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Disaggregated validation of disaster-resilience indicators using household survey data: A case study of Hong Kong

Abstract

A disaster resilience index aggregates numerous observed individual indicators into a numeric value, for the purpose of gauging various communities' disparate disaster resilience capacities as part of decision-making in resilience management. There have been abundant studies on the creation of such indices, but only a few have sought to empirically validate individual indicators' practical efficacy in explaining disaster-related outcomes. Therefore, this study performs such disaggregated empirical validation of nine disaster-resilience indicators' efficacy at explaining two outcome measures: the resistant capacity and recovery capacity of households in Hong Kong. It reveals that certain indicators including education, income, and place attachment can be empirically valid, but that their explanatory power varies substantially across the two outcome measures. For instance, place attachment has divergent relationships with households' resistant and recovery capacities. The robustness of the indicators' explanatory power is also unequal, due to the disparate effect sizes of the outcome measures and to indicators' interdependence. Based on these findings, we provide recommendations indicator selection and index creation that should be useful to those seeking to create parsimonious and robust sets of indicators that are explanatory of the actual resilience capacities of local communities.

Keywords: Disaster resilience; Empirical validation; Index; Indicator; Natural disasters

1. Introduction

Human settlements worldwide are suffering from substantial losses due to natural disasters. According to the World Health Organization (WHO, 2020), around 160 million people each year are affected by natural disasters, and 90,000 are killed. In 2019, a total of 409 natural disasters occurred globally, causing around US$232 billion economic loss (Statista, 2020) and affecting 95 million people (CRED, 2020). As well as severe direct economic losses and fatalities, natural disasters can cause long-term indirect social losses. For example, residents are still recovering from the 2011 East Japan Earthquake and Tsunami, and as of 2017, one-third of the original 150,000 evacuees were still living in temporary housing (Oskin, 2017). For these reasons, improving community resilience to natural disasters is increasingly considered a major policy objective of governments worldwide (Bakkensen et al., 2017; Cariolet et al., 2019).

The concept of *resilience* was firstly proposed by ecologist C. S. Holling (1973), who explained it as "the ability of ecological systems to absorb changes caused by a disturbance and still persist" (p. 17); and Timmerman (1981) was the first to adapt the concept to the field of hazards/disasters, defining disaster resilience as "a system's capacity to absorb and recover from the occurrence of a hazardous event" (p. 21). Since then, a large number of studies have applied the concept of disaster resilience to human communities (Buckle, 1999; Mileti & Noji, 1999; Adger, 2000). Mileti and Noji (1999), for example, emphasized the importance of building up sustainable communities by achieving local resiliency, i.e., the ability of localities, without significant external assistance, to tolerate and overcome disaster damage and disaster-related reductions to their quality of life. Because disaster resilience has been applied in a wide array of disciplines, including economics (Rose, 2007; Qiang et al., 2020), social sciences (Maguire & Hagan, 2007; Cui & Li, 2020), engineering (Bruneau et al., 2003a; Yang et al., 2019), and public health (Keim, 2008; Hatvani-Kovacs et al., 2016), its definition varies according to their different research orientations and perspectives (Miller et al., 2010). Yet, despite there being no universal definition of disaster resilience, two common elements of it have become widely accepted (**Table A.1**). These are 1) resistant capacity, i.e., the ability to withstand or absorb disaster impacts and still persist, and 2) recovery capacity, i.e., the ability to bounce back from disaster impacts in a timely manner (Peacock et al., 2010; Bakkensen et al., 2017; Links et al., 2018). These two common elements can also be reflected by National Research Council (2012)'s definition of resilience, i.e., "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" (p. 16).

1.1 Disaster-resilience indices

To facilitate policymakers' better understanding of communities' disaster resilience, numerous researchers have divided that concept into quantitative measures using indices (Cutter, 2016). An index, also known as a composite indicator, is a statistical tool that aggregates numerous observed indicators into a single numeric value for measuring a theoretical construct that cannot be directly observed (Bakkensen et al., 2017; Spielman et al., 2020). Thus, the rationale of a disaster-resilience index is to mathematically combine a set of widely available indicators, such as residents' ages and socioeconomic statuses, or the number of civic organizations, as proxies for different disaster-resilience dimensions (Cutter et al., 2010; Morath, 2010). Such indices allow policymakers to compare communities' disaster resilience across time and space, and from such comparisons derive authoritative guidance for decision-making. For example, disaster-resilience indices can be used to determine which communities should be given priority when allocating resources such as funds and personnel to disaster response and recovery, or to monitor changes in communities' disaster resilience over time, as a means of quantifying the effectiveness of community resilience-enhancement programs (Prior & Hagmann, 2012; Kontokosta & Malik, 2018).

Due to these policy-making benefits, many scholars have developed disaster-resilience indices. The fundamental studies in this area include Cutter et al. (2010)'s Baseline Resilience Index for Community (BRIC), Peacock et al. (2010)'s Community Disaster Resilience Index (CDRI), Sherrieb et al. (2010)'s Economic Development and Social Capital (EDSC) index, and Foster (2012)'s Resilience Capacity Index (RCI). Based on these leading scholars' groundwork, numerous additional disaster-resilience indices have been developed, varying in terms of their disaster-resilience dimensions, hazard types, focal geographic areas, and analysis scales (Cutter, 2016; Asadzadeh et al., 2017; Ran et al., 2020). Although most researchers engaged in such work have claimed that their indices have sound theoretical and methodological justifications, a recent study by Bakkensen et al. (2017) found that when different indices were applied to the same disaster and geographic region, widely divergent results were obtained. That finding gives rise to an important research question: When a disaster-resilience index is developed, how can one ensure that it is an empirically valid tool for explaining the actual disaster-resilience levels of local communities?

1.2 Empirical validation studies

Index creation involves several essential stages, including the application of a theoretical framework, indicator selection, indicator aggregation, and empirical validation (Asadzadeh et al., 2017). Most existing disaster-resilience indices have selected their indicators based on meta-analyses of the prior literature, coupled with theoretical justifications (Prior & Hagmann, 2012), and such indicators as proximal representations of disaster resilience are therefore not necessarily explanatory of the actual resilience levels of real communities (Bakkensen et al., 2017). To ensure the practical efficacy of a disaster-resilience index, it is important to examine its validity (and that of the indicators used in constructing it) vis-à-vis real-world outcomes: a process called empirical validation (Drost, 2011; Bakkensen et al., 2017; Trochim, 2020).

However, few of the many extant disaster-resilience indices have been empirically validated. Ran et al. (2020)'s systematic literature review of social-vulnerability and disaster-resilience indices in low- and middle-income countries found that only four out of 68 index-creation studies had conducted empirical validation. In the absence of such validation, policymakers can have little confidence in the practical efficacy of an index for measuring the actual disaster-resilience levels of communities, let alone in its use to support their decision-making about investment in resilience-enhancement programs (Cai et al., 2016; Bakkensen et al., 2017).

