

Increasing sensitivity of results by using quantile regression analysis for exploring community resilience



Odeya Cohen^{a,b,*}, Arkady Bolotin^c, Mooli Lahad^{d,e}, Avishay Goldberg^{a,b,f},
Limor Aharonson-Daniel^{a,b}

^a Department of Emergency Medicine, Recanati School for Community Health Professions, Faculty of Health Sciences, Ben-Gurion University of the Negev, P.O. Box 653, Beer-Sheva 84105, Israel

^b PREPARED Center for Emergency Response Research, Ben-Gurion University of the Negev, P.O. Box 653, Beer-Sheva 84105, Israel

^c Department of Public Health, Faculty of Health Science, Ben-Gurion University of the Negev, PO Box 653, Beer-Sheva 84105, Israel

^d Department of Psychology, Tel-Hai Academic College, Galil-Elyon 12208, Israel

^e The Community Stress Prevention Centre (CSPC), P.O. Box 797, Kiryat-Shmona 11016, Israel

^f Department of Health Systems Management, Faculty of Health Sciences & Guilford Glazer Faculty of Business and Management, Ben-Gurion University of the Negev, P.O. Box 653, Beer-Sheva 84105, Israel

ARTICLE INFO

Article history:

Received 10 November 2015

Received in revised form 28 January 2016

Accepted 2 February 2016

Available online 22 February 2016

Keywords:

Community resilience

Resilience

Emergency preparedness

Emergency response plan

Quantile regression

CCRAM

ABSTRACT

Community resilience offers a conceptual framework for assessing a community's capacity for coping with environmental changes and emergency situations. It is perceived as a core element of sustainable lifestyle, helping to mitigate the community's reaction to crises by facilitating purposeful and collective action on the part of its members. The conjoint community resilience assessment measure (CCRAM) provides a standard measure of community resilience including five factors: leadership, collective efficacy, preparedness, place attachment, and social trust. The mean scores of each the factors portray a community resilience profile and the overall CCRAM score is calculated as the average of the scores of the 21 survey items with an equal weight.

Two regression models were employed. Logistic regression, a commonly used tool in the field of applied statistics, and quantile regression, which is a non-parametric method that facilitates the detection of the effect of a regressor on various quantiles of the dependent variable.

The study aims to demonstrate the innovative use of quantile regression modeling in community resilience analysis.

The results demonstrate that the quantile regression was significantly more sensitive to sub-populations than the logistic regression.

Having an income below average, which was negatively correlated with perceived community resilience in the logistic model was found to be significant only in the lower (Q10, Q25) resilience quantiles. Age (per year) and previous involvement in emergency situations which were not noted as significant in the logistic regression, were found to be positively associated with perceived community resilience in the lowest quantile. A difference between quantiles of perceived community resilience was noted in regard to size of community. The association between size of community and perceived community resilience which was negative in the logistic regression (residents of larger towns had lower community resilience), was found to be such only up to quantile 75, but it reversed in the highest quantile.

It was concluded that the utilization of quantile regression analysis in studies of community resilience can facilitate the creation of tailored response plans, adapted to the needs of sub (such as weaker) populations and help enhance overall community resilience in crises.

© 2016 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Community resilience (CR) offers a conceptual framework for gauging a community's capacity for coping with environmental changes and emergency situations (Adger, 2006; Cutter et al., 2014; Bonanno et al., 2015). Community resilience is perceived as a core

* Corresponding author at: PREPARED Center for Emergency Response Research, P.O. Box 653, Beer-Sheva 8410501, Israel. Tel.: +972 8 6428430; fax: +972 8 6472136.

E-mail address: odeyac@post.bgu.ac.il (O. Cohen).

element of sustainable lifestyle (Magis, 2010; Wilson, 2012), and indeed it can both help shorten response time during emergencies and mitigate the community's reaction to crises by facilitating purposeful and collective action on the part of its members (Pfefferbaum et al., 2013). As such, CR is increasingly recognized as an important concept in the field of emergency preparedness and response (Aldunce et al., 2015). Community resilience has been explored by a wide variety of specialists, including psychologists (Ungar, 2011; Norris et al., 2008), geographers (Cutter et al., 2008, 2010, 2014), public health professionals (Castleden et al., 2011; Poortinga, 2011), engineers (Zoback, 2014), governance specialists (Wilson, 2013), and globalization process managers (Wilson, 2012). This multidisciplinary background is responsible for the fact that the term has diverse definitions and has generated more theoretical models than strong empirical evidence (Engle, 2011; Chandra et al., 2010; Cutter et al., 2008).

