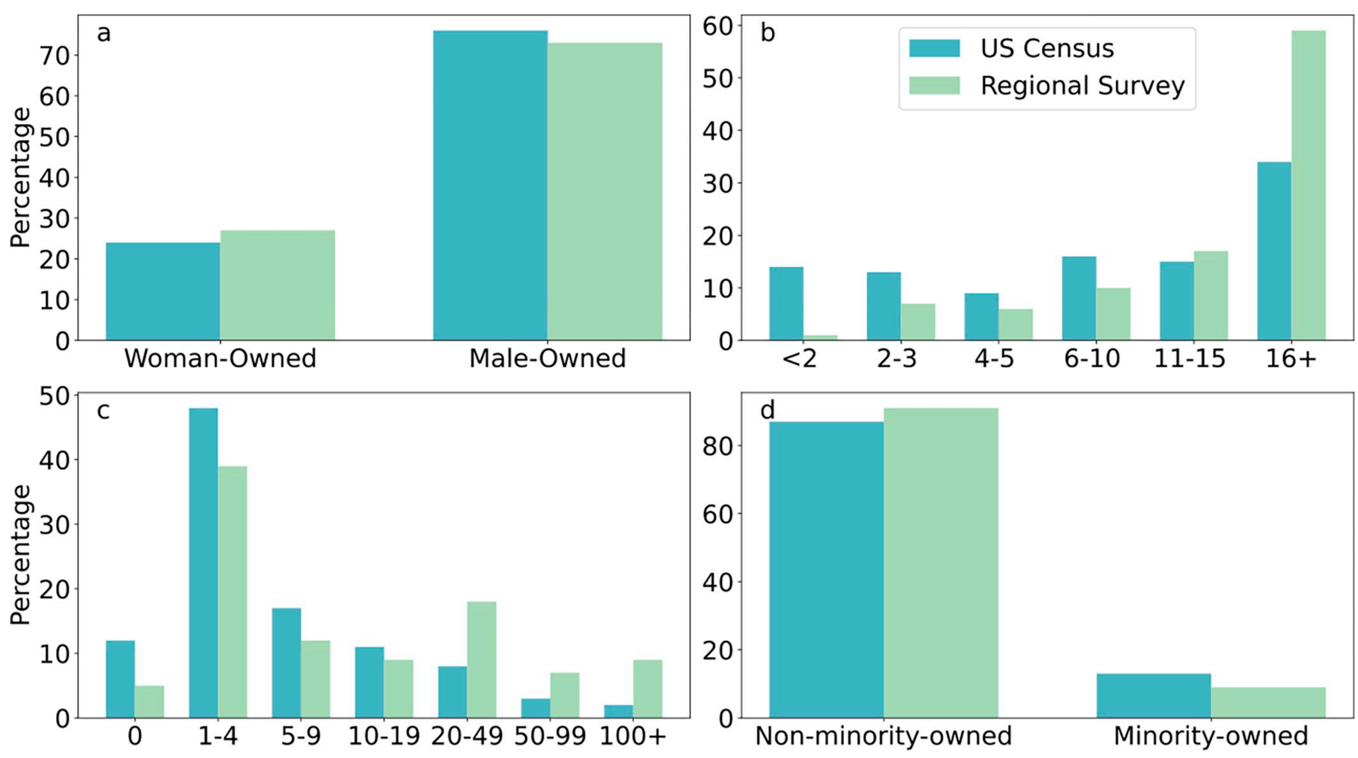

Fig 2. Comparison of Coastal Carolinas Survey responses and US Census 2018 Annual Economics Survey data by (a) Gender, (b) Employee count, (c) Age of Business, and (d) Minority status.