The small but growing number of empirical-validation studies of disaster-resilience indices are summarized in **Table 1**. Based on the types of explanatory variables that they use, existing empirical-validation studies can be categorized into two major types: aggregated-level and disaggregated-level validation. Aggregated validation focuses on the empirical validity of the entire disaster-resilience index for explaining disaster-related outcomes, with typical examples including Peacock et al. (2010), Bakkensen et al. (2017), and Kontokosta and Malik (2018). For example, Peacock et al. (2010) examined the empirical validity of the CDRI by using 2000-05 property-damage and fatality data from counties on the U.S. Gulf Coast, and found that counties with higher CDRI scores experienced less damage and fewer deaths. However, aggregated validation is subject to one major limitation, that is it can only determine whether a particular index is empirically valid in explaining specific disaster-related outcomes, but it is not able to reveal what underlying reasons may lead to a poor empirical validity of an index, and which set of indicators of the index could be improved for enhancing real communities' disaster resilience in practice (Bakkensen et al. (2017).

Disaggregated validation, in contrast, focuses on the examination of the empirical validity of individual indicators that are commonly used to construct a disaster-resilience index, with typical studies including those of Burton (2015), Lam et al. (2015), Lam et al. (2016) and Cai et al. (2016). Burton (2015), for instance, examined the empirical validity of 64 disaster-resilience indicators using photographic evidence of the 2005-10 built-environment reconstruction process on the Mississippi Gulf Coast in the aftermath of Hurricane Katrina. Of those 64 indicators, just 41 (including educational attainment, employment status, and homeownership) appeared to be suitable for measuring the disaster resilience of the relevant Gulf Coast communities with analytical soundness and statistical significance at the census-block level. The major advantage of this type of validation over aggregated validation is that it reveals which individual indicators are empirically valid for explaining specific disaster-related outcomes. This can help index creators select better indicators, and direct policymakers' attention to the empirically valid indicators during their efforts to build community resilience in practice. Nevertheless, as the indicators deemed to be empirically valid by disaggregated validation studies vary widely across hazard contexts, analysis scales, and outcome measures; and, because this type of validation study remains relatively rare, it is difficult to make any meaningful generalizations about which indicators will consistently explain disaster-related outcomes. Thus, more methodological research on disaggregated validation is clearly called for.

The basic design of a disaggregated-validation study can be broken down into three essential steps, comprising one's choices of 1) analysis scales, 2) disaster-resilience indicators as explanatory variables, and 3) disaster-related outcome measures as response variables. The multiple potential scales of analysis include country, region, county, census block, census tract, and household. According to Lindell and Prater (2003), natural disasters not only cause direct physical impacts on communities, such as building damage and fatalities, but also social impacts on households, such as anxiety and psychological trauma, and socio-demographic impact, e.g., the displacement of people from one area to another. However, existing disaggregated-validation studies have mainly focused on individual indicators' validity for explaining the direct physical impacts of disasters at a county or census-tract level, and paid scant attention to either indirect social impacts or the household level, as indicated in **Table 1**. Given that empirically valid disaster-resilience indicators may vary across different analysis scales (Burton, 2015), it would appear timely to conduct a household-level validation study to complement existing disaggregated validation research. There are also some other good reasons for using this scale. One is that household-level validation could help researchers better understand the empirical validity of individual indicators for explaining disaster-related outcomes at a finer spatial resolution. Another, more important reason is that it enables the use of outcome measures that reflect the social aspects of disaster resilience: for example, the behaviors and perceptions of households in relation to their resilience capacities during different disaster phases.

The choice of which outcome measures to use for empirical validation must be grounded in theory (Bakkensen et al., 2017). To ensure rigorous validation, the chosen outcome measures should be logically related to the theoretical elements of disaster resilience, i.e., resistant capacity and recovery capacity. Prior empirical validation studies have commonly used property damage, fatalities, and disaster declarations as their outcome measures (**Table 1**). These measures are logically related to the resistant capacity of communities, insofar as those communities with high resistant capacity can be expected to experience less property damage, fewer fatalities, and less frequent disaster declarations. To date, only Burton (2015) has empirically validated these three indicators' explanatory power for the recovery capacity of communities. Typically, however, Burton (2015) disaster-related outcome measures focused on the census-block level and on physical damage, rather than on social impacts or the recovery capacity of households.

1.3 Research objectives

To help fill the aforementioned research gaps, the present study conducts a disaggregated validation of disaster-resilience indicators, focusing on their explanatory power for the resistant capacity and recovery capacity of households. Hong Kong, a megacity prone to typhoon hazards, has been chosen as the study area, in part due to the availability of a well-sampled questionnaire-based household survey that can serve as the validation data. Specifically, nine disaster-resilience indicators extracted from households' demographic profiles will serve as explanatory variables; and two outcome measures extracted from questionnaire measurements, disaster preparedness (as a proxy for household-level resistant capacity) and psychological resilience (as a proxy for household-level recovery capacity) will serve as response variables. The following research questions will be addressed:

1. Which disaster-resilience indicators explain the resistant capacity of households?

2. Which disaster-resilience indicators explain the recovery capacity of households?

3. Which disaster-resilience indicators consistently explain both the resistant capacity and recovery capacity of households?

The methodology section, below, provides further details of the study area and validation data, the chosen disaster-resilience indicators, and the outcome measures, along with our data analysis methods. Then, in the results section, we report the explanatory power of the disaster-resilience indicators for each of the two outcome measures; while the discussion and conclusion sections set forth our major findings, their implications, this study's limitations, and potentially fruitful directions for future research in this area.

Table 1. A review of empirical validation for disaster resilience indices and indicators.

No.	Study	Study area	Hazard	Scale	Validation method	Explanatory variables	Outcome measures	Statistically significant findings
1	Kontokosta and Malik (2018)	The New York City (NYC)	Hurricane	Census tract	ARIMA model	Resilience to Emergencies and Disasters Index (REDI)	NYC's 311 service requests after Hurricane Sandy	+REDI
2	Bakkensen et al. (2017)	The southeastern U.S. states	Coastal hazards	County	Multivariate regression model	1)BRIC, 2) CDRI, 3)RCI, 4) SoVI, 5)SVI	1) Damages, 2) fatalities, 3) disaster declarations	Damages: -CDRI, -RCI, +SoVI, +SVI Fatalities: -CDRI, -RCI, +SVI Declarations: +SoVI
3	Lam et al. (2016)	The northern Gulf of Mexico	Climate-related hazards	County	RIM model: K-means clustering and discriminant analysis	28 indicators of demographic, social, economic, government, environmental, health dimensions	Resiliency calculated by 1) exposure - the number of times hit by hurricanes, 2) damage - property damage, and 3) recovery - population growth	+civilian labor force, -poverty, -low education, -female-headed households with children
4	Cai et al. (2016)	The Lower Mississippi River Basin	Coastal hazards	Census block group	RIM model: K-means clustering and discriminant analysis	25 indicators of social, economic, infrastructure, community, environmental dimensions	Resiliency calculated by 1) exposure - the number of times hit by coastal hazards, 2) damage - property damage, and 3) recovery - population growth	+housing units with telephone, -female-headed households, +income, -native-born population

