

# Assessing small & medium-sized enterprises' resilience capacity to flooding: Evidence from a structural equation model

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**Abstract** In this study a model that comprises of factors linked to the resilience capacity of small and medium-sized enterprises (SMEs) to flooding is tested. A sample of 343 enterprises from flood-prone areas was administered a structured questionnaire on cognitive, managerial and contextual factors that influence the ability to shape effective responses to flood challenges. Structural Equation Modeling is employed to identify associations between the various observed items forming the individual latent sub-constructs, as well as the associations between these latent sub-constructs with the flood resilience capacity construct (FRCI). Findings reveal that the major contributor to the FRCI is the sub-construct of 'behavioral/managerial' factors ( $\beta = 0.893$ ;  $p\text{-value} < 0.001$ ). Moderate associations are observed with the 'cognitive' factors ( $\beta = 0.157$ ;  $p\text{-value} < 0.1$ ), whereas no associations are found with the 'contextual' parameters linked to FRCI. Through the proposed approach, an analytical framework is set forth that will help standardize such assessments with an overarching aim of reducing the vulnerability of SMEs to flooding. This is achieved by identifying major internal and external attributes explaining the resilience capacity which is particularly important given the limited resources these enterprises have at their disposal and that they tend to be primary sources of vulnerabilities in supply chain networks.

**Keywords:** Floods; SMEs; organizational resilience capacity; structural equation modeling.

## 1. Introduction - Background

Floods incur significant socio-economic impacts worldwide which are expected to increase in light of climate change (CC) (Munich Re, 2017). These high impact – low probability events are one of the most frequent, widespread and destructive natural disasters, affecting approximately 250 million people, representing about 40% of the damages caused by all natural disasters and causing USD 40 billion in losses on an annual basis (OECD, 2016). Such environmental perturbations can cause abrupt changes and disruption to business entities in flood-prone areas in terms of asset damages, operational interruptions and increased costs which result in loss of capital and labor, declining revenue and growth (Winn et al., 2011). It is therefore critical for businesses to identify such risks, to reduce their vulnerability to EWE threats and, ultimately, to effectively build their resilience to climate-induced physical challenges (Weinhofer & Busch, 2013). Resilience indicates the ability to withstand, to adapt, and to quickly recover from stresses and shocks (EC, 2012). In this respect, organizational resilience capacity

signifies a blend of cognitive, managerial and contextual properties that allow a business entity to effectively absorb, develop situation-specific responses to, and ultimately engage in transformative activities to capitalize on disruptive events that potentially threaten its very survival (Lengnick-Hall et al., 2011). Fostering the resilience capacity of a firm enables it to overcome survival threats and ultimately secure its longevity and prosperity under a complicated, uncertain, and volatile environment (Korhonen & Seager, 2008).

SMEs are more vulnerable to face floods compared to their larger counterparts, so they are disproportionately affected by such extreme weather events. The limited resources at their disposal, the lack of time and skills all conduce to inadequate preparedness to challenges posed by floods (Sullivan-Taylor & Branicki, 2011). SMEs tend to plan in the short-term, reacting to circumstances as they arise and focusing on their very survival. Likewise, they share less formalized structures and codified policies while they are most usually owner-managed, resulting in a command-and-control management culture (Ates et al., 2013). Such characteristics result in them having limited opportunities to recover from flooding and quickly turnaround their operation from a loss-making to a profit-making one.

Organizational resilience capacity to EWEs has sparked a growth in scholarly attention over few years as an essential aspect in business continuity management, with supporting evidence for this claim to suggest that it retains a key role in successful responses to adverse situations, crises and shocks (Linnenluecke, 2017). Linnenluecke and Griffiths (2010) frame the capacity of business entities to be resilient upon an EWE disturbance (such as flooding) as the rate of recovery and restoration of organizational performance to pre-disturbance conditions, the amount of disturbance (i.e. threshold level) a business can absorb before losing structural and/or functional components that will alter or cease operation, as well as the extent to which the organization maintains its function (i.e. impact resistance) before performance levels are driven to zero.