The conjoint community resilience assessment measure (CCRAM) is recognized as a valid tool for assessing community resilience by household sampling (Leykin et al., 2013; Cohen et al., 2013; Cutter, 2015). CCRAM encompasses the various factors, or components, of a community's resilience that are the basis for planning interventions. The factors were identified through a statistical process, yet they are also anchored in the professional literature surrounding the concept of community resilience (Leykin et al., 2013; Cohen et al., 2013). So far, studies using CCRAM have applied common descriptive or basic statistical regression analyses. The objective of this study is to demonstrate a statistical approach, which is novel to the measurement of community resilience data. Quantile regression, has been used previously in various areas of ecology research (e.g. Cade et al., 1999; Magzamen et al., 2015) and this is, to the best of our knowledge, its first application in the field of social ecological resilience context.

Quantile regression complements the estimation of conventional mean models by providing a more sensitive insight into the distribution of the dependent variable (Magzamen et al., 2015). As presented by Fitzenberger and Wilke (2015), conventional modeling has focused on the mean of the dependent variable, quantile regression can detect whether the partial effect of a regressor on the quantile is the same for all quantiles or differs across quantiles.

2. Material and methods

2.1. Study instrument

The CCRAM tool (Leykin et al., 2013) is a self-reported questionnaire with 28 items, 21 of which have been grouped into five factors: leadership, collective efficacy, preparedness, place attachment, and social trust. The mean scores of each the factors portray a community resilience profile (range from 1 to 5). The overall CCRAM score is the average of the scores of 21 survey items with an equal weight. In addition, a single item enquired about *perceived community resilience* (also on a five point Likert scale) after defining resilience as "the ability to quickly return to routine after an emergency event".

2.2. Data collection

The study was conducted from 2011 to 2014 in Israel. It included 23 small and rural communities (up to 10,000 inhabitants) and six medium-size cities (up to 50,000 inhabitants), with 28% average sampling ratio of households. Data were collected by using door to door surveys at randomly selected addresses and by distributing electronic questionnaires in small settlements with a complete electronic mailing list using Qualtrics

(www.qualtrics.com), a web-based survey software. The study was approved by the institutional review board of the Faculty of Health Sciences at Ben-Gurion University of the Negev. Participants gave their written informed consent to take part in the study.

2.3. Statistical analysis

The reliability of both the CCRAM score and its factors were examined using Cronbach's alpha for internal validity. Pearson and Spearman correlation coefficients were then calculated and used to examine the association between CCRAM factors and various background variables. For comparing means of CCRAM scores between sub-groups of participants, an independent *t* test and analysis of variance (ANOVA) followed by post hoc tests were employed.

Two regression models were used to find the association between dependent variable: *perceived community resilience* as defined by the single item, and the socio-demographic covariates: gender, age, faith, community type, reported income level, and previous involvement in emergency situations. CCRAM factors were added to the regression equation. The analysis of the two models, examined the regression coefficients of independent variables, along with 95% confidence intervals (CI).

For the *logistic regression* it was necessary to dichotomize the dependent variable, thus it was recoded into two levels: low (1–2) versus high (4–5), while the intermediate level (3) was omitted from the analysis.

For a non-parametric method of statistical analysis, we exploited *quantile regression* models, specifically, their most common form – median regression (Gould, 1992; Hao and Naiman, 2007). Median regression finds a line through the data that minimizes the sum of the absolute residuals rather than the sum of the squares of the residuals, as in ordinary regression.

Both regression models (the ordinary and the quantile) describe the central tendency of the data, of which the mean is one measure and the median another. Since mean, and therefore ordinary linear regression, are sensitive to outliers, the ordinary regression might produce results that do not reflect the central tendency well.