5	Lam et al. (2015)	The Caribbean region	Hurricane	Country	RIM model: K-means clustering and discriminant analysis	Eight socio-environmental indicators	Resiliency calculated by 1) exposure - the number of times hit by hurricanes, 2) damage - storm damage, and 3) recovery - population growth	-population density, -population living below six meters
6	Burton (2015)	The Mississippi Gulf Coast	Hurricane	Census block group	Ordinal logistic regression model	64 indicators of social, economic, institutional, infrastructural, community, environmental dimensions	Photographic evidence of the recovery process of built-environment reconstruction after Hurricane Katina	+educational attainment, +employment status, +homeownership, +housing density, +schools, +the presence of religious organizations
7	Sherrieb et al. (2010)	The U.S. Mississippi counties	General	County	Correlation	Community resilience index of Economic Development and Social Capital	Survey measures of social cohesion and social control	+Social Capital
8	Peacock et al. (2010)	The U.S. Gulf Coast region	Floods, hurricanes, storms	County	OLS regression model	CDRI	1) property damages, 2) fatalities	-CDRI

Note: BRIC refers to Baseline Resilience Index for Community; CDRI refers to Community Disaster Resilience Index; RCI refers to Resilience Capacity Index; SoVI refers to Social Vulnerability Index; SVI refers to Social Vulnerability Index; + denotes the explanatory variables were positively correlated with the outcome measures; – denotes the explanatory variables were negatively correlated with the outcome measures.

2. Methodology

2.1 Study area and validation data

Located in a sub-tropical climate zone, Hong Kong is exposed to typhoon-related hazards every summer season, including heavy downpours, tropical cyclones, storm surges, and floods (PreventWeb, 2018). These hazards cause severe economic and social losses there, including disruptions to economic activity and infrastructure services, injuries, and deaths (HKO, 2004; DSD, 2013). In 1962, for example, Typhoon Wanda took 130 lives, and more recently, between 400 and 500 injuries were caused by Typhoons York (1999) and Typhoon Mangkhut (2018) (SCMP, 2017; HKO, 2018). Moreover, due to global warming and sea-level rises, the frequency and intensity of typhoons in Hong Kong are both expected to increase, and enhancing community resilience to climate change and typhoon hazards has become a major goal of Hong Kong's government (PlanD, 2016).

The household survey on disaster risk and response in Hong Kong that was used as the validation data was conducted via telephone from July 16 to July 29, 2018, using the random digital dialling method. Only adult Cantonese-speaking residents with Hong Kong citizenship were considered as respondents. To reduce non-response sample bias, all calls were placed between 6:30 p.m. and 10:30 p.m. on weekdays and from 2:00 p.m. to 10:30 p.m. during weekends. Each telephone number was dialled five times or until someone answered. Calling 4,300 telephone numbers yielded a sample of 2,008 households that were eligible to participate. After excluding incomplete or otherwise invalid interviews, 1,015 households remained, a response rate of 50.5% among the eligible respondents.

To establish whether the sampled respondents were representative of Hong Kong's population, three of their basic characteristics – gender, age, and district of residence – were compared against 2016 Hong Kong Census data (CSD, 2016). **Table A.2** presents the chi-square tests results of this comparison, which show that the sample was consistent with the population in terms of gender (chi-square=.003, p=.995), age (chi-square=.443, p=.999), and residential location (chi-square=1.034, p=1.000). Therefore, we are reasonably confident that the analysis results of the sample data are generalizable to Hong Kong's population.

2.2 Disaster-resilience indicators as explanatory variables

Disaster-resilience indicators can be categorized into two types: compositional and contextual (Sherrieb et al., 2010). Compositional indicators describe the population characteristics of communities, and reflect the possibility that differences in inter-community levels of disaster resilience are due to uneven population compositions (e.g., percentage of the population over 65 years old) (Cummins et al., 2005). Contextual indicators, on the other hand, are geographical characteristics, reflecting that such resilience differences are due to variation in communities' human-made and natural environments (e.g., area of wetlands) (Macintyre et al., 2002). The present study only focuses on the validation of compositional indicators that could be extracted from the households' demographic profiles in the survey data.

Table 2 sets forth basic information about the nine disaster-resilience indicators used in the present study's validation. These indicators cover three dimensions of disaster resilience: human, economic, and social capital. The indicators in the human-capital dimension measure the differential social capacities embedded in communities' demographic attributes, including *age*, *education*, and *disability*. Those in the economic-capital dimension gauge the differential economic vitality and stability embedded in communities' socioeconomic attributes, including homeownership, *employment*, *income*, and *poverty*. Lastly, the indicators in the social-capital dimension capture the differential social cohesion and community connectivity inherent in communities' social networks, including *place attachment* and *social support*. All nine of these indicators have been widely adopted by well-known disaster-resilience indices including the

BRIC, CDRI, RCI, and EDSC (Cutter et al., 2010; Peacock et al., 2010; Sherrieb et al., 2010; Foster, 2012), among others (Asadzadeh et al., 2015; Burton, 2015; Lam et al., 2015; Cai et al., 2016; N. Lam et al., 2016; Yoon et al., 2016; Kontokosta & Malik, 2018). To facilitate data analysis, the nine indicators were transformed into dummy variables. *Age*, for example, was coded as 0 if the respondent was 65 years old or above, and otherwise coded as 1. This reflects our hypotheses regarding the impact of disaster-resilience indicators on households' resilience capacity, in that the more indicators for a given household are coded as 1, the higher the resilience capacity that household ought to have.

Table 2. Nine disaster resilience indicators.

Dimension	Indicator	Description	Sources			
			BRIC	CDRI	RCI	EDSC
Human	1. Age	Population aged below 65 years old	X		X	
	2. Education	Population with at least a high school diploma	X	X	X	X
	3. Disability	Population without physical or mental disability	X		X	
Economic	4. Homeownership	Population with self-owned housing		X		
	5. Employment	Population employed	X	X		X
	6. Income	Population above median household income[a]	X	X	X	X
	7. Poverty	Population above the poverty line			X	
Social capital	8. Place attachment	Native-born population	X		X	
	9. Social support	Population with household size larger than one				X

Note: [a]Median household income in Hong Kong is around $19,000.