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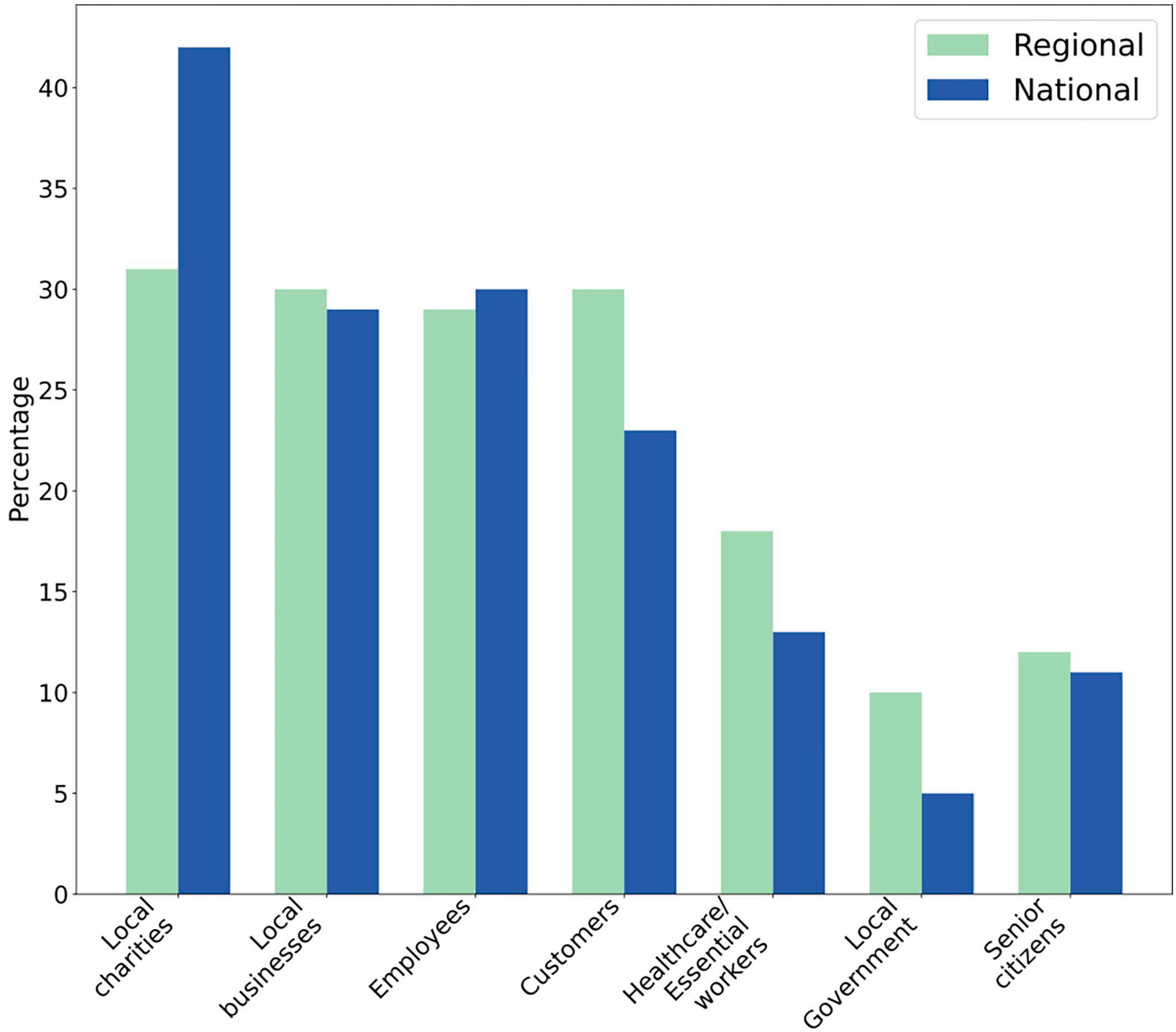

Fig 3. Percent of small businesses that gave support during the COVID-19 pandemic by recipient group (Question allowed multiple selections).

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local institutions and groups including local charities, other businesses, and both working and non-working employees (Fig 3). Small businesses were innovative with their community support and found synergistic support mechanisms. For example, one event-focused small business donated their tents to a local hospital to be used for COVID-19 patient triage.

