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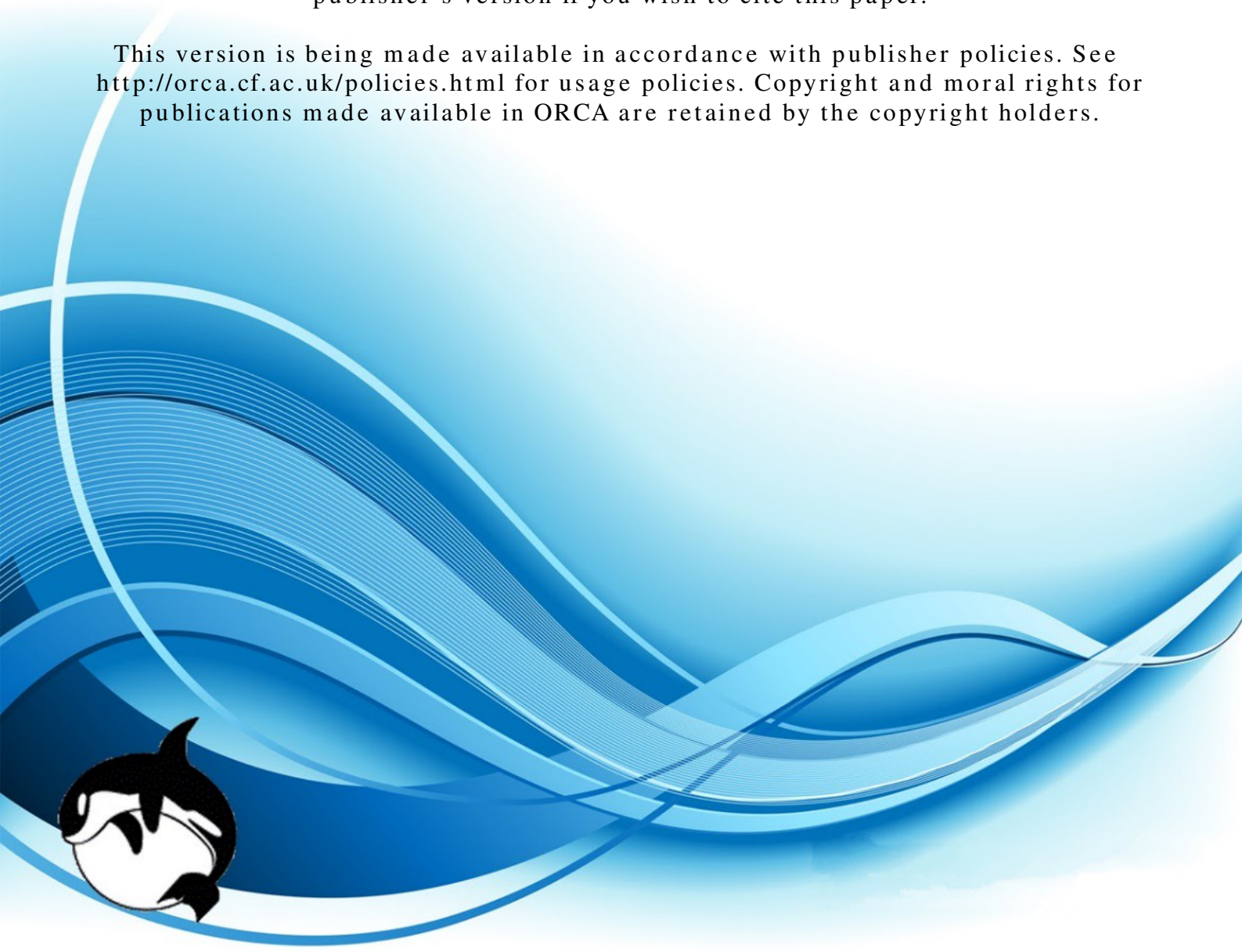

Surviving or thriving: The role of learning for the resilient performance of small firms

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Abstract

Building on a longitudinal dataset of 245 small firms covering the period of the Global Financial Crisis, this study uses, in combination with fuzzy clustering, the N-State Classification and Ranking Belief Simplex (NCaRBS) technique. This technique, able to deal with ambiguous outcome variables, small datasets, incomplete data and relationships that have the potential to be non-linear, is used to explore the relationship between learning and the resilient performance of small firms. Our findings provide a fine-grained picture of the complex relationships between strategic, cognitive and behavioural learning mechanisms and three resilient performance clusters – sustained performance, stability, and survival – which has implications for theory, as well as practice. By examining learning at the level of the individual owner-manager and also the organisation, we contribute to a better understanding of the role of specific learning mechanisms, a role that is still not well understood.

Keywords: SMEs**,** fuzzy clustering, NCaRBS, learning, global financial crisis, cognition

1. Introduction

During 2008 and 2009, the world economy experienced its severest recession and financial crisis since the 1930s (IMF, 2010). The Global Financial Crisis (GFC) presented an uncertain and turbulent economic environment for small firms, but these conditions do not necessarily have detrimental performance effects on individual firms. On the contrary, small firms that are able to learn and adapt have proven to be surprisingly resilient (Smallbone, Deakins, Battisti & Kitching, 2012). According to Altinay, Madanoglu, De Vita, Arasli and Ekinci (2016, p.879), learning enables "firms to question the status quo on a regular basis and push for continuous improvement, leading to a more flexible and adaptable way of doing things". Furthermore, learning helps firms to overcome inertia that they might have developed in stable environments, where the likelihood of encountering only familiar and predictable challenges is higher than in more uncertain environments (Fiol & Lyes, 1985). Broadly speaking, learning allows firms to be resilient during times of uncertainty and turbulence (Weick & Sutcliffe, 2011), but some small firms are better at adapting to changing environments than others (Friedman, Carmeli & Tishler, 2016). However, it is not clear what the *specific learning mechanisms* are that lead to different resilient performance effects over time. It is therefore of theoretical and practical importance to better understand the specific learning mechanisms that explain the resilient performance of small firms.

Building on organisational learning (OL) theory (Crossan, Lane & White, 1999; Easterby-Smith & Lyes, 2011; Fiol & Lyes, 1985), the overarching aim of this study is to better understand the role learning plays for the resilient performance of small firms over an extended period of time. We identify specific strategic, cognitive and behavioural learning mechanisms of small firms that have survived for a minimum of five years inclusive of the GFC.

This study uses a longitudinal dataset of small firms from New Zealand, covering a five-year time period from 2007 to 2011. Pettigrew (1990) argues that longitudinal studies are likely to produce complex patterns of change as a result of shifting contextual conditions. The analytical approach therefore needs to be able to reflect the complex and often ambiguous ways in which performance

changes over time, and needs to allow for potentially non-linear patterns to occur. The nature of learning means that relationships between learning mechanisms and resilient performance could potentially be non-linear, as it is unlikely that increased learning will result in a corresponding increase in the performance of firms, particularly when considered over an extended time period. For these reasons, fuzzy clustering of the outcome variable is used, because it is a technique able to maintain greater information pertaining to proportionate membership of the three outcome clusters (subsequently identified as *sustained performance*, *stability* and *survival*) used in the study. The N-State Classification and Ranking Belief Simplex (NCaRBS) technique (Beynon, Andrews & Boyne, 2015) is also used, because it is able to deal with small, incomplete datasets where relationships may be non-linear, as is the case here.