The analysis examined the regression coefficients across quantiles 10, 25, 50, 75 and 90 of the dependent variable. Inter-quantile regression analysis estimated the differences between regression coefficients of independent variables between quantile 10 and quantile 90. Data were analyzed using the Statistical Package for the Social Sciences (SPSS) version 21, and STATA software version 12.1.

3. Results

3.1. Participants

This study was conducted from August 2011 to June 2014. The study included 3152 adults (mean age 41.3, range 18–94, SD = 14.9, median age – 40 years), 1758 (55.8%) from small towns, and 1384 (43.9%) from medium-size cities in Israel. Most (56.1%) participants were women ($n = 1767$), 70.6% in a permanent relationship ($n = 2226$). Nearly half (49.1%) had an academic education ($n = 1547$). Jews comprised 59.7% of participants ($n = 1882$) and 45.4% were secular ($n = 1432$). Income: 38.7% reported their income as average ($n = 1219$), while 24.3% reported their income as less than average ($n = 767$). Responders reported living in their community for an average of 24.62 years (range 1–92 years, SD = 16.2). 40.7% of the responders noted that they had previously been involved in emergency situations ($n = 1284$). Major study population characteristics are described in Table 1.

Table 1

Study population distribution with mean CCRAM and mean perceived CR score.

	<i>n</i>	%	Mean CCRAM Score	<i>p</i> -Value (<i>t</i> -test or ANOVA)	Mean perceived CR score	<i>p</i> -Value (<i>t</i> -test or ANOVA)
Total	3152	100	3.24		3.33	
Gender						
Female	1767	56.1	3.25	0.872	3.31	0.228
Male	1332	42.3	3.24		3.36	
Faith						
Jewish	1882	59.7	3.51	<0.001	3.68	<0.001
Non-Jewish	1257	39.9	2.86		2.83	
Community type						
Small towns	1758	55.8	3.39	<0.001	3.52	<0.001
Medium-size cities	1384	43.9	3.06		3.08	
Income						
About average	1219	38.7	3.23	<0.001	3.25	<0.001
Less	767	24.3	3.08		3.16	
More	1037	32.9	3.36		3.53	
Previous involvement in emergency situation						
No	1667	52.9	3.17	<0.001	3.26	0.025
Yes	1284	40.7	3.29		3.35	

3.2. The Conjoint Community Resiliency Assessment Measure (CCRAM)

The reliability of the CCRAM score as given by Cronbach's α was 0.94, while that of the factors was as follows: leadership ($\alpha = 0.9$), collective efficacy ($\alpha = 0.87$), preparedness ($\alpha = 0.81$), place attachment ($\alpha = 0.75$), and social trust ($\alpha = 0.78$). All are considered to be satisfactory. The mean CCRAM score were 3.24 (SD = 0.80), with no differences between genders (see Table 1; Table A.1). With reference to the participants' demographic background, Jewish responders were found to have a significantly higher mean CCRAM score than non-Jewish responders ($p < 0.001$). This difference was found to be significant in all CCRAM factors, but the widest gap between Jewish and non-Jewish scores was found in the collective efficacy factor ($p < 0.001$). The CCRAM score was strongly correlated with *perceived community resilience* as described by a single item ($r = 0.604$, $p < 0.001$) and had a weak positive correlation with age ($r = 0.216$, $p < 0.001$).

3.3. Logistic regression model

A logistic regression was performed ($p < 0.001$). After dichotomizing the dependent variable as described above, it included two levels: low ($n = 609$) versus high ($n = 1384$), while the intermediate level ($n = 1037$) was excluded from this analysis.

Table 2 presents the results of the regression. In this analysis the significant socio-demographic covariates were: being of non-Jewish faith, living in medium-size cities versus small towns, and having less than average income. Regarding the CCRAM factors, leadership, collective efficacy and place attachment were found to have a significant positive association with perceived community resilience.

3.4. Quantile regression model

A quantile regression model (Gould, 1992; Hao and Naiman, 2007) was used to analyze the association between demographic covariates and CCRAM factors, as well as *perceived community resilience*. Fig. 1 presents the significant socio-demographic covariates in the different quantiles of perceived community resilience. Having an income below average, was found to be significant in the lower (Q10, Q25) resilience quantiles. Having an income above average was found to be positively significant in Q75. Age (per year) and previous involvement in emergency situations were found to be positively associated with perceived community resilience in

the lowest quantile. A difference between low and high (Q10, Q25, Q50, Q75 versus Q90) was noted in regard to size of community. The association between size of community and perceived community resilience was found to be negative (residents of larger towns had lower community resilience), up to quantile 75, but reversed in the highest quantile.