Nevertheless, while it seems to be accepted as an essential trait of firms effectively transcending uncertain conditions (Linnenluecke and Griffiths, 2010), research

deconstructing the enabling conditions and/or inhibitory factors of SMEs resilience capacity to natural hazards is still sparse, fragmentary and mostly fueled by anecdotal evidence or normative assumptions (Linnenluecke, 2017). Focusing on the individual level of analysis, i.e. the individual enterprise and its endeavors to succeed, the emergent picture from this relatively new research strand delineates the specification of variables, conceptual relationships or dynamic boundaries of resilience capacity components [39] in an attempt to provide prescriptions for policy-making as well as business management.

## 2. Material and methods

### 2.1. Sample identification

A sample of 343 SMEs owners-managers from flood-prone areas was administered a structured questionnaire on factors that influence the ability to shape effective responses to flooding. Out of these enterprises, 74% pertain to the service/retail sector, 17% are manufacturing firms and 8% are SMEs operating in the primary sector. The majority of sample firms are micro and small enterprises (82%), ranging from newly created ones (<3yrs old; 6%) to SMEs founded more than 40 years ago (11%). Most SMEs had experienced flooding once in recent years (74%), while the rest had encountered floods more than once. Lastly, 29% of the respondents indicated that the severity of flood damages to their business was substantial.

### 2.2. Model specification

A thorough review of the literature on factors influencing organizational resilience capacity was performed, emphasizing on SMEs vis-à-vis weather extremes and with a particular focus on floods (Linnenluecke & Griffiths, 2012; Kuruppu et al., 2013; Vakilzadeh & Haase, 2020). This allowed to frame three main groups of parameters (namely, cognitive, behavioral/managerial and contextual factors) that influence an enterprise's ability to withstand, adapt and recover from floods. Cognitive factors pertain to attitudes and perceptions around risk awareness and proactivity as well as the level of knowledge/understanding of CC impact and underlying links to extreme weather. Behavioral/managerial factors refer to organizational behavior, management culture, organizational planning and learning, technological and financial resources as well as organizational leadership capabilities. Contextual factors encapsulate the critical role of key stakeholders (local enterprises and community members, business partners, suppliers, customers, friends and relatives, consultants as well as business chambers and associations, providers of capital and local/central government entities) in SMEs' ability to adapt and recover from flooding.

An initial pool of items was created, utilizing existing knowledge/studies and developing new items-statements. Scales measuring the various aspects of SME resilience capacity to flooding were drawn following the systematic review of prior research and

utilizing expert input. This process resulted to an initial pool of items comprising the resilience capacity measurement instrument. This composite research instrument was pre-tested on a small group of SMEs using convenience sampling. Following the pilot survey, the number of items was re-examined and this information was used for finalizing the structured measurement instrument focusing on factors defining SMEs' resilience capacity to flooding. The proposed model is presented in Figure 1 and seeks to provide insights about the direct effects between the various constructs and sub-constructs forming the flood resilience capacity construct-index (FRCI).

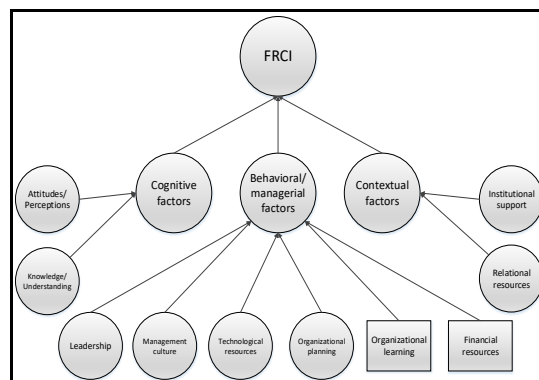


Figure 1. Conceptual model

Our attempt is to identify associations between the various observed items forming the individual latent sub-constructs, as well as the associations between these individual latent sub-constructs with the composite FRCI. In line with the suggestions of Muthén and Muthén (2002) on appropriate sample size for conducting structural equation modeling analysis, the total number of 343 SMEs owners/managers responses were analyzed to obtain meaningful and valid results.