The New Zealand context makes for an interesting case to study resilient performance of small firms. Due to the country's small domestic market and relative geographical isolation, New Zealand firms need to learn and adapt out of necessity. Further, the specific context impacts on the adaptive strategies that are available to firms, particularly in periods of uncertainty and turbulence, such as the GFC. Smallbone et al. (2012), for example, showed that small firms in the UK were more likely to have increased their sales effort in response to the GFC, while New Zealand firms were more likely to have invested in human capital, reflecting structural differences between the two economies. A number of previous studies have therefore considered New Zealand to be an ideal context to investigate resilience (e.g. De Vries & Shields, 2006; Hamilton & de Vries, 2016; Seville, 2016; Seville et al., 2008; Smallbone et al., 2012).

The study makes several contributions. First, existing studies are mostly based on cross-sectional data (Fainshmidt et al., 2016), and this study adds much needed longitudinal data that allows novel insights into the role of learning for the resilient performance of small firms. This is important because our findings illustrate that the effects of learning on longer-term performance are different to the effects on short-term performance. Second, building on OL theory, we examine learning at the level of the individual owner-manager as well as the organisation, which is particularly relevant in small firm

contexts, where the role of the owner-manager is much more pronounced (Deakins, Battisti, Coetzer & Roxas, 2012). As a result, our findings allow us to better understand the role of owner-managers' cognition and behaviour in driving firm performance in the longer term. Third, our study makes a methodological contribution. Using NCaRBS, combined with fuzzy clustering, we are able to provide a fine-grained picture of the complex relationships between individual- and organisational-level learning mechanisms and the resilient performance of small firms.

2. Theoretical background

In this section, we first introduce the concept of resilient performance of small firms. We then build on OL theory to identify specific individual- and organisational-level learning mechanisms that are relevant to the small firm context.

2.1 Resilient performance of small firms

Resilience has been shown to be a suitable indictor of small firm performance during turbulent economic times (Smallbone et al., 2012; Pal, Torstensson & Mattila, 2014). As argued previously, it is likely that we find different patterns of resilience when considered over an extended period of time. Theoretically, we can distinguish between three different patterns of resilience (Conz, Denicolai & Zucchella, 2017). Two of these utilise engineering and ecological principles and relate to the capability to respond to an external disturbance and return to a previous equilibrium. This capability can be seen as a *stability* pattern of resilience. The third, evolutionary, view, proposed by Conz et al. (2017) themselves, sees resilience as an ongoing adaptive capacity, which appears to be more in keeping with a *long-term sustained performance* pattern of resilience. Conversely, entrenched organisational cultures, which form as a result of resilience, particularly when embedded in broader local systems and clusters (see Conz et al., 2017), can also create rigidities in an organisation. Such rigidities can lead to an inability or reluctance to change (Cardoso & Ramos, 2016), which can enable firm *survival* in the medium term, but where deteriorating performance is a signal for eventual system failure. These three patterns of resilient performance will be utilised in the clusters identified in our research, and in the subsequent discussion.

Previous research has already identified learning as a key driver of resilient performance in small firms. Small firms have a relative advantage in their capacity to learn fast, compared to large firms (Vossen, 1998), and this learning capacity allows them to be resilient in uncertain and turbulent environments (Weick & Sutcliffe, 2011). Similarly, Salavou, Baltas and Lioukas (2004) argue that a small firm's learning orientation makes it more resilient. More importantly, however, Pal et al. (2014), in their study of small firm resilience during the recent economic crisis, found that learning increased firm performance in the long-term. While these findings highlight its relevance as a driver of resilient performance, learning has so far been considered in broad terms only. The *specific learning mechanisms* that lead to small firms achieving resilient performance through a prolonged period of uncertainty and turbulence are still unknown. In the next section, we build on theoretical assumptions about organisational learning to argue why it is important to understand these learning mechanisms in more detail, and how they drive resilient performance.

2.2 Organisational learning theory

As indicated in the previous section, for small firms to show resilient performance, they have to - at the bare minimum - survive, be stable, or achieve sustained performance. To achieve resilient performance, firms need to continuously adapt to changing environments. To adapt and take effective action, firms must learn (Fiol & Lyes, 1985; Kim, 1993). It is the combination of learning and adaptation to changing environments that makes OL a relevant theoretical perspective to explain firm performance in uncertain and turbulent environments (Zhou, Battaglia & Frey, 2018). OL theory is grounded in a long history of research (Easterby-Smith & Lyes, 2011) and we next discuss its main theoretical assumptions (Fiol & Lyes, 1985).

First, learning ensures environmental alignment. OL broadly refers to the study of learning within or of firms (Tsang, 1997). What exactly constitutes learning depends on the disciplinary perspective that is taken. From a strategic management perspective, learning is a strategic resource that drives the competitiveness of small firms (Zhao, Li, Lee & Chen, 2011; Covin & Lumpkin, 2011). Altinay et al. (2016, p.872), for example, define learning as "the ability of an organisation to create, transfer, and

integrate knowledge and modify its behaviour with a view to improving performance". Learning also decreases inertial forces and increases the resource base, ensuring better alignment with the environment (Fainshmidt et al., 2016). Throughout the literature, it has therefore been argued that learning contributes to the survival of firms by helping them achieve environmental alignment (Fiol & Lyes, 1985).

Second, learning has been conceptualised as a multi-level construct, and throughout the literature, it has been argued that a distinction must be made between individual- and organisational-level learning (Crossan, Lane & White, 1999; Fiol & Lyes, 1985). Learning always starts at the individual level. Individuals can, however, learn independently of the organisation, and not all individual learning has consequences for the organisation. The organisation, however, can only learn through its key members (Kim, 1993). In the small firm context, a key member is the owner-manager, as his or her role in driving the strategic direction of the firm is much more pronounced (Deakins et al., 2012). Consequently, through their owner-managers, small firms develop their strategic posture. As such, it is important to consider the roles of both individual- and organisational-level learning for firm performance.

Third, there are both cognitive and behavioural components of learning. The OL literature argues that learning encompasses cognition and behaviour, and that it is important to distinguish between the two mechanisms because they have different performance effects (Fiol & Lyes, 1985; Kim, 1993). While behavioural learning explains how knowledge is acquired, cognitive learning explains why learning happens in the first place (Kim, 1993). As such, behavioural learning is concerned with the actions that individuals take, but cognitive learning is more concerned with the motivational aspects of learning (Yeo, 2005). The two different learning mechanisms are, however, interrelated, as cognition guides behaviour and vice versa (Crossan et al., 1999).