The complete results for the regression coefficients of the independent variables, along with the 95% confidence intervals (CI) for quantiles 10, 25, 50, 75 and 90, are presented in Table A.2.

3.4.1. Community resilience factors

Fig. 2 presents the significant factors according to quantile. In the results derived from the regression equations among quantiles 25 and 50, all the CCRAM factors were found to be associated significantly with *perceived community resilience*. However, in quantile 10 place attachment and social trust factors were not significant, while in 90 quantile only collective efficacy and place attachment factors were significant. The collective efficacy factor yielded the highest association in all quantiles (RC range 0.336–0.282), but in quantile 10 no significant difference was found between the regression

Table 2

Factors associated with perceived community resilience, a logistic regression.

	Odds ratio (OR)	<i>p</i>	95% C.I. for OR	
			Lower	Upper
Gender				
Female	1			
Male	1.288	.100	.953	1.743
Age	.999	.808	.988	1.009
Faith				
Jewish	1			
Non-Jewish	.278	<0.001	.202	.383
Community type				
Small towns	1			
Medium-size cities	.690	.026	.498	.957
Income				
About average	1			
Less	.608	.008	.421	.877
More	1.224	.270	.855	1.753
Previous involvement in emergency situation				
No	1			
Yes	1.256	.150	.921	1.713
CCRAM factors				
Leadership	1.708	<0.001	1.331	2.192
Collective efficacy	2.188	<0.001	1.641	2.916
Preparedness	1.094	.457	.863	1.387
Place attachment	1.527	<0.001	1.266	1.843
Social Trust	1.199	.094	.970	1.482