We fit a structural equation model (SEM; Bollen, 1989) in order to test the conceptual model set forth. The suggested modeling scheme can be realized by the fit of a complex 3-layer structural equation model. Specifically, the fitted SEM model first explores the direct connections between the observed items forming the sub-constructs of cognitive, behavioral/managerial and contextual factors. At a second stage, the associations between the sub-constructs and the three previously mentioned (cognitive, behavioral/managerial and contextual) factors are estimated whereas, at the third layer of the SEM model, a final connection between the three constructs and the FRCI construct was added.

The SEM model was estimated using the AMOS software (Arbuckle, 2006) and, for the estimation of the model's parameters, the method of weighted least squares (WLS) was employed as the most suitable estimation approach for this type of collected data (i.e. Likert scale values gathered from a structured questionnaire).

In order to assess the reliability and validity of the latent constructs of SEM modeling, Cronbach's alpha, and percentage of variance explained were respectively

employed. The latter analyses were conducted using the Statistical Package for the Social Sciences software (SPSS; IBM, 2017).

To evaluate the goodness-of-fit of the SEM model, various goodness-of-fit (GoF) measures were utilized, such as the root mean square error of a pproximation (RMS), the goodness-of-fit index (GFI), the adjusted goodness-of-fit index (AGFI) and the Root Mean Square Error of Approximation (RMSEA). Typically, for an excellent fit the indices GFI and AGFI should be above 0.9, and accordingly RMS and RMSEA should be generally below 0.08.

### 3. Results

#### 3.1 Validity and reliability results

Validity and reliability results for the sub-constructs of the fitted SEM model are presented in Table 1. The results of the analysis reveal that the specific model conceptualization provides a moderate to good fit to the data and indicate the acceptance of reliability and validity (in the study's sample) as values are within acceptable limits.

Construct	Sub-construct	Cronbach's alpha	% of variance explained
Cognitive factors	Attitudes/Perceptions	0.688	59.73
	Knowledge/Understanding	0.730	62.21
	Leadership	0.683	62.28
Behavioral/managerial factors	Management culture	0.746	67.59
	Technological resources	0.753	60.42
	Organizational planning	0.654	56.79
	Organizational learning	---	---
	Financial resources	---	---
Contextual factors	Relational resources	0.878	69.82
	Institutional support	0.781	54.39

**Table 1.** Cronbach's alpha and % of variance explained for the latent constructs of SEM modeling

#### 3.2 Goodness-of-fit for the SEM model

The obtained measures from the fit of the SEM model are RMS = 0.089, GFI = 0.817, AGFI = 0.878 and RMSEA = 0.0841. The GoF values are acceptable, indicating a moderate to good fit of the data to the hypothesized model structure.

#### 3.3 SEM results

The standardized path coefficient estimates, as obtained through the fit of the SEM model and estimation via the method of WLS are presented in Table 2 (and Figure 2). Dashed lines in the graphical representation of the estimated SEM model indicate the non-significance of the association between the two latent structures. Along with the estimated values of the standardized path coefficients, the statistical significance of each association is also indicated in the table and corresponding figure.

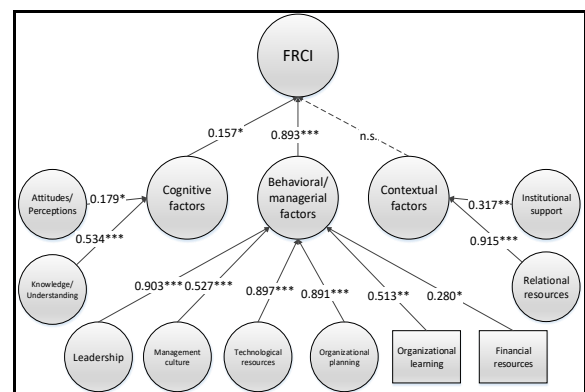
Results of SEM modeling indicate that not all three sub-constructs are equally associated with the latent FRCI factor. The major contributor to the FRCI is the sub-construct of 'behavioral/managerial' factors (beta = 0.893; p-value<0.001). Moderate associations are observed with the sub-construct of 'cognitive' factors (beta = 0.157; p-value<0.1), whereas no statistically significant association is found with the 'contextual' factors of SMEs flood resilience capacity. With respect