2.3 Outcome measures as response variables

As noted above, disaster preparedness and psychological resilience were adopted to measure households' resistant capacity and recovery capacity, respectively. Disaster preparedness measures the behaviors of households during the pre-disaster phase, while psychological resilience measures their mental-health status during the post-disaster phase. The rationale for choosing these two measures and their corresponding questionnaire measurements are introduced in detail below.

2.3.1 Disaster preparedness as a measure of resistant capacity

Disaster preparedness is highly relevant to an individual's natural-disaster resistant capacity. It refers to pre-disaster actions taken to help ensure that one's personal response in the face of natural disasters is effective (Maguire & Hagan, 2007). Many empirical studies have found that populations with higher levels of disaster preparedness are better able to withstand natural disasters' negative impacts, and thus experience less disaster damage and loss (Paton et al., 2006; Keim, 2008). The "prepare and plan for" component of the above-cited National Research Council (2012)'s definition of community resilience also encompasses an element of disaster preparedness (p. 16).

Disaster preparedness was measured using 13 items adapted from the Federal Emergency Management Agency (FEMA)'s Citizen Corps National Survey (FEMA, 2009, 2014). Among these items, six measure the respondent's material preparedness, i.e., the extent to which s/he gathers disaster supplies at home. They are "Water for three days", "Food for three days", "First aid kit", "Evacuation plan", "Information receiving device", and "Flashlight". The remaining seven items measure the respondent's participation preparedness, i.e., the extent to which s/he participated in disaster-response training programs or drills during the previous 12 months. These items are "First-aid training", "Psychological first-aid training", "Emergency evacuation drill”, “Fire drill”, “Workshop for how to make a plan for an emergency response”, “Light search and rescue training”, and “Volunteer activity related to emergency response”. Each item is measured by a dummy variable, meaning that the presence and absence of the 13 items are coded as 1 and 0, respectively. We examined the reliability of this 13-item questionnaire instrument using Kuder-Richardson Formula 20 (KR-20), which has been found useful in testing the internal consistency of dichotomously scored test items (Kuder & Richardson, 1937). The KR-20 value of the disaster preparedness instrument was .67, i.e., larger than .5 and thus suggesting that it has good reliability (Glen, 2016). Hence, we use the sum of the scores for these 13 items as our measure of each respondent’s *resistant capacity*, which accordingly has a value ranging from 0 to 13.

2.3.2 Psychological resilience for measuring recovery capacity

Psychological resilience is highly relevant to an individual’s natural-disaster recovery capacity. In this context, it has been defined as the extent to which one could mentally recover from stress or depression that arises during the post-disaster phase (Lee et al., 2018). A number of empirical studies have presented evidence that populations with higher levels of psychological resilience are less likely to experience post-disaster mental-health problems such as post-traumatic stress disorder (Osofsky et al., 2011; Funakoshi et al., 2014; Kukihara et al., 2014; Turner, 2015). Norris et al. (2008) also reported that post-disaster psychological wellness is an essential element of successful individual-level recovery after disasters.

Here, psychological resilience was measured using the 10-item Connor-Davidson Resilience Scale (CD-RISC), which has been validated and widely utilized in clinical and public-health studies (Connor & Davidson, 2003; Campbell-Sills & Stein, 2007). The 10 items of the CD-RISC are “I am able to adapt to change”, “I can deal with whatever comes”, “I try to see the humorous side of problems”, “I believe coping with stress can strengthen me”, “I tend to bounce back after illness or hardship", "I can achieve goals despite obstacles", "I can stay focused under pressure", "I am not easily discouraged by failure", "I think of myself as a strong person", and "I can handle unpleasant feelings". The respondents were asked to rate each item from 0 (strongly disagree) to 4 (strongly agree). The Cronbach's alpha for the CD-RISC is .92, which being larger than .7 indicates its good reliability (Nunnally, 1994). The sum of each respondent's ratings of these 10 items, ranging from a minimum of 0 to a maximum of 40, is used as our measure of that respondent's *recovery capacity*.

To facilitate data analysis, we divided the respondents into three resilience groups according to their resistant-capacity and recovery-capacity scores, as shown in **Table 3**. The criterion for this population grouping was based on the quartiles of their scores, as recommended by Davidson (2018): i.e., the group deemed least resilient comprised those individuals with scores within the first quartile of the population (lowest 25%); the moderately resilient group's scores were within the second and third quartiles (between 25% and 75%); and the most highly resilient group's scores fell within the fourth quartile (above 75%). These low, moderate, and high resilience groups were coded as 1, 2, and 3, respectively.

Table 3. The categories of outcome measures.

Resilience groups (code)	Scores (percent of the total sample)	
	Resistant capacity	*Recovery capacity*
Lowest level (1)	0-3 (27.8%)	0-19 (22.7%)
Moderate level (2)	4-6 (50.3%)	20-28 (52.3%)
Highest level (3)	7-13 (21.9%)	29-40 (25.0%)

2.4 Data analysis

The explanatory power of disaster-resilience indicators for our two outcome measures was examined by ordinal logistic regression, because both are ordinal variables. The Proportional

Odds Model (POM) was adopted to fit the nine indicators to the two outcome measures, as shown as **Eq. (1)**,

$$logit\left(P(Y \leq j)\right) = log(odds) = log\left[\frac{P(Y \leq j)}{1-P(Y \leq j)}\right] = \beta_{0j} + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k \qquad (1)$$

where the *logit* function is used to transform probabilities in the range 0 to 1 to values over the entire real number range $(-\infty, +\infty)$; $P(Y \leq j)$ is the probability of the response variable Y falling in or below a given category j; the *log* is the logarithmic function; the *odds* are the ratio of the probability of Y falling in or below vs. above a given category j; $j = 1,2, \ldots, J-1$ is the jth ordered outcome category; X_k refers to the kth explanatory variable; β_{0j} is the model intercept; and β_k is the coefficient for the X_k explanatory variable.

The parameters of the POM, $\beta_{0j}$and β_k, are estimated by the maximum-likelihood method. The POM should satisfy the parallel-lines assumption, i.e., the coefficient β_k should be the same for all categories, as assessed by Brant's Wald Test (Brant, 1990). The goodness of fit of the POM is assessed using the Hosmer-Lemeshow, Lipsitz, and Pulktenis-Robinson tests, in which the p-values should exceed .05 in each case (Fagerland & Hosmer, 2016).

Based on our regression results, the explanatory power of a disaster resilience indicator X_k can be observed in two aspects, including 1) whether the explanatory power is statistically significant, and 2) if significant, it can be expressed as an Odds Ratio (OR). The OR_k of X_k can be calculated using **Eq. (2)**:

$$OR_k = e^{\beta_k} \qquad (2)$$

Regression modeling is useful when examining the explanatory power of one indicator while controlling the effects of others. However, considering that the influence of one indicator may be affected by its relations with others within a regression model, we also examined the relationship between each indicator and the two outcome measures using chi-square tests of independence. Specifically, we looked at 1) whether there was a statistically significant relationship between each indicator and either or both outcome measures, and 2) the strengths of any such significant relationship that were found, as indicated by effect sizes. To express effect sizes in the present study, Cramer's V – which gives a normalized value from 0 to 1 – was chosen due to its demonstrated usefulness in describing the association between two categorical variables, regardless of the table size or the sample size (**Table 4**).