2.3. Relationship between learning mechanisms and resilient performance

Considering the issues summarised in the discussion above, we identified three specific learning mechanisms that are of particular importance in the small firm context: (1) the firm's proactive posture,

(2) the owner-manager's learning goal orientation, and (3) his or her knowledge acquisition activities. Proactive posture represents a strategic learning mechanism at the organisational level. The owner-manager's learning goal orientation represents a cognitive learning mechanism at the individual level, and the owner-manager's knowledge acquisition activities represent a behavioural learning mechanism at the individual level. Next, we discuss each of the three mechanisms in detail and argue for their importance in explaining resilient performance in small firms.

2.3.1 Proactive posture as a firm's strategic learning mechanism

Strategic learning is considered to be transformational in nature. Siren, Hakala, Wincent and Grichnik (2017, p.145) define it as a "long-term adaptive capability that allows organisations to break away from their current strategic path". The long-term perspective is of particular relevance, because over time, strategic learning manifests itself in a firm's strategic posture (Teece, Pissano & Schuen, 1997). Lopez, Peo and Orda (2005, p.230) argue that learning at the organisational level "encourages proactive rather than reactive behaviour". A proactive strategic posture, defined as a firm's "strategic and behavioural readiness to respond to early warning signals of change in the organization's internal and external environment" (Lee, Vargo & Seville, 2013, p.34), enables the firm to respond to change. Through its strategic posture, a firm interprets and responds to its environment by adapting to changing requirements (Mintzberg, 1978; Porter, 1985). This conceptualisation is comparable with Covin and Slevin's (1989) entrepreneurial strategic posture, from which they argue that small firms benefit, particularly in hostile environments, as it helps them respond to the adversity inherent in such environments (Sullivan-Taylor & Branicki, 2011; Miller, 1983).

Whilst it has been long assumed that strategic learning contributes to superior firm performance (Senge, 1990), empirical findings are, however, ambiguous. Hakala and Kohtamaeki (2011), for example, found that strategic learning was a distinguishing characteristic of faster-growing firms in their sample of 164 small software firms. In contrast, Altinay et al. (2016), in their cross-sectional study of 350 small firms, did not find a relationship between strategic learning and firm performance (measured as sales or employee growth). It can be argued, that the relationship between strategic

learning and firm performance is not direct, but instead occurs indirectly through the firm's strategic posture. Indeed, a positive relationship between pro-activeness and sales growth has been previously confirmed, but only for short-term performance (Gupta & Sebastian, 2017; Lumpkin & Dess, 2001). As indicated earlier, firm performance patterns are more complex when considered from a longer-term perspective (Pettigrew, 1990). Consequently, we cannot expect that the relationship between a firm's strategic posture and its performance is the same in the short term as it is in the longer term.

2.3.2 The owner-manager's learning goal orientation as an individual cognitive learning mechanism

Goal orientation is a cognitive pattern resulting from consistent pursuit of a particular achievement goal (Dragoni, Tesluk, Russell & Oh, 2009). Dweck (1986) distinguished between two achievement goals that form the opposite ends of a continuum: learning goal orientation and performance goal orientation.

Learning goal orientation reflects an individual's propensity to continuously develop through learning new skills and gaining new experiences. Conversely, performance goal orientation reflects an individual's propensity to try and get positive judgment (or avoid negative judgment) by demonstrating competence. Goal orientation impacts the ways in which individuals interpret situations and respond to challenges. Individuals holding a performance goal orientation consider challenging situations as risky and are afraid to fail and fearful of the consequences of the failure, especially how others may judge them. This maladaptive response pattern results in individuals avoiding challenging situations and adversity. Learning goal orientation is associated with adaptive response patterns. These are of particular interest for this study, because individuals are more likely to demonstrate perseverance, increased effort and problem-solving when faced with challenging situations, as they consider them opportunities to learn and develop (Dweck & Leggett, 1988). Learning goal orientation has received only scant attention in entrepreneurship and small business management research. With the exception of De Clercq, Honig and Martin (2013), who consider the role of individual learning goal orientation in the formation of entrepreneurial intentions, learning orientation has predominantly been considered

at the organisational level (e.g. Frank, Kessler, Mitterer & Weismer-Sammer, 2012; Wang, 2008; Keskin, 2006; Real, Roldán & Leal, 2014; Wolff, Pett & Ring, 2015). Differences in individual cognition have, however, been shown to lead to differences in firm behaviour (Felin, Foss, Heimeriks & Madsen, 2012; Felin & Zenger, 2009; Gavetti, 2005; Laureiro-Martínez, Brusoni & Zollo, 2010). Exploring the role of the owner-manager's learning goal orientation is therefore important, in order to understand the micro-foundations that contribute to the resilient performance of small firms.

2.3.3 The owner-manager's knowledge acquisition as an individual behavioural learning mechanism

The degree of learning orientation of managers also contributes to the extent to which they seek access to external sources of learning (Dragoni et al., 2009). The combination of knowledge from within the firm and knowledge from sources external to the firm is important for performance (Lin & Wu, 2014). Engagement in learning activities has previously been used as a manifestation of knowledge acquisition within a small firm context (Roxas, Battisti & Deakins, 2014; Edvardsson, 2006; Cantu, Criado & Criado, 2009; Wang & Han, 2011). When owner-managers of small firms engage in a variety of learning activities, they potentially absorb knowledge-based resources necessary to identify or develop new business ideas, operational, production or marketing techniques, solutions to strategic or operational problems, and business opportunities (Cantu et al. 2009; Edvardsson, 2006; Wang & Han, 2011). Three types of learning have been shown to be particularly relevant for small firm performance, namely, practice-based, proximal, and distal learning.

Practice-based learning includes learning activities embedded in the goal-directed activities of everyday management practice, such as learning through reflection on challenging work experiences, learning through observing, and learning through trial and error (Deakins, Battisti, Roxas & Coetzer, 2012). This type of learning is experimental (Dess et al., 2003), because individuals exploit the firm's existing internal knowledge without necessarily broadening its knowledge base (Zhao et al., 2011). The advantage of internal sources of knowledge is that they are based on the firm's experience and history, making them inimitable and unique (Barney, 1991).

Proximal learning activities involve learning from peers and trusted advisers, such as accountants and bank managers. Distal learning activities include management training programmes, university courses and seminars run by chambers of commerce (Deakins et al., 2012). Proximal and distal types of learning are acquisitive, relying on acquiring and embedding knowledge from the firm's external environment (Dess et al., 2003). Acquiring knowledge from beyond the firm's boundaries allows for acquisition of new knowledge that facilitates exploration and development of new products or services (Zhao et al., 2011). Acquisitive learning through distant sources, however, also requires more resources. Its benefits are also uncertain (March, 1991), as external knowledge might have limited uniqueness (Hughes, Hughes & Morgan, 2007) or usability (Mowery, Oxley, & Silverman 1996) and consequently might not translate into increased performance (Dess et al., 2003). Zhao et al. (2011) found that acquisitive learning does not directly impact on firm performance, but indirectly through complementing experimental learning, and that firms derive greater value from internal sources of knowledge.