Most of the predictors of giving had insignificant or negligible correlations with community disaster support. Only Pre-COVID-19 Community Involvement ($\rho = 0.27$, $p < 0.001$), Ownership Type ($\rho = 0.28$, $p < 0.001$), Employee Care Metric ($\rho = 0.34$, $p < 0.001$), Disaster Planning ($\rho = 0.29$, $p < 0.001$), Community Support Received ($\rho = 0.22$, $p = 0.003$), and Government Financial Support Received ($\rho = 0.2$, $p = 0.038$) were significantly correlated with community disaster support at the 95% level. Each of these predictors had low correlation strength (rho < 0.4) which Random Forest Classification can address [43].

4.3 Machine learning

Random Forest is a common method for predicting behavior in many fields, with the F_1 score and Matthews Correlation Coefficient (MCC) (see Statistical Analysis Section) consistently used as a primary metric for model performance with values ranging from 0 (low) to 1 (high) [51]. This is the first application of this methodology for predicting community disaster support.

In comparing the Coastal Carolinas and National models, we find that both result in low F_1 scores for the two variables (Financial Security and Government Financial Support Received) through five variable iterations (Community Support Received, Disaster Planning, Rural Location, respectively) (Fig 4). This suggests that the success of our final model is truly a result of

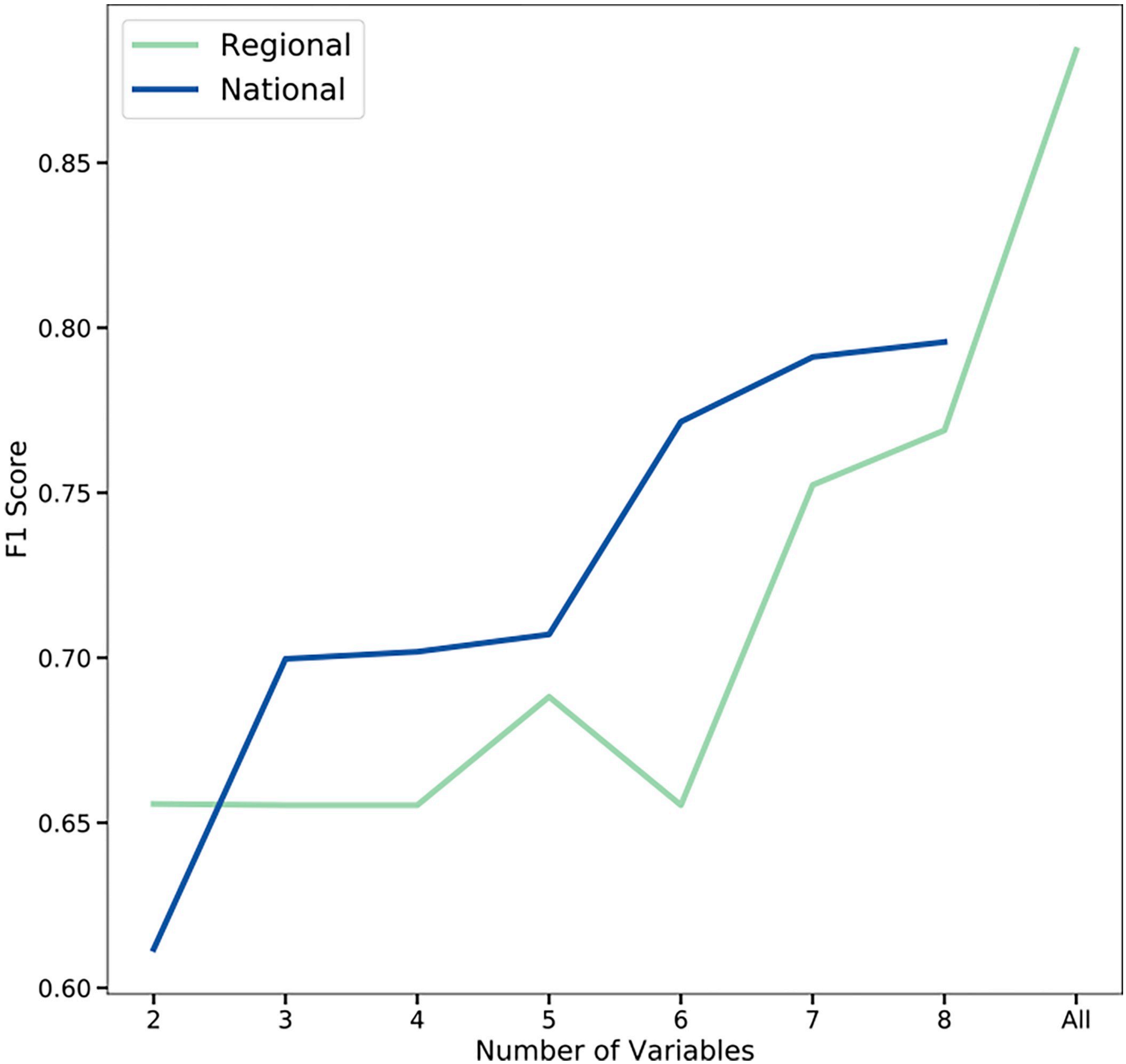

Fig 4. Model F1 scores with iterations from two to eight variables illustrating the trend similarity between the Coastal Carolinas and National datasets.

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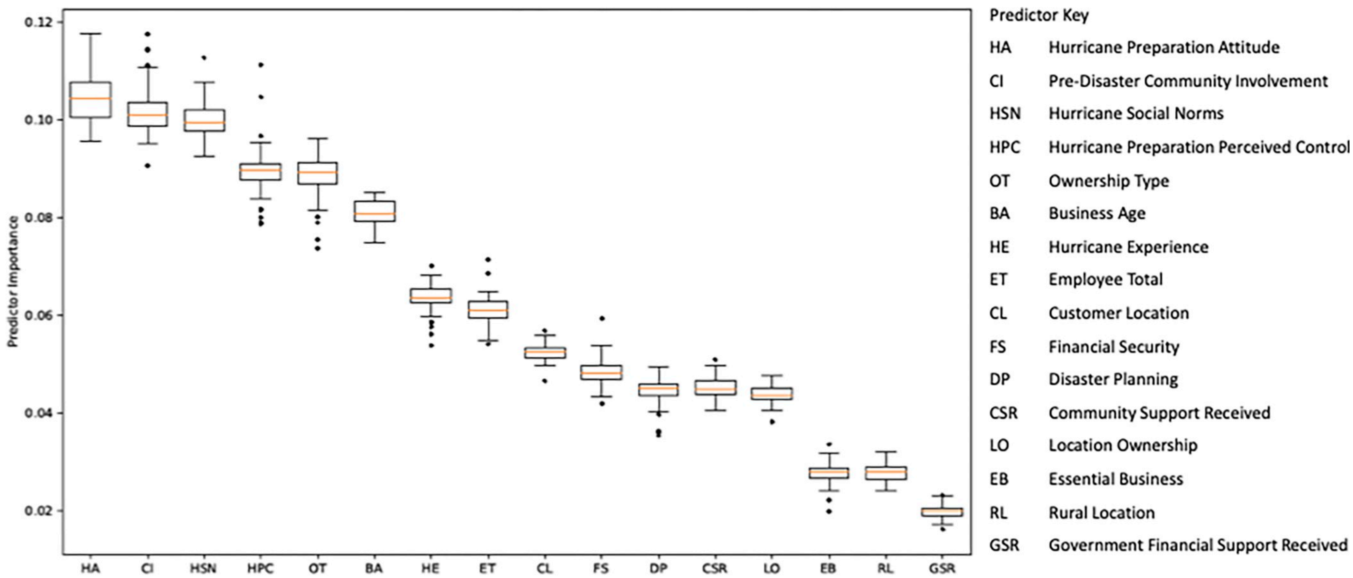

Fig 5. Random forest predictor importance. Importance distribution is determined by implementing a randomized hyperparameter search with cross-validation on 40 randomly selected (25%) test and (75%) training datasets. Predictors are listed in the order of importance in the final model.