Table 4. The interpretation of Cramer's V (adopted from Akoglu (2018))

Cramer's V	Interpretation
0.25 and higher	Very strong association
0.15-0.25	Strong association
0.1-0.15	Moderate association
0.05-0.1	Week association
0-0.05	No or very week association

3. Results

3.1 Ordinal logistic regression

Our model-assumption and goodness-of-fit tests indicated that the ordinal logistic regression results were satisfying. Specifically, Brant tests (**Table A.3**) showed that parallel-line assumptions held for both regression models; and Lipsitz and Hosmer-Lemeshow tests (**Table A.4**) and Pulkstenis-Robinson tests (**Table A.5**) indicated that the data observations fit the two models well. Therefore, we have high confidence in our regression results, which are reported in detail below.

Fig. 1 visualizes the explanatory power of our nine disaster-resilience indicators for the two outcome measures. Surprisingly, only a few of the former had statistically significant effects (**Table 5**, p<.05). On the one hand, *education*, *income*, and *place attachment* explained households' resistant capacity, and in the anticipated direction (OR>1). For example, the well-educated households' odds of having high resistant capacity were 78% higher than those of the poorly educated households, with a true population effect of between 20% and 165%. On the other hand, only one indicator, i.e., *place attachment*, explained the sampled households' recovery capacity, and the directionality of its influence was the opposite of what we expected (OR<1). Native-born households, meanwhile, had 35% lower odds of having high recovery capacity than the immigrant households did, with a true population effect of between 9% and 53%. In short, only one of the nine indicators, *place attachment*, could consistently explain both the resistant capacity and recovery capacity of households, albeit with divergent directions of influence.

That being said, however, one other indicator – *disability* – also could be empirically valid in explaining Hong Kong households' recovery capacity. This is mainly because its *p*-value is very close to .05 (i.e., .056) and because it has a high point-estimate OR value. Specifically, this meant that households in which no-one was disabled were 66% more likely to have a high level of resistant capacity than those in which someone was. Nonetheless, opportunity differences ranging from a 1% decrease and a small negative association, to a 178% increase and a substantial positive association, are also reasonably compatible with our data.

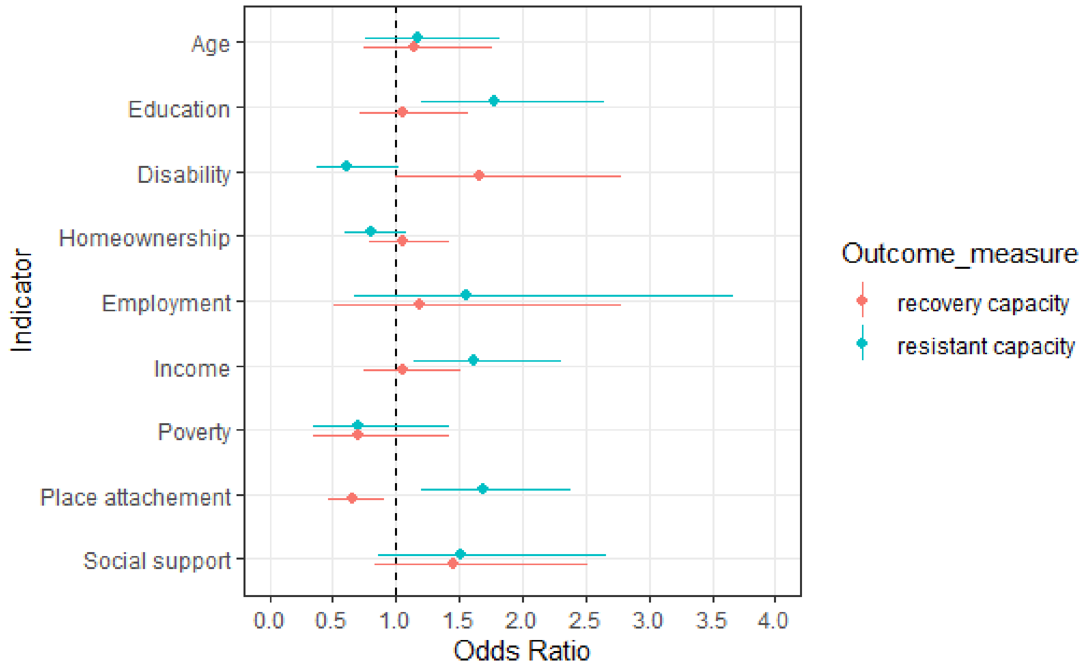

Fig. 1 The odds ratio of disaster resilience indicators

Table 5. Ordinal logistic regression results.

Disaster resilience indicators	*Resistant capacity*		*Recovery capacity*	
	OR (95% CI)	P-value	OR (95% CI)	P-value
1. Age	1.18 (0.76-1.83)	0.457	1.14 (0.74-1.76)	0.565
2. Education	1.78 (1.20-2.65)	0.004**	1.06 (0.71-1.57)	0.779
3. Disability	0.61 (0.37-1.03)	0.063	1.66 (0.99-2.78)	0.056
4. Homeownership	0.81 (0.60-1.09)	0.160	1.06 (0.79-1.42)	0.692
5. Employment	1.56 (0.67-3.67)	0.305	1.19 (0.51-2.79)	0.691
6. Income	1.62 (1.14-2.31)	0.007**	1.05 (0.74-1.51)	0.776
7. Poverty	0.70 (0.35-1.42)	0.328	0.70 (0.35-1.42)	0.326
8. Place attachment	1.69 (1.20-2.38)	0.003**	0.65 (0.47-0.91)	0.012*

9. Social support	1.51 (0.86-2.67)	0.631	1.45 (0.83-2.52)	0.193
Akaike information criterion	1501.156		1526.258	
MacFadden's R-squared	0.295		0.275	

Note: Coding categories are explained in the text; OR refers to Odds Ratio; CI refers to Confidence Interval; * p-value < 0.05; ** p-value < 0.01.

3.2 Chi-square test of independence

The results of the above-mentioned chi-square tests of independence (**Table 6**) show that, if dependencies between indicators are not considered, the number of empirically valid indicators is larger than the ordinal logistic regression results would lead us to suppose. Specifically, these tests showed that *age*, *education*, *income*, *place attachment*, and *social support* all had moderate to strong associations with households' resistant capacity (Cramer's V>.1, p<.001); while *age*, *education*, *disability*, *income*, and *place attachment* all had weak to moderate associations with households' recovery capacity (Cramer's V>.05, p<.05). In short, four out of the nine studied indicators (i.e., *age*, *education*, *income*, and *place attachment*) could consistently explain both resistant and recovery capacity at the household level.