Roxas et al. (2014) demonstrate in a sample of small firms that all three types of learning are related to firm innovation and, in turn, short-term performance, but that effects are strongest for practice-based learning, reinforcing the importance of internal knowledge sources. Their study, however, pointed to the curvilinear nature of relationships and the finite effects that engagement in learning activities has on innovation and short-term firm performance. The authors argue that individuals obtain different types of knowledge depending on the type of learning they engage in, which in turn affects firm performance differently.

In Figure 1, we summarise the above discussion about the relationships between learning and resilient performance in small firms. As pointed out, learning and resilient performance are related to resources, manifesting themselves in terms of firm size and age (e.g. Dhanaraj & Beamish, 2003; George, 2005), but also owner education level (Pickernell, Packham, Jones, Miller & Thomas, 2011; Unger, Rauch, Frese & Rosenbusch, 2011). The empirical basis of most of this previous research has, however, been cross-sectional data, there being scant evidence in relation to longer-term effects. Due to the lack of

longitudinal research, the temporal and potentially non-linear aspects of the relationship between learning mechanisms and resilient performance are still not well understood. Given the number of learning mechanisms in which non-linear relationships may manifest themselves, Figure 1 is a simplified conceptual representation, illustrating the importance of utilising a technique able to identify if and when this is the case.

Insert Figure 1 about here

3. Methodology

Data for this study was sourced from an existing longitudinal survey that tracked the performance of small firms in New Zealand annually over five years between 2007 and 2011, using annual questionnaires. Small firms were defined as enterprises with fewer than 50 employees (OECD, 2005). The panel study aimed at understanding individual- and organisational-level factors that impact on changes in small firm performance in the longer term. Data for the first wave was collected in October-December 2007. New Zealand was in recession from the first quarter of 2008 until the second quarter of 2009. Data for subsequent waves was collected in October-December in 2008, 2009, 2010 and 2011, thus covering a two-and-a-half-year period after the end of the recession in the second quarter of 2009. Pettigrew (1990) argues that there is no correct answer to the question of how long the timeframe of a longitudinal study should be, but that it is important to allow for enough time for the change phenomenon under investigation to reveal itself, while at the same time taking into account resourcing issues. Consequently, we considered the five-year time period as adequate to reveal the changes in firm performance caused by the GFC and the role learning played in these changes. Before discussing the methodological approach in more detail, we first outline the context of this study: the GFC in New Zealand.

3.1.Context

New Zealand fell into recession in the first quarter of 2008, the recession in New Zealand initially resulting from domestic monetary tightening, decreasing housing market activity, and temporary

drought conditions, which affected agriculture and related activities (OECD, 2009). Businesses were affected by decreasing household demand, and unemployment doubled from 3 to 6.5 percent by the third quarter of 2009. Although a large increase, it is modest by the standards of other countries belonging to the Organisation for Economic Co-operation and Development (OECD). Positive growth of 0.2 percent in the second quarter of 2009 marked the end of a five-quarter recession, during which time the New Zealand economy had contracted by 3.3 percent. The depth of the recession in New Zealand compares favourably with other OECD countries, being the seventh least affected of 30 member states (The Treasury, 2010). Unlike other OECD countries, the New Zealand government of the time did not have to intervene to support the country's domestic financial institutions, such as the commercial banks, as they had not engaged in over-lending to property markets. Nevertheless, the country's growth rate itself continued to fluctuate after the recession ended, highlighting a level of uncertainty that is relevant to the study of longer-term resilience of small firms.

3.2.Sampling

In 2007, the population of New Zealand small firms comprised 339,245 private sector enterprises employing fewer than 50 staff. Of those, 87 percent were micro-sized firms, employing five staff or fewer, the remaining 13 percent being small firms employing between six and 49 staff. From this population, a stratified, random sample of firms was drawn, with equal numbers of respondents in firm size strata of zero to five employees and six to 49 employees. Similarly, the sample comprises equal representation of manufacturing and service enterprises, including a spread of sub-sectors within each major sector. The sampling strategy was chosen to allow comparison of important firm size groups and industry sectors. The sample was derived from Martins, a commercial provider of business-to-business information in New Zealand that offers the largest and most comprehensive business database in New Zealand.

The initial survey in 2007 was sent to 4,627 firms, with 1,355 usable responses returned, which corresponds to a response rate of 29 percent. This is well above the minimum for this type of mail survey (Bartholomew & Smith, 2006). This number subsequently reduced at each of the five waves to

245 firms in 2011, which corresponds to a panel survival rate of 18 percent. Detailed survival rates are provided in Table 1. Given the nature of the study, survival bias has to be expected. However, this is not considered problematic, as the study focuses on firms that – at a minimum – have *survived* a five-year period. The sample, despite the potential for survivor bias, is therefore specifically suited to examine the drivers of different types of resilience, as previously defined.

Insert Table 1 about here

Of the final sample of 245 firms in 2011, 58 percent (n=142) were micro-sized firms and 40 percent were small firms (n=99). The remaining two percent (n=4) were medium-sized firms that represent a small group that has 'outgrown' the initial sampling frame. Further, 60 percent were from the manufacturing sector (n=146) and 40 percent from the services sector (n=99). The average age of firms was 23 years, ranging from a minimum of one year to a maximum of 107 years. In relation to the highest level of qualification, 32 percent of owner-managers had a secondary qualification only, 27 percent had achieved certificate level, 16 percent diploma level and 25 percent degree level.

3.3.Data collection

The study followed Dillman's (2007) Total Design Method (TDM) in choosing the sample as well as in developing, designing, pilot-testing and distributing the postal, self-administered questionnaire. The survey was carried out over four mail outs between October and December each year.

As data was gathered at the firm but also individual levels, it was important to ensure stability of the sampling unit, meaning that we had to ensure that the same person answered the survey for the same firm in each wave. We addressed the surveys to the same owner-manager of the same firm initially identified, and specified the relevance of ownership stability. That means owner-managers who sold or passed on their businesses no longer qualified, as the person unit had changed, despite the firm unit remaining unchanged. Similarly, if owner-managers changed the firm they were involved with between waves (e.g. by starting a new business), they no longer qualified, because the firm unit had changed despite the person unit being stable. The consequence of this approach was that the sample,

by definition, consisted of firms that had continued in existence with the same owner-manager, for the entirety of the time period. The measurements used, therefore, are interpreted in this context, where the firms can be seen as resilient, at the minimum of having survived the five-year period, and at a maximum of showing sustained positive performance during this time.

3.4.Data measurement

Martynov and Shafti (2016) conclude in a review of long-term performance of firms that very few studies use more than two performance measures in the same study. In this study, the outcome variable, *resilient firm performance*, was created (as described in the next section) from measures taken each year for three items using a five-point Likert scale (1-strongly decreased, to 5-strongly increased) that asked respondents to indicate the firm's current performance (i.e. at the time of the survey) relative to that of the previous 12 months, in terms of turnover, profitability and market share. These measures of performance have been used in previous studies to capture other facets of the multi-dimensional nature of firm performance (Darroch, 2005; Wang & Han, 2011; Delmar, Davidsson & Gartner, 2003; Stenholm, 2011). Whilst acknowledging the limitations of this type of data (in comparison with traditional measurements such as actual growth rates or profit margins, for example) it is believed to be suitable to examine the relative performance-based issues under discussion, when used in conjunction with the fuzzy clustering (to create the final outcome variables used) and NCaRBS techniques discussed below.