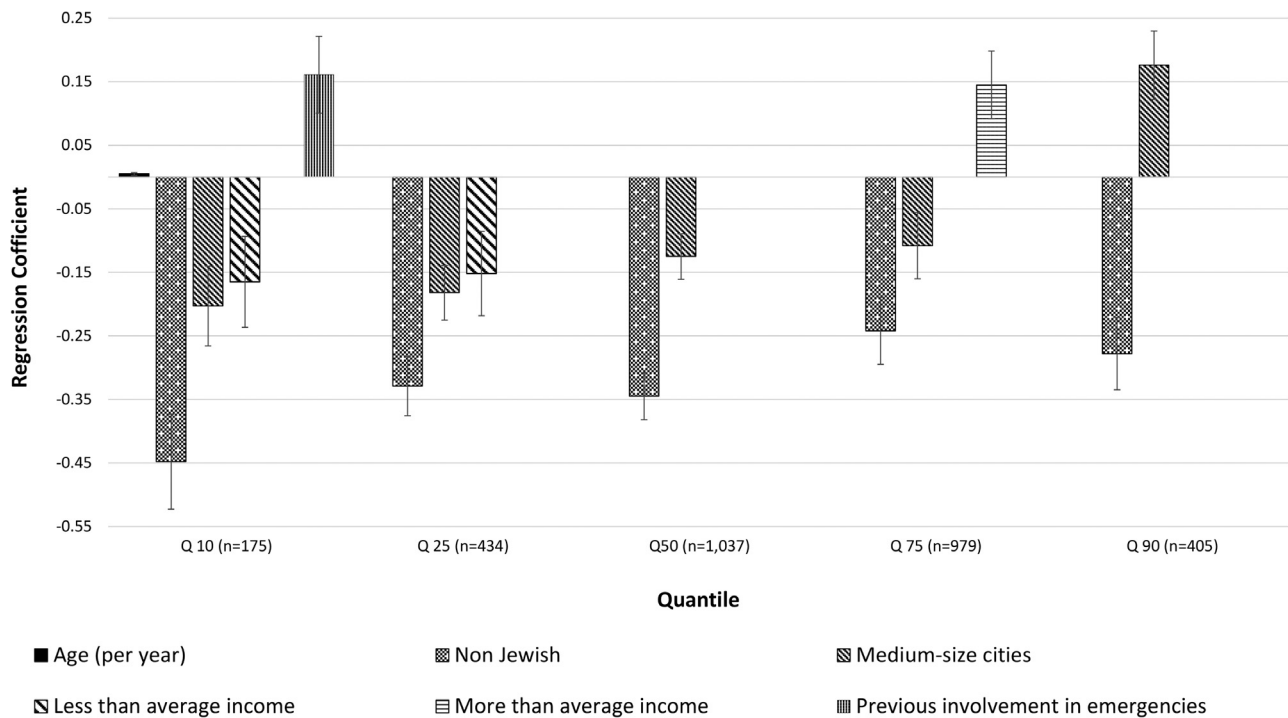


Fig. 1. Significant positive and negative socio-demographic covariates across the quantiles of perceived community resilience.

coefficients of the leadership and collective efficacy factors. The leadership factor was found to be significantly different as between quantile 10 and quantile 90 ($RC = -0.18$, $p < 0.001$, 95% CI -0.265 to -0.0952).

A summary of the differences between the significant results of the logistic and quantile regression models is presented in Table 3.

4. Discussion

Measuring the factors associated with a community's ability to cope with change or disturbance can be a challenging task (Castleden et al., 2011; Chandra et al., 2010). This manuscript

presents an innovative approach based on a 'bottom-up' assessment which takes into account the attitudes of the community's members. This empirical study explores the factors that contribute to *perceived community resilience* at five levels. The variable *perceived community resilience* is taken as an indicator of overall community resilience, thereby facilitating the introduction of community resiliency factors as independent variables into the regression equation (Leykin et al., 2013; Cohen et al., 2013).

In addition to presenting the statistical approach, this paper also demonstrates the wealth of information that can be derived by quantile regression analysis as compared with more traditional models, such as logistic regression.

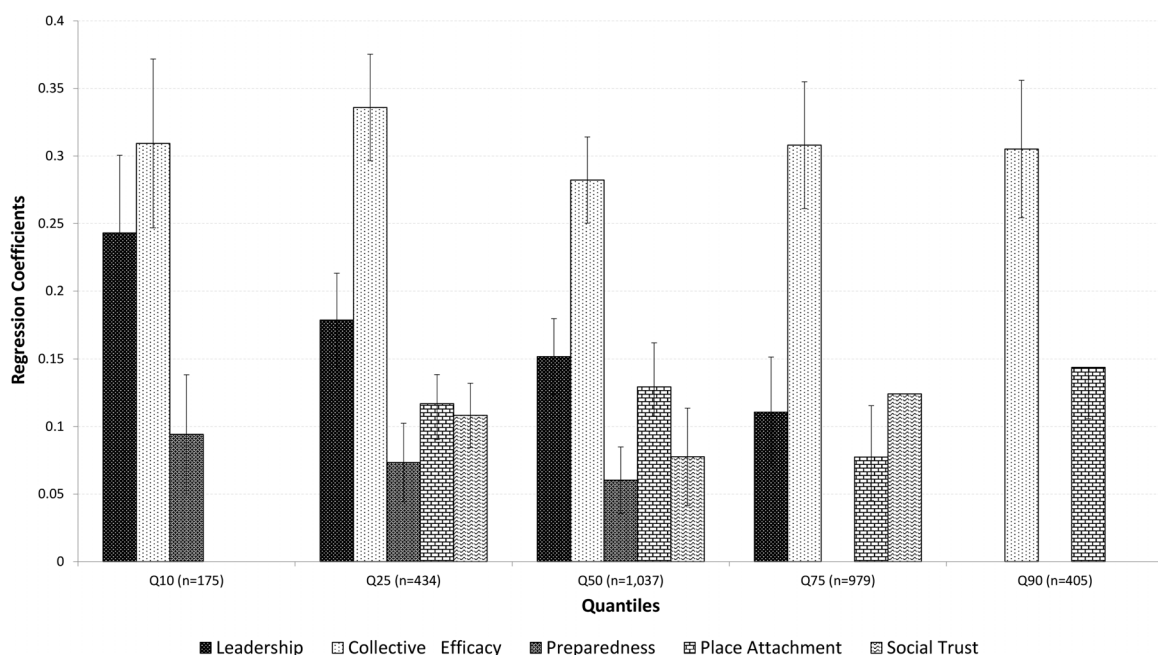


Fig. 2. Regression coefficients of significant community resilience factors in quantiles of perceived community resilience.