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more robust predictor variables, and is not simply due to an increase in the number of predictor variables. At the sixth variable (Hazard Experience), there is an increase in the National level and a slight decrease at the Coastal Carolinas level, this may be due to differences in hazard types as the Coastal Carolinas survey focused on hurricane experiences. There are then consistent increases for the seventh variable (Hurricane Preparation Perceived Control) and eighth variable (Pre-Disaster Community Involvement).

Our optimized Coastal Carolinas model with all variables produced an F_1 score of 0.88 and an MCC of 0.67, which suggests our model successfully predicts community disaster support [51]. We see that there is a further increase in F_1 score by adding the predictors only included in the Coastal Carolinas survey (those that predict business ownership and age), indicating that active support of community resilience is a multi-dimensional decision for small businesses, which is nevertheless reliably predicted by a Random Forest methodology.

One advantage of the Random Forest classifier is its inherent ability to rank the relative importances (I) of the features used as predictors. The four most important predictors are related to the perceptions of hurricane preparation and social capital ($I > 0.1$), while previously used indicators of the significance of small business to community resilience, such as Employee Total and Financial Security, have an importance of less than 0.06 (Fig 5). Although variable importance varies between models with values between zero and one, the ranking of importance is reasonably stable [59]. For interpretation, we focus on the relative ranking of predictors.

5. Discussion

This is the first study to empirically demonstrate the factors that determine active business participation in community resilience. The most important predictors of CDS ($I > 0.1$) are the three constructs of the Theory of Planned Behavior and Pre-Disaster Community Involvement. Constructs related to disaster preparation, especially perceived social norms, have been previously shown to impact decisions to take hazard-related actions [37, 38]. However, these studies did not connect these behaviors to community resilience. Studies on business

Table 2. Coastal Carolinas survey: Mean number of recipient groups supported by ownership type (Mutually exclusive).

	n	Mean (μ)	STD (σ)	SE	Min	Max
Non-Minority Non- Woman owned	111.0	1.3	1.6	0.15	0.0	6.0
Woman- owned	23.0	1.5	1.3	0.3	0.0	4.0
Family- owned	28.0	1.8	1.7	0.3	0.0	6.0
Minority- owned	8.0	1.9	2.0	0.7	0.0	6.0
Minority woman- owned	7.0	3.0	2.0	0.8	1.0	6.0

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community giving demonstrated the relationship with community involvement, though these are not related to disaster response [1, 23]. Our findings suggest that locally involved and disaster prepared small businesses could be a component of relief planning to facilitate community support during a disaster.

Ownership Type is the next most important predictor of community disaster support. Further analysis of the predictor identifies that minority woman-owned businesses give to an average (μ) of more recipient groups than non-minority non-woman owned businesses ($\mu = 3$ groups vs. 1.3 groups, respectively) indicating increased horizontal social capital and active support of community resilience (Table 2). Other ownership types such as women-owned ($\mu = 1.5$ groups), family-owned ($\mu = 1.8$ groups), and non-female minority-owned ($\mu = 1.9$ groups) businesses also demonstrate these increased horizontal social capital connections. Using a Mann-Whitney U Test, we find that the ownership categories are significantly different ($p < 0.004$). These results are in line with previous research which has found greater giving among family-owned businesses and minority-owned businesses [1, 32].

The predictors with mid-range importance (0.06 to 0.08) include variables from literature on institutional resilience and economic resilience. Two were previously used to represent passive small business impact on community resilience: Employee Total and Financial Security [17]. Hazards Experience is significantly correlated with community disaster support during COVID-19 (Carolinas: $\rho = 0.14$, $p = 0.063$; National: $\rho = 0.21$, $p < 0.001$). At the national scale, businesses gave to more groups when they had experienced a hazard previously ($\mu = 2.3$ groups), compared to those who had never experienced a hazard ($\mu = 1.6$ groups). This may suggest that hazard experience builds lasting horizontal social capital. Two measures of social capital were included in this section: Customer Location and Location Ownership. They may be less important in this study due to changing customer purchasing behaviors during the pandemic and should be investigated for future disaster events, especially natural hazards that are geographically localized.