to the associations between the three sub-factors of FRCI and their respective sub-constructs, the following have been derived. First, the 'cognitive' factors sub-construct is mostly associated with the construct of 'knowledge/understanding' (beta = 0.534; p-value<0.01), and less associated with 'attitudes/perceptions' (beta = 0.179; p-value<0.1). Second, the majority of contributions to 'behavioral/managerial' factors is from the sub-constructs of 'leadership', 'technological resources' and 'organizational planning', with much less contributions from 'financial resources', 'management culture' and 'organizational learning'. Lastly, the sub-construct of 'contextual' factors is highly associated with the 'relational resources' construct (beta = 0.915; p-value<0.001) and moderately associated with the 'Institutional support' construct (beta = 0.317; p-value<0.05).

Sub-construct	Construct	coefficient	p-value
Cognitive	→ FRCI	0.157	*
Behavioral/managerial	→ FRCI	0.893	***
Contextual	→ FRCI	0.039	n.s.
Attitudes/Perceptions	→ Cognitive	0.179	*
Knowledge/Understanding	→ Cognitive	0.534	***
Leadership	→ Behavioral/managerial	0.903	***
Management culture	→ Behavioral/managerial	0.527	***
Technological resources	→ Behavioral/managerial	0.897	***
Organizational planning	→ Behavioral/managerial	0.891	***
Organizational learning	→ Behavioral/managerial	0.513	**
Financial resources	→ Behavioral/managerial	0.280	*
Relational resources	→ Contextual	0.915	***
Institutional support	→ Contextual	0.317	**

**Table 2.** Estimated (standardized) coefficients of the fitted SEM model

(\*) Significant at the 10% significance level; (\*\*) Significant at the 5% significance level; (\*\*\*) Significant at the 1% significance level; n.s.: non-significant



**Figure 2.** Path diagram with estimated standardized coefficients

(\*) Significant at the 10% significance level; (\*\*) Significant at the 5% significance level; (\*\*\*) Significant at the 1% significance level; n.s.: non-significant

### 4. Concluding remarks

Through this study we seek to contribute to an important, yet paradoxical, gap identified in current scholarship delineating that while SMEs are at the frontline of suffering losses and damage from flood disasters, their capacity as well as willingness to engage in resilience-building actions is far from understood (Neise et al., 2018). Gaining a better understanding of whether and how these firms drive forward resilience individually and, thus, contribute to collective



adaptation towards such natural hazards, is of key importance given: a) the further growth in the intensity and frequency of EWEs expected in the future, driven by CC as well as regional environmental degradation (IPCC, 2014) and, b) the continued development of economic infrastructure and productive assets in proximity to flood-prone areas (EEA, 2016). In this context, our findings (primarily) on the impact of owner-manager attitudes, financial resources and contextual factors on SMEs resilience capacity warrant further attention and investigation.

While statutory or voluntary schemes have been developed and relevant surveys on CC adaptation have been conducted in European countries, they fall short in offering a quantification and explicit identification of parameters facilitating SMEs capacity to withstand and transcend floods, which is where our study seeks to contribute. Through the proposed FRCI we seek to engage SME owners/managers to take action to mitigate adverse flood impacts and provide them with a benchmarking tool that local economic actors can employ in assessing the ability of (local) SMEs to adapt and recover from floods. With this in mind, the study makes three contributions to the extant literature. First, a composite metric is developed to assess determinants of SMEs resilience capacity, offering insights on how various parameters affect organizational ability to confront floods. Second, the analysis provides evidence from Greek enterprises for the first time, pointing out facilitating factors and underlying barriers. Third, a replicable research approach for analyzing SME resilience capacity characteristics is formulated, potentially contributing to regional studies, business sustainability research and the theorization of organizational resilience to extreme weather events. Findings such as ours can feed into actionable and practical guidelines, manuals and/or standards on business preparedness to extreme weather events. They can assist governmental bodies in how to incentivize SMEs to proactively prepare for such natural hazards (in terms of financial and/or other means of support) as well as by facilitating the coordination of multi-stakeholder partnerships for mobilizing actions through the dissemination of best-practices and screening tools, such as the suggested self-assessment FRCI-based tool.