Table 3
Significant results and trends of logistic and quantile regression models.

Variable	Logistic regression	Q10	Q25	Q50	Q75	Q90
Gender						
Female						
Male						
Age		+				
Faith						
Jewish						
Non Jewish	—***	—***	—***	—***	—***	—***
Community type						
Small towns						
Medium-size cities	—*	—**	—***	—***	—*	+**
Income						
About average						
Below average	—**	—*	—**			
Above average					+**	
Previous involvement in emergencies						
No						
Yes		+**				
CCRAM factors						
Leadership	+***	+***	+***	+***	+**	
Collective efficacy	+***	+***	+***	+***	+***	+***
Preparedness		+	+	+		
Place attachment	+***	+***	+***	+***	+	+***
Social trust		+***	+	+	+	

* $p < 0.05$.

** $p < 0.010$.

*** $p < 0.001$.

Trends: — = negative association, + = positive association.

The use of quantile regression has been more widespread in the context of economic aspects of vulnerability studies (Nordhaus, 2010; Maloney et al., 2004) and less on psychological aspects of vulnerability studies (Bühler et al., 2012).

One of the earliest quantile regression models, presented by Koenker and Bassett in the late 1970s (1978) in the field of economy, estimated functional relations between variables for all portions of a probability distribution (Cade and Noon, 2003). While this approach has recently gained currency, we have not encountered any record of it being applied in the social context of community resilience in the face of change. In the present study, the application of quantile regression allowed us to examine and compare the impact of various factors on *perceived community resilience* among sub-populations with various levels of community resilience.

The use of quantile regression makes it possible to critically examine, verify or disprove accepted truths. For example: Community resilience studies perceived economic resources as a significant factor (e.g. Cutter et al., 2014). Our results show that 'less than average income' is negatively correlated with community resilience in the logistic regression model, but the sensitivity of the quantile regression model, enabled to see that in fact, it had a negative significant association only among the lower levels of perceived community resilience (Q10–Q25). Nevertheless, 'more than average income' was not identified as significant by logistic regression, while quantile regression revealed this variable to be positively associated with perceived community resilience in quantile 75.

Previous involvement in an emergency situation was found to have a positive effect in the lower quantile (Q10), contrary to previous studies (Cohen et al., 2013; Leykin et al., 2013) that used conventional statistical approaches, and to the finding of the logistic regression of the current study which also found it with no significant association.

These findings are of relevance when planning focused intervention plans as it helps identify the most vulnerable population that can benefit most from engagement.

In regard to the CCRAM factors, there were important differences between the two regression models. The preparedness and

trust factors were not found to be significant factor associated with perceived community resilience in the logistic regression model, yet quantile regression revealed these factors to be significant, though only among the lower quantiles (Q10–Q50). The impact of each CCRAM factor on perceived community resilience was examined based on the 95% CI of the logistic regression model, but no significant differences were found between the coefficients of the factors. Quantile regression, on the other hand, indicated that the collective efficacy factor had the highest association with perceived community resilience in all groups except quantile 10. As demonstrated in Fig. 2, the most important factor associated with perceived community resilience is collective efficacy. Since it has been documented that a crisis is usually followed immediately by a rise in mutual support and solidarity (Hawdon et al., 2012), intervention plans can be devised, based on the assumption that the population will be willing to help. Collective efficacy may therefore not only contribute to the initial strength and resilience of the society, but it may also help in supporting and enhancing recovery measures.

A community is a multifaceted configuration made up of various elements (individuals) and the connections between them (Yang and Leskovec, 2015). Connections vary in strength and significance, and together they weld this formation into a structure. A community is therefore challenging to study. Research into such a complex entity, with its diverse traits and characteristics, calls for a multidimensional approach.