Further, three characteristic variables were included. *Proactive posture* was measured with three items, adapted from Stephenson, Vargo and Seville (2010), to assess firms' strategic and behavioural readiness to adopt, acquire and create new capabilities and resources to be able to respond to early warning signals of change in their internal and external environments. All items to assess proactive posture were measured using a five-point Likert scale (1-strongly agree, to 5-strongly disagree). *Learning orientation* refers to an individual´s attitude towards engaging in learning, measured using six items from VandeWalle (1997). All six items were measured using a five-point Likert scale (1-strongly agree, to 5-strongly disagree). *Engagement in learning activities* was measured using Roxas

et al.'s (2014) three types of learning, namely, practice-based, proximal, and distal. Practice-based learning was measured using three items, proximal learning was measured using four items, and distal learning was measured using four items. The items use a five-point Likert scale (1-not at all, to 5-large extent) to measure the extent of engagement in a learning activity. Confirmatory factor analysis was conducted for all characteristic measures to confirm uni-dimensionality, as well as adequate validity and reliability (see Appendix A).

Lastly, firm size, age and level of owner education were included. *Firm size* refers to the total number of employees. *Firm age* refers to the number of years a firm has been operating since inception. Based on theoretical arguments grounded in the resource-based view of the firm (Barney, 1991), firm size and age are often used as proxies for resource slack in the context of small firms (e.g. Dhanaraj & Beamish, 2003; George, 2005). *Education* describes the highest level of formal educational achievement of the owner-managers. In the case of owner-manager education, 11 small firms' details were missing, these firms were retained in the analysis due to the ability of NCaRBS to analyse incomplete data (see Beynon et al. [2016] for details).

3.5.Data analysis

3.5.1 Common method bias analysis

Because of the mono-methodological nature of the study, Harman's single factor test was performed (Harman, 1976). The results show that no single factor emerged and no factor accounted for more than 50 percent of variance. These findings suggest that common method bias does not appear to be an issue in the current study.

3.5.2 Response bias analysis

Response bias was examined for all waves. For the first wave in 2007, non-response bias was examined by comparing early respondents (respondents after initial survey mail-out) with late respondents (respondents after second survey or after reminder card mail-out) (Rogelberg & Stanton, 2007). Results of independent sample t-tests showed that the two groups did not differ significantly in terms

of firm size, sector, age and education. In the subsequent waves undertaken in 2008, 2009, 2010 and 2011, non-respondents were compared to respondents in the same wave, as well as respondents in the first wave. The insignificant differences suggested that non-response bias was non-existent or too small for detection in terms of these control variables.

3.5.3 Outcome Variable Creation via Fuzzy clustering

The study employs nascent fuzzy *c*-means (FCM) clustering (explained in more detail in McDermott, Heffernan & Beynon, 2013; Haddoud, Beynon, Jones & Newbery, 2017) to generate the outcome variable used in the study from the factor-analysed firm performance data for turnover, profitability and market share, across the five years of the study. Specifically, fuzzy clustering is used to allocate each firm to one of three clusters, according to majority association, as discussed below; this technique also allows NCaRBS to utilise each firm's degree of association with all three cluster types in the final analysis.

FCM (Bezdek, 1980; 1981) is a development of the well-known crisp *k*-means technique (MacQueen, 1967; Kanungo et al., 2002), which allows objects to have degrees of association (membership) to all individual clusters. This separation in what happens when employing fuzzy clustering and 'crisp' non-fuzzy clustering is pertinent to this analysis. Given that the clustering is prevalent on factor scores from *resilient firm performance*, which are exhibiting grades of opinion themselves, the resultant cluster memberships should encompass these grades of opinion (McDermott et al., 2013), resulting in a preference for fuzzy clustering over alternative techniques.

The fuzzy cluster analysis is performed on the assumption that each firm will be associated, to varying degrees, with different firm performance clusters. In this regard, cluster solutions were provisionally investigated for between three and five clusters, theoretical defence arguments, as well as granularity of cluster case membership suggesting the three-cluster solution was appropriate for the analysis here (following the approach in Andrews & Beynon, 2010; 2017; McDermott et al., 2013). To simplify consideration of groups of firms, in the case of fuzzy *c*-means, firms were visually allocated according to majority association to a cluster (for each firm, the largest membership values across the clusters

identified the cluster they are most associated with), allowing a description of the established clusters, using the established groupings of firms, given in Figure 2.

Insert Figure 2 about here

In Figure 2, the spread of values of the five performance factors (over 2007 to 2011) from the 245 small firms considered is represented by the grey-shaded, notched-boxplots. For each established cluster of firms (C1, C2 and C3, based on majority association), their constituent mean values over the five performance factors are shown, connected by solid lines based on the cluster with which they are associated (For example, the constituent cluster mean values for C1 over the five performance factors are connected by solid lines labelled c1). ANOVA results indicate that year performance differences between some of the constituent cluster means are statistically significant across all factors (not all the mean values are equal). Further, Bonferroni post-hoc tests showed two pairs of cluster constituent mean values which were not significantly different to each other (at 0.05 significance level), denoted by dark grey ovals surrounding the respective constituent mean values (see C2 and C3 clusters over 2007 and 2008 performance factors). Also shown in Figure 2, to the right of the graph, are the number of firms that are majority associated with each cluster, here found to be C1 - 84 (34.286 percent), C2 - 83 (33.878 percent) and C3 - 78 (31.837 percent).

Each firm's association to the three clusters is represented by three membership score values, which sum to one; this ambiguous association is represented as single points (for each firm) in a simplex plot, in Figure 3.

Insert Figure 3 about here

In Figure 3, the association of each firm to the notion of cluster-based, year-on-year performance is presented graphically as a point 'simplex coordinate' in the presented simplex plot. Each vertex, labelled C1, C2 and C3, shows where there would be unambiguous association to a single cluster. As can be seen, each firm has an ambiguous association across these clusters. The dashed straight lines inside the simplex plot define the boundaries on either side of which there is majority association to

one of the individual clusters C1, C2 and C3. The number of points in each of these three sub-regions of the simplex plot is found to be 84 in C1, 83 in C2 and 78 in C3 (as also shown in Figure 2). It is important to note that the clusters should be interpreted in the context of all the firms having existed with the same owner-manager across the entire time period. This requires all the clusters to be seen as identifying patterns of resilient performance. Subsequent descriptions of the clusters are given as follows (noting the Likert scale employed across the items used in the factor analysis):

C1 - Termed here *Sustained Performance*, noting across each of the 5-year performance factors, they are consistently the lowest scale value across the three clusters (the lower the factor values, the better the performance inferred – and comparing to notched-boxplots also).