## References

- Arbuckle J.L. (2006). *Amos 7.0 User's Guide*. Chicago: SPSS.
- Ates A., Garengo P., Cocca P. and Bititci U. (2013), The development of SME managerial practice for effective performance management, *Journal of Small Business and Enterprise Development*, 20, 28-54.
- Bollen K.A. (1989). *Structural equations with latent variables*. New York: Wiley-Interscience.
- EC (2012), *The EU approach to resilience*. EC.
- EEA (2016), *Climate change, impacts and vulnerability in Europe 2016 - An indicator-based report*, European Environment Agency.
- IBM Corp. Released 2017. *IBM SPSS Statistics for Windows, Version 25.0*. Armonk, NY: IBM Corp.
- IPCC (2014). *Climate Change 2014: Impacts, Adaptation, and Vulnerability*. IPCC.
- Korhonen J. and Seager T.P. (2008), Beyond eco-efficiency: a resilience perspective, *Business Strategy and the Environment*, 17, 411-419.
- Kuruppu N., Murta J., Mukheibir P. Chong J. and Brennan T. (2013), Understanding the adaptive capacity of Australian small-to-medium enterprises to climate change and variability. National Climate Change Adaptation Research Facility.
- Lengnick-Hall C.A., Beck T.E. and Lengnick-Hall M.L. (2011), Developing a capacity for organizational resilience through strategic human resource management. *Human Resource Management Review*, 21, 243-255.
- Linnenluecke M.K. (2017), Resilience in business and management research: a review of influential publications and a research agenda, *International Journal of Management Reviews*, 19, 4-30.
- Linnenluecke M. and Griffiths A. (2010), Beyond adaptation: resilience for business in light of climate change and weather extremes. *Business and Society*, 49, 477-511.
- Linnenluecke M.K. and Griffiths A. (2012), Assessing organizational resilience to climate and weather extremes: complexities and methodological pathways, *Climatic change*, 113, 933-947.
- Munich Re (2017), *Natural catastrophes 2016: Analyses, assessments, positions: Year of the floods*, Munich Re.
- Muthen, L.K. and Muthen, B.O. (2002). How to Use a Monte Carlo Study to Decide on Sample Size and Determine Power. *Structural Equation Modeling: A Multidisciplinary Journal*, 9, 599-620.
- Neise T., Revilla Diez J. and Garschagen M. (2018), Firms as drivers of integrative adaptive regional development in the context of environmental hazards in developing countries and emerging economies—a conceptual framework. *Environment and Planning C: Politics and Space*, 36, 1522-1541.
- OECD (2016), *Financial Management of Flood Risk*, OECD Publishing.
- Sullivan-Taylor B. and Branicki L. (2011), Creating resilient SMEs: why one size might not fit all, *International Journal of Production Research*, 49, 5565-5579.
- Vakilzadeh K. and Haase A. (2020), The building blocks of organizational resilience: a review of the empirical literature, *Continuity & Resilience Review*, 3, 1-21.
- Winn M., Kirchgeorg M., Griffiths A., Linnenluecke M.K. and Günther E. (2011), Impacts from climate change on organizations: a conceptual foundation, *Business Strategy and the Environment*, 20, 157-173.
- Weinhofer G. and Busch T. (2013), Corporate strategies for managing climate risks, *Business Strategy and the Environment*, 22, 121-144.

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