Bonanno et al. (2015) suggest the use of average-level data on adjustment in studies of adversity. Their approach focuses on the event, rather than on individual reactions to the event, and seeks to characterize differences (on average) between exposed groups and non-exposed groups, or to some other comparative baseline. Their assumption is that the statistical average represents the normal or modal responses to adversity in a community, and therefore that by analyzing only a summary statistic of the dependent variable (such as the mean), we can only see a narrow and incomplete picture (Fitzenberger and Wilke, 2015; Bonanno et al., 2015).

In this paper we demonstrate that by slicing the population into discrete and more homogeneous slices created by quantiles, we can provide more accurate insights into the community. Departing from the agreed compromise of using the mean in order to describe a group opens up a wide spectrum of opportunities, not only for descriptive or analytic statistics, but also for the practical study of community resilience (and other community characteristics as well). The ability to explore each centile or quantile will facilitate identification not only of persons who need more assistance, but also of those who can help their peers. On the other hand, it will also help us discern what factors exist across the community's sub-groups and which factor is capable of enhancing all of the sub-groups. One limitation of this study is the fact that it was cross-sectional, thus we could identify association but not causality. Future longitudinal studies, particularly those following an intervention or occurrence that influences community resilience, will shed more light on the causes of change identified in the different quantiles. Another limitation is the imperfection of information regarding the response rate, due to the fact that electronic mailing lists were used to approach some of the study population and we are unable to detect mail which did not reach its destination or was not opened.

5. Conclusion

In this study the use of quantile regression analysis for modeling community resilience was shown to yield more sensitive results than traditional regression models, potentially contributing to a deeper understanding of the issues at hand. We recommend that quantile regression be routinely incorporated into the study

of community behavior. Quantile regression analysis can play an important role in the development of tailored, more effective response plans for communities facing change and crisis.

Acknowledgement

The authors would like to thank Mr. Dmitry Leykin and Ms. Aviva Goral for their assistance with data analysis. We would like to express our sincere gratitude to Prof. Friger from the department of Public Health in the faculty of Health Sciences at BGU for exposing us to the potential of using quantile regression analysis in community resilience data and for being the ultimate teacher for Biostatistics. The Conjoint Community Resiliency Assessment Measure (CCRAM) was developed through the group work of a multidisciplinary group of researchers from seven academic institutions in Israel, as detailed in Leykin et al. (2013). We thank them all.

Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecolind.2016.02.012>.