C2 - Termed here *Stability*, noting across each of the five-year performance factors, they are consistently around the 3-value (noting no difference to C3 cluster for 2007 and 2008, which could indicate that they have started from a bare survival position, so could be viewed as rescuing their performance position).

C3 - Termed here *Survival*, noting across each five-year performance factor, their values start off similar to that of C2 for 2007 and 2008, but increase to be significantly higher over 2009 to 2011, indicating deteriorating performance but with continued existence across the time period.

Use of majority association of firms here allows understanding of individual clusters, but also, as shown in Figure 3, each firm is ambiguously associated with all three clusters, which is of relevance and used in conjunction with the NCaRBS analysis (next undertaken). The established clusters and degrees of membership of each firm to each cluster are next considered in relation to other characteristic (independent) variables.

3.5.4 N-State Classification and Ranking Belief Simplex (NCaRBS)

The analysis next employs the N-State Classification and Ranking Belief Simplex (NCaRBS) technique (Beynon et al., 2016). The technique is based on the Dempster–Shafer theory (DST) of evidence (see for example Denoeux and Masson, 2012), often described in terms of belief functions.

Describing DST, Liu (2003, p.1) states that the "Dempster–Shafer theory of belief functions has become a primary tool for knowledge representation that bridges fuzzy logic and probabilistic reasoning."

The NCaRBS technique is a form of regression type analysis, where independent variables (characteristic variables here) are modelled against a dependent variable (outcome variable here). However, unlike alternative multinomial regression, the outcome variable is actually made up of more than one value (the N-state part of its name), in this study, the three membership scores making up the association of each small firm to the three defined clusters (found from the fuzzy cluster analysis), namely, Sustained performance (C1), Stability (C2) and Survival (C3). Considering the three clusters, Survival, Stability and Sustained Performance, all pertinent in this analysis but not necessarily linear in their relationships with the characteristic variables, NCaRBS is particularly suitable for this type of data (see Beynon et al., 2016).

As an optimisation technique, NCaRBS is run to find values for a series of parameters to optimise the fit considered (configuration process), here on the 245 small firms and their actual ambiguous association to the clusters C1, C2 and C3. NCaRBS is able to deal with relatively small datasets, as illustrated by Beynon et al. (2015), who utilised NCaRBS to analyse a dataset of 148 organisations. Moreover, the fit function here is based on minimising the Euclidean distance of a predicted triplet of 'belief'-based membership scores to each cluster against actual membership scores to each cluster (as visually shown in Figure 3). Based on the considered characteristic variables describing each firm, NCaRBS was run to fit the firms' predicted points in a simplex plot with vertices C1, C2 and C3 to the actual points in the simplex plot shown in Figure 3. The configuration process was run 10 times (see Beynon et al., 2016), with the best fit details used in the results next described.

4. Results

The NCaRBS results shown here are partitioned into two: i) elucidation of the predicted fit of the model, and ii) elucidation of the contribution of the characteristic variables to the fitted model.

4.1 Predicted fit

As described previously, the notion of fit here is the level of predictive fit to the points shown in Figure 3, each representing the association of a firm to each of the three clusters, C1, C2 and C3. Using NCaRBS, the predictive outcome, is in graphical terms also a point in a simplex plot, namely, a set of three values which sum to one. In NCaRBS notation, each firm's (indexed with i) predicted fit is described by the values assigned to a body of evidence BOE, in technical terms the triplet of values $BetP_i(C1)$, $BetP_i(C2)$ and $BetP_i(C3)$, which sum to one (see Beynon et al., 2016). It follows that the predicted outcome BOE (the triplets of $BetP_i(\cdot)$ values) can be shown in a simplex plot, see Figure 4. In Figure 4, the three simplex plots shos the predicted outcome positions of three sets of firms, known to be majority associated with the clusters C1 (3a), C2 (3b) and C3 (3c). (Again we remind the reader that the analysis was predicting to the actual points shown in Figure 3). The breakdown of the 245 firms to these groups is to show levels of predicted fit of the firms. That is, in each simplex plot, shaded regions indicate where the predicted cases shown in each simplex plot should be in terms of being in the correct region in terms of majority association.[1]

Insert Figure 4 about here

Inspection of the individual graphs, noting the grey shaded regions (and looking back at Figure 3), shows that the analysis has attempted to fit to the actual points as shown in Figure 3. For example, in both Figures 4a and 4c, the points known to be most associated with the clusters C1 and C3 lie predominantly in that direction, even more noticeably in Figure 4b. Continuing with the notion of majority association, in terms of predicted fit, a numerical breakdown of the correct/incorrect classification of small firms is given in Table 2 (in majority association terms).

Insert Table 2 about here

[1] Please note that we talk here about majority association to a cluster because NCarbs undertakes regression-type analysis but with three outcome values simultaneously.

The results presented in Table 2 are for indicative purposes only, since the analysis (using NCaRBS) includes predicting to a point on or near the boundaries between the majority association cluster regions (see Figures 3 and 4), but shows that a total of 134 (55 percent) of firms are predicted to be in the same majority association region as their actual association based on the fuzzy cluster analysis undertaken previously.

Moving forward, the results in Figure 4 and Table 2 show that the NCaRBS based analysis has offered an optimised, fitted model of the ability to model the cluster based on ambiguous understanding of small firm performance, and the considered characteristic variables, further described next.

4.2. Contribution of characteristic variables

NCaRBS also enables identification of non-linear changes in the contribution of characteristic variables' values over their respective scales to the firm performance predictions. With NCaRBS having analysed a form of outcome variable made up of the three membership score values associating each firm with the three clusters C1, C2 and C3, the contribution of each characteristic variable is similarly in terms of contribution to the three clusters (which are at the limit of the ambiguous association considered here, namely C1 - Sustained Performance, C2 – Stability, and C3 - Survival). In technical terms, contribution comes from an intermediate form of a BOE to the final, firm BOEs used to undertake the final predicted fit shown in Figure 4. Moreover, variable BOEs can be constructed, termed defined mi,j,-(·), for ith SMALL FIRM and jth characteristic variable, found during the NCaRBS configuration process. Presentation of these variable BOEs is based on their pignistic probability form (see Beynon et al., 2016): see Figure 5.

In Figure 5, for each characteristic value, the three elements of the respective variable BOE ($m_{i,j,-}(\cdot)$), showing the individual evidence towards three clusters C1, C2 and C3, are shown across the identified respective domain for that variable (though not in the case of owner education, where the ordinal variables are spread evenly out). That is, each graph line shows how the changing values over a characteristic may change the level of association of a firm to a particular cluster (labelled at each end of the variable domain with cluster label c1, c2 or c3).