Table 6. Chi-square test of independence between indicators and outcome measures.

Disaster resilience indicators	*Resistant capacity*		*Recovery capacity*	
	Cramer's V	P-value	Cramer's V	P-value
1. Age	0.191	0.000***	0.114	0.004**
2. Education	0.185	0.000***	0.086	0.024*
3. Disability	0.026	0.702	0.113	0.001**
4. Homeownership	0.021	0.805	0.024	0.761
5. Employment	0.015	0.893	0.049	0.304
6. Income	0.191	0.000***	0.118	0.001**
7. Poverty	0.069	0.090	0.037	0.493

8.	Place attachment	0.152	0.000***	0.095	0.010*
9.	Social support	0.123	0.000***	0.066	0.109

Note: * p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001.

3.3 Comparison between the chi-square test and regression-modeling results

Next, we conducted a further comparison between the results of our chi-square tests and those of our regression models, as shown in **Table 7**. This confirmed that, while some indicators had statistically significant associations with the two outcome measures according to the chi-square tests, these indicators were non-significant in the regression models. We define an indicator as having robust explanatory power if it is deemed to be significant by both chi-square tests and regression models. The robustness of an indicator's explanatory power is impacted by two factors: 1) the effect size of the explanatory power, and 2) its dependency upon, or association with, other indicators. For example, chi-square testing suggested that the indicator *age* had a strong association with households' resistant capacity (**Table 6**, Cramer's V=.191, p<.001). However, because of *age*'s very strong association with other, more robust indicators, e.g., *education* (**Table 8**, phi=.432, p<.001), *income* (**Table 8**, phi=.384, p<.001), and *place attachment* (**Table 8**, phi=.344, p<.001), people's chronological ages in fact were not significantly relevant to their households' resistant capacity, as ordinal logistic regression showed (**Table 5**, p=.457). Likewise, the indicators *age*, *education*, *disability*, and *income* were non-robust when it came to explaining households' recovery capacity, due to their relatively weak effect sizes and their strong associations with the robust indicator *place attachment*.

Table 7. Comparison of the influential effect of significant disaster resilience indicators on two outcome measures.

Disaster resilience indicators	*Resistant capacity*		*Recovery capacity*	
	Chi-square test of independence	Ordinal logistic regression	Chi-square test of independence	Ordinal logistic regression
Age	X		X	

Education	X	•	X	
Disability			X	
Income	X	•	X	
Place attachment	X	•	X	○
Social support	X			

Note: X indicates there is statistically significant association (no direction) between the indicator and the outcome measure; •Filled circle indicates the influential effect of the indicator is of the anticipated direction and statistically significant; ○Open circle indicates the influential effect is of the opposite direction and statically significant.

Table 8. Chi-square test of independence between significant indicators with Phi coefficient.

	Education	Disability	Income	Place attachment	Social support
Age	0.432***	0.063	0.384***	0.344***	0.258***
Education		0.093**	0.350***	0.227***	0.117***
Disability			0.096**	0.037	0.004
Income				0.161***	0.267***
Place attachment					0.112***

Note: Phi coefficient describes the strength of association (i.e., effect size) between two binary variables regardless of the sample size, and the interpretation of phi coefficient is the same as Cramer's V (Table 4); * p-value < 0.05; ** p-value < 0.01; *** p-value < 0.001.

4. Discussion

The present study's objective was to empirically validate how well nine commonly used disaster-resilience indicators explain the two essential elements of disaster resilience, namely resistant capacity and recovery capacity, at a household level. Our analysis results established that fewer than half the members of this set of indicators were empirically valid for this purpose, and also that their explanatory power varied substantially across the two outcome measures. Specifically, socioeconomic indicators such as education and income were explanatory of Hong Kong households' resistant capacity, but not of their recovery capacity. Conversely, disability was explanatory of recovery capacity, but not of resistant capacity. This finding is consistent with previous disaggregated validation studies, notably including Burton (2015)'s validation of disaster-resilience indicators, which found that some 36% of theoretically chosen indicators were not explanatory of the built-environment recovery process; and Tellman et al. (2020)'s validation of social-vulnerability indicators, which reported that the socioeconomic indicators that correlated well with fatalities (e.g., a high percentage of elderly and young residents) differed from those that correlated well with property damage (e.g., a high percentage of Black and Hispanic residents). Hence, our findings add further empirical support to the argument that indicators chosen based on theoretical justifications alone will not necessarily be meaningfully related to empirical disaster outcomes (Prior & Hagmann, 2012; Bakkensen et al., 2017). To select the indicators that are most relevant to specific empirical disaster outcomes, index creators may adopt a data-driven approach for the selection of individual indicators based on their predictability for pre-defined disaster-related outcomes. One typical example of data-driven approach is the Resilience Inference Model developed by S. N. Lam and her colleagues, who utilized the combination of K-means classification and discriminant analysis for identifying a significant set of indicators for predicting the Resiliency calculated by multiple disaster outcomes (e.g., property damage and population growth) (Lam et al., 2015; Cai et al., 2016; Lam et al., 2016).

Additionally, some indicators may exhibit divergent explanatory power for different elements of disaster resilience. In the present study, for example, while *place attachment* consistently explained both our selected elements of disaster resilience, the directionality of its influence was opposite for each of them, i.e., positive for resistant capacity but negative for recovery capacity. In most index-creation studies, however, *place attachment* has been cited as a positive explanatory variable for disaster resilience as a whole, mainly based on an argument that native-born populations are likely to have stronger emotional connections to their local communities than immigrants do, and that such connections may give them an advantage in resisting and recovering from the negative impacts of natural disasters (Scannell et al., 2016). In the present study, we found that, of these two groups, native-born households had a higher level of disaster preparedness, but immigrants demonstrated higher levels of post-disaster psychological wellness. This finding implies that disaster-resilience indices should be created with clear objectives regarding which essential elements of disaster resilience they aim to explain and follow this up with more rigorous justification of their selection of specific indicators that are most relevant to this objective. To set up clear objectives for index creation, one should recognize that disaster resilience is a multi-faced concept, involving multiple domains (physical or social) during different disaster phases (pre-, in-, or post-disaster). Linkov et al. (2013a)'s development of Resilience Matrix (RM) framework can be a possible solution for identifying indicators that are relevant to specific system domains at different disaster phases. Differing from traditional index model which uses a one-dimensional list of indicators, the RM framework adopts a two-dimensional approach, with one axis outlining four domains of any complex system (physical, information, cognitive, social) and another axis outlining four stages of disaster management (prepare, absorb, recover, adapt) (Linkov & Trump, 2019). The RM framework for resilience assessment has many applications in the field of cybersecurity (Linkov et al., 2013b), energy (Roege et al., 2014), engineering (Eisenberg et al., 2014), and coastal communities (Rand et al., 2020).