References

- Adger, W.N., 2006. Vulnerability. *Global Environ. Change* 16 (3), 268–281.
- Aldunce, P., Beilin, R., Howden, M., Handmer, J., 2015. Resilience for disaster risk management in a changing climate: practitioners' frames and practices. *Global Environ. Change* 30, 1–11.
- Bonanno, G.A., Romero, S.A., Klein, S.I., 2015. The temporal elements of psychological resilience: an integrative framework for the study of individuals, families, and communities. *Psychol. Inq.* 26, 139–169.
- Bühler, M.D., De Torres Curth, M., Garibaldi, L.A., 2012. Demography and socioeconomic vulnerability influence fire occurrence in Bariloche (Argentina). *Landsc. Urban Plan.* 110, 64–73.
- Cade, B.S., Noon, B.R., 2003. A gentle introduction to quantile regression for ecologists. *Front. Ecol. Environ.* 1 (8), 412–420.
- Cade, B.S., Terrell, J.W., Schroeder, R.L., 1999. Estimating effects of limiting factors with regression quantiles. *Ecology* 80, 311–323.
- Castleden, M., McKee, M., Murray, V., Leonardi, G., 2011. Resilience thinking in health protection. *J. Public Health Oxf. Engl.* 33, 369–377.
- Chandra, A., Acosta, J., Meredith, L.S., Sanches, K., Stern, S., Uscher-pines, L., et al., 2010. February. Understanding Community Resilience in the Context of National Health Security A Literature Review, Retrieved from: http://www.prgrs.edu/content/dam/rand/pubs/working_papers/2010/RAND-WR737.pdf.
- Cohen, O., Leykin, D., Lahad, M., Goldberg, A., Aharonson-Daniel, L., 2013. The conjoint community resiliency assessment measure as a baseline for profiling and predicting community resilience for emergencies. *Technol. Forecast. Soc. Change* 80 (9), 1732–1741.
- Cutter, S.L., 2015. The landscape of disaster resilience indicators in the USA. *Nat. Hazards*, 1–18.
- Cutter, S.L., Ash, K.D., Emrich, C.T., 2014. The geographies of community disaster resilience. *Global Environ. Change* 29, 65–77.
- Cutter, S.L., Burton, C., Emrich, C.T., 2010. Disaster resilience indicators for benchmarking baseline conditions. *J. Homel. Secur. Emerg. Manag.* 7 (1), 1–22.
- Cutter, S.L., Barnes, L., Berry, M., Burton, C., Evans, E., Tate, E., et al., 2008. A place-based model for understanding community resilience to natural disasters. *Global Environ. Change* 18, 598–606.
- Engle, N.L., 2011. Adaptive capacity and its assessment. *Global Environ. Change* 21, 647–656.
- Fitzzenberger, B., Wilke, R.A., 2015. Quantile Regression Methods. *Emerging Trends in the Social and Behavioral Sciences: An Interdisciplinary, Searchable, and Linkable Resource*, pp. 1–18.
- Gould, W.W., 1992. Quantile regression with bootstrapped standard errors. *Stata Tech. Bull.* 9, 19–21.
- Hao, L., Naiman, D.Q., 2007. *Quantile Regression*. Sage, Thousand Oaks, CA.
- Hawdon, J., Räsänen, P., Oksanen, A., Ryan, J., 2012. Social solidarity and wellbeing after critical incidents: three cases of mass shootings. *J. Crit. Incid. Anal.* 3, 2–25.
- Koenker, R., Bassett, R.G., 1978. Regression quantiles. *Econometrica: J. Econ. Soc.*, 33–50.
- Leykin, D., Lahad, M., Cohen, O., Goldberg, A., Aharonson-Daniel, L., 2013. Conjoint community resiliency assessment measure-28/10 items (CCRAM28 and CCRAM10): a self-report tool for assessing community resilience. *Am. J. Community Psychol.* 52 (3–4), 313–323.
- Magis, K., 2010. Community resilience: an indicator of social sustainability. *Soc. Nat. Resour.* 23, 401–416.
- Magzamen, S., Amato, M.S., Imm, P., Havlena, J.A., Coons, M.J., Anderson, H.A., Moore, C.F., 2015. Quantile regression in environmental health: early life lead exposure and end-of-grade exams. *Environ. Res.* 137, 108–119.
- Maloney, W.F., Cunningham, W.V., Bosch, M., 2004. The distribution of income shocks during crises: an application of quantile analysis to Mexico, 1992–95. *World Bank Econ. Rev.* 18, 155–174.
- Nordhaus, W.D., 2010. The economics of hurricanes and implications of global warming. *Clim. Change Econ.* 1 (1), 1–20.
- Norris, F.H., Stevens, S.P., Pfefferbaum, B., Wyche, K.F., Pfefferbaum, R.L., 2008. Community resilience as a metaphor, theory, set of capacities, and strategy for disaster readiness. *Am. J. Community Psychol.* 41, 127–150.
- Pfefferbaum, R.L., Pfefferbaum, B., Van Horn, R.L., Klomp, R.W., Norris, F.H., Reissman, D.B., 2013. The communities advancing resilience toolkit (CART): an intervention to build community resilience to disasters. *J. Public Health Manag. Pract.* 19 (3), 250–258.
- Poortinga, W., 2011. Community resilience and health: the role of bonding, bridging, and linking aspects of social capital. *Health Place* 18, 286–295.
- Ungar, M., 2011. The social ecology of resilience. Addressing contextual and cultural ambiguity of a nascent construct. *Am. J. Orthopsychiatr.* 81, 1–17.
- Wilson, G.A., 2013. Community resilience, policy corridors and the policy challenge. *Land Use Policy* 31, 298–310.
- Wilson, G.A., 2012. Community resilience, globalization, and transitional pathways of decision-making. *Geoforum* 43 (6), 1218–1231.
- Yang, J., Leskovec, J., 2015. Defining and evaluating network communities based on ground-truth. *Knowl. Inform. Syst.* 42 (1), 181–213.
- Zoback, M.L., 2014. Epicenters of resilience. *Science* 346 (6207), 283.