In terms of general comments, first, the levels of contribution occur over roughly the same levels, in terms of the ranges of the y-axes shown, often starting from near 0.160 and rising to near 0.600 (noticeable cases are distal learning with the largest range of BOE values, between 0.103 and 0.707, and also owner education with the smallest range of values, between 0.190 and 0.475). Comparison across these offers evidence of the relative strength of contribution of the individual characteristic variables. Secondly, above each graph is a notched-boxplot showing the spread of the respective sets of characteristic variable values over their domains (the diamond points shown are the mean values). This allows consideration of the directions of contribution to individual clusters over sub-domains, knowing where the main groups of firm values are (in contrast where a sub-domain may be only describing some outlier cases). It is the area beneath each notched-boxplot that is therefore of most relevance to the analysis, areas outside this representing potential outliers. Thirdly, the x-axis values are standardised values for the respective characteristic variables. It is noted that for the known scale for the learning-related values and for proactive posture, higher numeric values of the variable indicate lesser amounts of the performance activity.

Insert Figure 5 about here

In terms of analysing the data in Figure 5, the focus is on the *change* in contribution (rise and fall) in C1 (Sustained Performance), C2 (Stability) and C3 (Survival) as the values move from *right* to *left*, *within* the area between *each notched-boxplot.* Each characteristic variable is next described, beginning with brief mention of the contribution details over the whole domain of the variables, followed by focussed discussion of the notched-box subdomain shown.

For practice-based learning, overall, as the numeric value decreases (practice-based learning activity increases), there is a decline in association with C1 (Sustained Performance), to a lesser extent also for association to C2 (Stability), but an increase, particularly towards the lower variable values, in association with C3 (Survival). The notched-box sub-domains show that for the bulk of the variable values, the only difference is that C2 does not include the previously acknowledged decrease. These

results perhaps show two worlds, with contribution changing noticeably just above the right hand side of the notched-box.

For proximal learning, in contrast, as the numeric value decreases (inside the box part of the boxplot) there is a non-linear, almost "step change" in association of the cases, towards more association to both C1 (in particular) and C3 clusters, with equivalently less association to the C2 cluster. Using the interpretations of the clusters, it means that as proximal learning increases it is more associated with surviving and, particularly, sustained performance, being less associated with stability. It is also noteworthy that using notched-boxplots with the NCaRBS approach also illustrates the often over-impact aspects of outlier values, with dramatic changes in BOE associations for the lowest numerical values of proximal learning (which correspond to higher amounts of the activity).

For distal learning (inside the box part of the boxplot), as the numeric value decreases (distal learning increases), there is increased association with C2 (Stability) in particular, and C1 (Sustained Performance) and strongly reduced association with C3 (Survival). This characteristic's contributions are almost linear 'monotonic' in nature, in contrast to the non-linear contribution results from other variables.

For learning orientation (inside the box part of the boxplot), the contribution is also very much based around a non-linear, step change increase in association with C1 (Sustained Performance) and C2 (Stability), and a reduction in association with C3 (Survival) as learning orientation increases (the numerical value decreases).

For proactive posture (inside the box part of the boxplot), there is also a clear non-linear fluctuation in association: i) initially, as proactive posture increases (i.e. the numerical value decreases), there is increased association with C1 (Sustained Performance) and away from C2 (Stability), and ii) after a certain point, the relationship reverses, with further increased proactive posture then increasing in association with C2 (Stability) and away from C1 (Sustained Performance). Interestingly, however, there is a consistent decrease in association with C3 (Survival) as proactive posture increases (as the numerical value decreases).

For the variables used as controls in traditional regression analysis, increasing firm age logged (inside the boxplot) sees greater association with C2 (Stability) and particularly C3 (Survival) and lower association with C1 (Sustained Performance). For firm size logged there is an initially very strong association between greater firm size and C1 (Sustained Performance) and C2 (Stability) and away from C3 (Survival), but this then levels off. Finally, for owner education (inside the boxplot), a complex pattern emerges. Initially, higher levels of owner education see greater association towards C3 (Survival) and reduced evidence towards C1 (Sustained performance) and C2 (Stability). After this initial point, however, there is a consistent rise in association with C1 (Sustained Performance) and away from C2 (Stability) and C3 (Survival) up to a point, after which there is a levelling off and slight reversal, away from C1 (Sustained performance) and towards C3 (Survival), and at the higher end, C2 (Stability).

Overall, therefore, findings illustrate the complex and sometimes non-linear patterns (specifically with regards to proactive posture) that emerge when relationships between learning mechanisms and performance outcomes of small firms are explored over a prolonged period of economic turbulence. Table 3 provides a summary of the results of the contribution of variables.

Insert Table 3 about here

Sustained performance seems most associated with higher (but not the highest) levels of owner education, increasing (lower numeric values) learning orientation, distal learning, and increasing initial firm size, as well as (lower numeric values) increasing proactive posture, but only up to a peak level (after which the relationship becomes negative). Conversely, sustained performance seems to be negatively related to practice-based learning, and firm age. Stability, in contrast, is more related to increasing (lower numeric values) practice-based learning, distal learning, learning orientation, and, after an initial fall, increasing (lower numeric values) levels of proactive posture, as well as the highest levels of education, and increasing firm age and increasing initial firm size. Again conversely, stable firm is negatively related to proximal learning. Finally, survival is more related to increasing (i.e. lower numeric values) practice-based and proximal learning, and both lower and higher levels of owner

education, as well as higher firm age. There are, however, negative relationships between absolute declining firms and distal learning, learning orientation, initial firm size, firm age, medium levels of education, and proactive posture.

5. Discussion

Helfat and Peteraf (2015) argue that heterogeneity of managerial cognitions is likely to result in different firm performance outcomes. Findings from this study provide much needed empirical evidence in this regard. Results show that higher levels of owner-manager learning goal orientation are more strongly associated with sustained and stable performance, and lower levels are more related with survival (in the context of declining performance). While De Clercq et al. (2013) argue that learning goal orientation does not necessarily translate into financial outcomes, as individuals are more motivated by the learning itself rather than the reward, this study shows that owner-manager learning goal orientation contributes significantly to sustained performance. This suggests that during extended periods of uncertainty and turbulence, such as the GFC, it is the individual's adaptive response patterns associated with learning goal orientation that help firms to sustain their performance. This finding highlights the important role of owner-manager cognition in driving firm performance.

Our findings further show the importance of distinguishing between sources of knowledge as different sources are associated with different performance outcomes. The finding that higher levels of practice-based and proximal learning are associated with survival-only performance in some ways challenges previous findings about the important role of 'learning by doing' and 'learning from peers' for small firms (e.g. Billet et al., 2003; Fuller-Love, 2006). It might be that practice-based learning that is based on the existing experience and history of the firm (Barney, 1991) does not broaden the overall knowledge base of the firm (Zhao et al., 2011). Consequently, any positive performance effects may be short-term only (Roxas et al., 2014). Alternatively, it could be argued that the often uncritical and unreflective nature of practice-based learning (Mumford & Gold, 2004) leads at best to stability or survival, but does not allow for sustained performance of small firms, particularly during periods of uncertainty and turbulence.