Furthermore, we found that indicators' robustness for explaining household-scale resilience capacity can vary enormously. For example, *place attachment* emerged as the most robust of our nine selected indicators, remaining explanatory for both our outcome measures according to both chi-square testing and regression modeling. *Age*, in contrast, was the least robust indicator, being significant per chi-square testing but non-significant per regression modeling across both outcome measures. Here, such unequal robustness was mainly caused by disparate effect sizes for outcome measures and associations with other indicators. This finding implies that, to arrive at the most parsimonious and robust set of indicators for index creation, it will be necessary to assign weights to the indicators and reduce the multicollinearity between them. Although previous index-creation scholars have generally preferred to rely on principal component analysis (PCA) and explanatory factor analysis (EFA) for assigning weights or reducing multicollinearity (Asadzadeh et al., 2015; Asadzadeh et al., 2017; Chao & Wu, 2017), these kinds of internal-data-driven methods based on the indicators' underlying data structure (e.g., the factor loadings of indicators) are not necessarily useful to preserving the data variance that is explanatory for external empirical disaster-related outcomes. We therefore recommend that index creators choose alternative methods, for example, assigning weights based on the indicators' actual effect sizes, and removing some of the highly correlated indicators that have small effect sizes or little robustness in their explanatory power.

5. Conclusions

Disaster-resilience indices have been widely used in the resilience-management field, often by those aiming to gauge the disparate disaster resilience levels of local communities across space and time by aggregating numerous observed indicators into a numeric value. However, empirical validation studies of the resulting indices have been rare, especially in comparison to the abundance of index-creation studies. The major findings of the present disaggregated validation study of the empirical validity of nine disaster-resilience indicators for explaining two essential elements of household-scale disaster resilience – resistant capacity and recovery capacity – can be summarized as follows:

1) Only a few of the selected indicators were empirically valid for explaining Hong Kong households' resilience capacity, and their explanatory power varied substantially across our two outcome measures, disaster preparedness and psychological resilience.

2) Some indicators (e.g., place attachment) demonstrated divergent explanatory power for the sampled households' resistant capacity and recovery capacity.
3) Due to the disparate effect sizes of the outcome measures and indicators' interdependence, the indicators had unequal robustness in explaining these households' resilience capacity.

The above findings have rich implications for disaster-resilience indicator selection and index creation. First, these findings suggest that indicator selection simply based on theoretical insights and/or precedents in the literature is unwise, given that relatively few popular indicators are representative of or meaningfully related to empirical disaster outcomes. The inclusion of non-significant indicators or indicators with opposite effect directionalities in the same index could reduce its overall empirical validity after indicator aggregation. To provide decision-makers and other end users of disaster-resilience indices with confidence in their practical utility, it is vital that index creators empirically validate the explanatory power of their chosen indicators using whatever disaster-outcome measures are most relevant to specific policy objectives. In addition, the same set of indicators may exert disparate or even divergent influences on different essential components of disaster resilience; therefore, it is important for index creators to provide clear objectives regarding which such components they aim to explain and justify their selection of indicators rigorously in light of those objectives. Moreover, our results show that equally popular indicators can exhibit unequal robustness in explaining resilience capacity at the household scale. To arrive at the most parsimonious and robust set of indicators for index creation, we recommend the assignment of weights to the indicators based on their effect sizes for specific outcome measures, and the simultaneous reduction of the multicollinearity between indicators by removing highly correlated ones with small effect sizes or little explanatory robustness.

The present study complements existing empirical validation studies in two aspects. First, the present study helps to reveal the empirical validity of individual indicators in explaining disaster-related outcomes at a household level. Most previous studies focus on the empirical validation at a larger spatial resolution, e.g., county or census-tract level, rather than a finer resolution, e.g., household or individual level. Given that the empirical validity of disaster resilience indicators may vary across different analysis scales, validating indicators at various scales can help researchers better understand which indicators consistently explain disaster-related outcomes across scales and which indicators are sensitive to scales (Rufat et al., 2019; Tellman et al., 2020). Second, the present study uncovers the empirical validity of individual indicators in explaining two essential theoretical elements of disaster resilience, namely both resistant capacity and recovery capacity. Most existing validation studies using disaster-related outcomes in relation to the former element, with less focus on the later element. Considering that disaster resilience is not simply about resistance to disaster impacts, but more relevant to recover from adverse events, and then adapt (Linkov et al., 2014). Future studies are also encouraged to examine the empirical validity of disaster resilience indicators in explaining other elements of disaster resilience that have been more recently emphasized in socio-ecological research, such as the capacity of learning, adaptation, and self-organization (Folke, 2006; Lei et al., 2014).

The present study has some limitations that should be acknowledged. For example, the types and number of validated disaster-resilience indicators that we used were restricted by the demographic profiles that could be derived from our Hong Kong household survey data. Nonetheless, the purpose of this study is not to exhaustively validate all possible disaster resilience indicators; rather, it is to showcase disaggregated validation's important implications for indicator selection and index creation. Future work on this topic could usefully examine the empirical validity of contextual indicators, namely, those that describe the geographic characteristics of communities related to disaster resilience, in explaining specific disaster-related outcomes.

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Appendices

Table A.1. Selected definitions of resilience and key elements mentioned in the field of disasters/hazards.

Source[1]	Definition	Resistant capacity[2]	Recovery capacity	Others
Timmerman (1981)	The measure of a system's or part of the system's capacity to absorb and recover from occurrence of a hazardous event.	X	X	
Wildavsky (1988)	The capacity to cope with unanticipated dangers after they have become manifest, learning to bounce back.	X	X	
Buckle (1999)	The capacity that people or groups may possess to withstand or recover from the emergencies and which can stand as a counterbalance to vulnerability.	X	X	
Mileti and Noji (1999)	Local resiliency means that a locale is able to withstand an extreme natural event without suffering devastating losses, damage, diminished productivity, or quality of life without a large amount of assistance from outside the community.			
Buckle et al. (2000)	The quality of people, communities, agencies, and infrastructure that reduce vulnerability. Not just the absence of vulnerability rather the capacity to prevent or mitigate loss and then secondly, if damage does occur to maintain normal condition as far as possible, and thirdly to manage recovery from the impact.	X	X	
Bruneau et al. (2003b)	The ability of social units (e.g., organizations, communities) to mitigate hazards, contain the effects of disasters when they occur, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future earthquakes. Resilience consists of four	X	X	