Community disaster support does not appear to be a self-serving economic decision. While they gave to more groups, the majority of all minority-owned businesses estimated they had less than six months of operating expenses saved, while the majority of non-minority, non-woman-owned businesses estimated that they had a year or more of operating expenses saved. Community Support Received and community disaster support are weakly correlated (Carolinas: $\rho = 0.2$, $p = 0.003$; National: $\rho = 0.3$, 314 $p < 0.001$). This suggests multi-directional horizontal social capital in addition to business' access to vertical capital.

Receiving support is significantly correlated with providing support for other community members (Carolinas: $\rho = 0.2$, $p = 0.04$; National: $\rho = 0.2$, $p < 0.001$). Twice as many small businesses who received support gave to at least one community recipient group if they had received at least one type of support. This indicates that the small businesses that are able to access vertical capital then distribute it horizontally to other local businesses, nonprofits, and individuals, making them a potentially significant component of disaster aid redistribution at the community-level. However, receiving government support, in addition to Essential Business and Rural Location, are in the least important variable group ($I < 0.04$). This may be due to relatively low levels of government support received overall. In both surveys, only about 50% of small businesses received support during the pandemic. The primary financial support mechanism was federal aid through the Paycheck Protection Program and other grant and loan programs. This relationship between financial access and community is in agreement with previous research on community economic growth [23].

6. Conclusion

This research is the first to identify an expanded set of social factors behind the small business-community resilience interface and suggests that pre-disaster social capital characteristics of businesses are an important component of community disaster support. Previous studies have sought to model small business' role in community resilience through passive variables such as employment or financial security and often look at these businesses in isolation from the larger communities. We suggest that indicators of active community resilience engagement by small businesses through community disaster support may provide a more appropriate measure for small business importance during disaster response and recovery.

Resilience is a latent quality making it difficult to quantify pre-event. COVID-19 presented an opportunity to observe the latent factors of the small business-community resilience interface more broadly and over a long period compared with previous discrete disaster events. Our machine learning results suggest that the role of small businesses in community resilience would be more accurately measured by evaluating pre-disaster involvement and pre-disaster planned behaviors than previously used proxy variables, such as total employment.

Individual predictor analysis further indicates that targeting minority women-owned businesses would increase small business-community disaster resilience, as they provided active support to the most recipient groups, strengthening community resilience. Although receiving federal financial support is of low importance for predicting the act of giving, twice the number of businesses who received support provided community support compared to those who did not receive financial support.

Small businesses have generally low survey response rates which may be mitigated by offering remuneration. In conducting online surveys with incentives, we provide several security recommendations. We received over 10,000 false survey responses from a social media post about the survey and used IP address and response validation to remove false responses. We recommend that surveys use multiple links if there will be a social media post or if the link may be posted by a partner. We also recommend that financial incentives be manually provided to prevent online bots from automatically receiving rewards for false responses. These security features are built into the Qualtrics and Research Rewards software.

Our results suggest a promising avenue for community resilience research to inform planning for natural hazards which are increasing due to climate change. This is the first study to understand the multi-dimensional predictors for small business community disaster support and active support of community resilience. The research is limited by the relatively small sample size of the Coastal Carolinas survey and abbreviated National survey. Further research should investigate social capital and planned behavior variables identified as important in this research to determine the broader significance of the predictors. Additional research into these predictors is needed to understand the differences between a global disaster and more spatially discrete natural hazards.

Supporting information

S1 Text. Survey Variables from both the Coastal Carolina Survey and National survey.
(DOCX)

S1 Table. Percent of small businesses that gave support during the COVID-19 pandemic by recipient group (Could select more than one).
(DOCX)

S2 Table. Matrix of support for small businesses in both surveys (Coastal Carolinas n = 184, National n = 4,190).
(DOCX)

S3 Table. Coastal Carolinas survey (n = 184): Government Financial Support (PPP Wave 1, SBA, etc.) by ownership type.
(DOCX)

S1 Fig. Coastal Carolinas survey color map of predictor correlations. Stars symbolize significance at the 90th percentile or above.
(TIFF)

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