	properties: robustness, redundancy, resourcefulness, and rapidity.			
Walker et al. (2004)	The capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks.	X		
Adger (2006)	The magnitude of disturbance that can be absorbed before a system changes to a radically different state as well as the capacity to self-organize and the capacity for adaptation to emerging circumstances.	X		Self-organization and adaptation
Maguire and Hagan (2007)	Social resilience is the capacity of social entity e.g., group or community to bounce back or respond positively to adversity, which has three major properties - resistance, recovery, and creativity.	X	X	Creativity
Peacock et al. (2008)	The ability of social systems, be they the consistent element of a community or society, along with the bio-physical systems upon which they depend, to resist or absorb the impacts (deaths, damage, losses, etc.) of natural hazards, to rapidly recover from those impacts and to reduce future vulnerabilities through adaptive strategies.	X	X	Adaptation
UNISDR (2009)	The ability of a system, community, or society exposed to hazards to resist, absorb, accommodate to and recover from the effects of a hazard in a timely and efficient manner, including through the restoration of its essential basic structures and functions.	X	X	
Research Alliance (2010)	Resilience has three distinct dimensions: 1) the amount of disturbance a system can absorb and still remain within the same state or domain of attraction; 2) the degree to which the system is capable of self-organization; and 3) the degree to which the system can build and increase the capacity for learning and adaptation.	X		Self-organization and adaptation
Field et al. (2012)	The ability of a system to anticipate, absorb, accommodate, or recover from the effects of a hazardous event in a timely and efficient manner.	X	X	
National Research Council (2012)	The ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events.	X	X	Adaptation

Note:

[1]Some sources of definitions are adopted from Peacock et al. (2010) and Lei et al. (2014).

[2]Resistant capacity, also called resistance, is also referred as one important risk-management strategy for its ability to withstand the identified threats to an acceptable level and to prevent system failure

(Pelling, 2001; Linkov et al., 2014; Matyas & Pelling, 2015). To better distinguish the differences between risk management and resilience management, Linkov et al. (2014) provided a resilience-management framework and argued that risk management helps the system prepare and plan for adverse events (which is relevant to resistant capacity), while resilience management helps the system absorb and recover from adverse events (which is relevant to recovery capacity). In this context, resilience management complements risk management for better addressing residual risk as well as enhancing overall system performance in the face of unknown disasters (Linkov et al., 2018; Linkov & Trump, 2019). However, given that resistant capacity as one element of disaster resilience has been widely cited in early ecological and social research (Folke, 2006), the present study still adopts both resistant capacity and recovery capacity as two elements of disaster resilience for empirical validation.

Table A.2. Chi-square tests for the sample data and census data.

Test 1: Sample number = 1,015; Census number = 6,320,875[a]; $\chi^2(df=1)=0.003$; $p-value=0.995$		
Gender	Sample proportions	Population proportions
Male	44.7%	45.1%
Female	55.3%	54.9%
Test 2: Sample number = 1,015; Census number = 6,320,875[a]; $\chi^2(df=7)=0.443$; $p-value=0.999$		
Age	Sample proportions	Population proportions
18-19 years	2.5%	3.8%
20-29 years	15.4%	13.7%
30-39 years	16.9%	18.2%
40-49 years	17.7%	18.0%
50-59 years	20.5%	20.0%
60-69 years	14.8%	14.1%
70-79 years	6.9%	6.8%
80 or above	5.3%	5.4%
Test 3: Sample number[b] = 1,011; Census number = 7,335,384; $\chi^2(df=17)=1.034$; $p-value=1.000$		
Residential location	Sample proportions	Population proportions
1. Central & Western	2.8%	3.3%
2. Wan Chai	1.7%	2.5%

3.	Eastern	9.6%	7.6%
4.	Southern	3.6%	3.7%
5.	Yau Tsim Mong	4.9%	4.7%
6.	Sham Shui Po	4.3%	5.5%
7.	Kowloon City	6.7%	5.7%
8.	Wong Tai Sin	6.2%	5.8%
9.	Kwun Tong	10.0%	8.8%
10.	Kwai Tsing	5.9%	7.1%
11.	Tsuen Wan	4.7%	4.3%
12.	Tuen Mun	6.2%	6.7%
13.	Yuen Long	8.6%	8.4%
14.	North	4.0%	4.3%
15.	Tai Po	3.8%	4.1%
16.	Sha Tin	9.3%	9.0%
17.	Sai Kung	6.0%	6.3%
18.	Islands	1.5%	2.1%

Note: [a]The census number was the number of populations aged 18 or above; [b]The sample number excluded 4 null value.

Table A.3. Brant tests for parallel lines assumption.

Disaster resilience indicators	*Resistant capacity*		*Recovery capacity*	
	Chi-squared	P-value	Chi-squared	P-value
1. Age	3.471	0.062	2.189	0.138
2. Education	0.347	0.555	0.030	0.860
3. Disability	1.081	0.298	0.006	0.934
4. Homeownership	0.092	0.761	0.126	0.721
5. Employment	0.524	0.468	0.639	0.423
6. Income	0.857	0.354	0.600	0.435

7.	Poverty	1.827	0.176	0.585	0.444
8.	Place attachment	3.232	0.072	0.145	0.702
9.	Social support	1.664	0.196	0.507	0.476

Note: P-value > 0.05 means the parallel lines assumption holds.

Table A.4. Lipsitz and Hosmer-Lemeshow tests.

	Resistant capacity		*Recovery capacity*	
Lipsitz Test	LR statistic	P-value	LR statistic	P-value
	12.275	0.198	5.154	0.820
Hosmer-Lemeshow test	Chi-squared	P-value	Chi-squared	P-value
	4.869	0.675	5.187	0.637

Note: P-value > 0.05 means the data fit the model well.

Table A.5. Pulkstenis-Robinson tests.

Disaster resilience indicators		*Resistant capacity*				*Recovery capacity*			
		Chi-squared	P-value	Deviance-squared	P-value	Chi-squared	P-value	Deviance-squared	P-value
1.	Age	5.850	0.210	5.685	0.223	10.430	0.033	10.410	0.034
2.	Education	1.873	0.759	1.865	0.760	6.963	0.137	6.954	6.954
3.	Disability	3.723	0.444	3.698	0.448	2.264	0.687	2.239	0.691
4.	Homeownership	2.359	0.669	2.346	0.672	5.176	0.269	5.034	0.283
5.	Employment	4.802	0.308	5.630	0.228	1.917	0.751	1.949	0.745
6.	Income	1.797	0.773	1.783	0.775	12.814	0.012	12.836	0.012
7.	Poverty	2.585	0.629	2.699	0.609	3.215	0.522	3.310	0.507
8.	Place attachment	5.353	0.252	5.256	0.261	6.559	0.161	6.539	0.162
9.	Social support	8.362	0.07	7.077	0.131	4.583	0.332	4.412	0.353

Note: P-value > 0.05 means the data fit the model well.

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