Our results further indicate that proximal learning is positively associated with both sustained performance and survival but not stability. Whilst this finding seems confusing at first, it may be linked to the sources of the knowledge itself. Banks for example, as a source of proximal learning, might less likely be consulted by small firms that are stable, as compared to those who are growing or are in decline. Indeed, Han et al. (2014) argue that the primary motivation for small firms to engage with banks is the need for external finance. Arguably small firms are therefore more likely to approach banks as a source of support if they are either struggling to survive or are thriving, but less so if they show a stable performance pattern.

For sustained performance, in addition to knowledge acquisition from proximal sources, other more distal sources as well as the owner-manager's cognitive prevalence towards learning and a proactive posture at the firm level are also relevant. In contrast, these relationships were all negative in relation to the survival-only performance outcome. This may indicate that it is wider (distal) knowledge sources, firm strategy and the owner-manager's cognitive characteristics that are of greater importance for thriving rather than surviving firms.

This is also an interesting contrast to existing literature. Acquiring (distal) knowledge from beyond the firm's boundaries is more likely to facilitate exploration and the development of new products or services (Zhao et al., 2011). This acquisitive learning requires more resources, but its benefits are more uncertain (March, 1991) and the knowledge acquired might have limited uniqueness (Hughes et al., 2007) and/or usability (Mowery et al., 1996). This may mean that knowledge from beyond the firm's boundaries is only useful to those with a stronger learning orientation who are also able to utilise proximal sources of learning to achieve long-term advantage.

Lastly, our findings in relation to proactive posture challenge previous research that suggests that a strong proactive posture results in positive performance outcomes for firms (Gupta & Sebastian, 2017; Lumpkin & Dess, 2001). While this might be the case for short-term performance, the relationship is more complex when taking a longer-term view. Our findings suggest a non-linear relationship between a small firm's proactive posture and its longer-term performance. Initially, as proactive posture

increases, there is increased association with the sustained performance cluster and away from the stable performance cluster. However, after a certain point the relationship reverses, with proactive posture increasingly being associated with stable performance and not sustained performance. Further, we find a consistent negative association with the declining performance cluster. The finding of this non-linear relationship, together with other variable associations found, is novel, because it means that adopting a stronger proactive posture is not by itself sufficient to generate sustained performance during periods of uncertainty and turbulence. Proactiveness describes a forward-looking perspective through which firms actively anticipate future opportunities in the market and introduce innovation ahead of their competition (Venkatraman, 1989; Lumpkin & Dess, 1996). It may be, therefore, that initial levels of increasing proactiveness (along with the combination of learning mechanisms discussed earlier) provide the most beneficial outcomes. This effect, however, reduces after a certain point, leading to more stable (though again not survival-only) outcomes.

Consequently, this study makes several contributions. In using data covering a five-year time period, it reacts to ongoing calls for longitudinal research (Altinay et al., 2016). More importantly, the data allows examination of learning at individual owner-manager level, particularly relevant in small firm contexts, where the role of the owner-manager is much more pronounced. Previous research focuses mostly on learning at the organisational level (e.g. Frank et al., 2012; Wang, 2008; Keskin, 2006; Real, Roldán, & Leal, 2014; Wolff, Pett, & Ring, 2015), but the role of individual level cognitive and behavioural learning mechanisms has not been well understood. Findings from this study therefore provide a fine-grained picture of the complex relationships between individual and organisational level learning mechanisms and the longer-term performance of small firms, and they have the potential to make a theoretical contribution to the organisational learning literature, as well as a contribution to knowledge of the relationship between learning and resilient performance in small firms.

Further, this study makes a methodological contribution through the use of NCaRBS combined with fuzzy clustering of the outcome variable. Fuzzy clustering allows the complex and often ambiguous nature of resilient firm performance to emerge, where over, time actual small firm performance can be

seen to lie across notions of sustained performance, stability and survival. NCaRBS is then able to use this data (more fully than alternative multinomial regression approaches) to identify if and where non-linear relationships exist between specific learning mechanisms and resilient performance. Overall, this approach is particularly suitable to identify changes over time without losing the complexity that is inherent in the resilient performance patterns of small firms. This has better allowed us to capture both the differing aspects of firm performance and also their episodic nature in individual firms, as discussed in Coad, Frankish, Roberts and Story (2013), for example. This is also important because previous studies mostly assume linear positive relationships between learning-related variables and performance, often reflecting the methodological choices used to measure the relationships. Given the potential for relationships to be more complex, NCaRBS, crucially, allows for non-linearity, and was therefore deemed a suitable choice for this study. A further attribute of NCaRBS is its ability to analyse incomplete data without needing to manage missing values (see Beynon, Jones, Pickernell & Packham, 2016). While there were only a small number of missing values in the learning variables considered, an important development offered by NCaRBS is to be inclusive of cases (small firms) previously deleted or transformed in other ways.

6. Conclusions

Overall, therefore, this study, by offering a longitudinal perspective, contributes to the learning and resilience literature in the specific context of small firms, literature which still, predominantly, builds on cross-sectional data (Fainshmidt et al., 2016). The findings provide much needed evidence of the potentially non-linear and complex relationship between learning mechanisms and resilient performance, over an extend time period characterised by uncertainty and turbulence. By examining learning not only at the level of the organisation but also the individual owner-manager, we contribute to a better understanding of the role of individual-level cognitive and behavioural learning mechanisms which have not been well understood.

We have also identified a number of limitations of this study that provide fruitful avenues for future research. First, this study draws on existing survey data for longitudinal analysis, which creates

limitations with regards to the measures available. Second, the data for this study comes from a single country, with a unique contextual environment that will differ from other OECD nations, limiting the generalisability of the findings. Repeating this study in different contextual environments would increase our understanding of the connections between individual owner-manager learning and organisational learning, the ambiguous nature of the impacts of learning on both the sustained performance and survival of small firms, and the nature of other factors that can impact on learning in uncertain and turbulent environments. As well as additional longitudinal studies with panel data sets of small firms, there is also a need for qualitative studies examining sustained performance and stable and surviving-only small firms, which will help understand the complexity and causality of such relationships. Lastly, it must be stressed that the results represent only surviving small firms and findings in relation to the role of learning in the longer-term performance more generally (i.e. outside the scope of the resilience measure utilised in this study) of small firms must be carefully interpreted in the light of this survivor bias.

Despite these limitations, the findings of this study have a number of implications, specifically for policy makers who are concerned with the performance of the SME sector in the long-term. Findings point to the important role of individual learning mechanisms: small business owners' propensity to learn and their actual engagement with learning activities. Policy is currently predominantly focused on *firm* practices and strategies, but a stronger consideration of the *person* is strongly recommended. This could be in the form of support programs for personal coaching and mentoring that specifically address cognitive and behaviour learning mechanisms.

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Table 1: Panel survival rates

Year	Sample size (n)	Survival rate (percent)
2007	1355	-
2008	738	54
2009	441	33
2010	325	24
2011	245	18

Table 2. Confusion matrix of classification results (using majority association)

Actual / Predicted	Sustained Performance	Stability	Survival	Total
Sustained Performance	48	24	12	84
Stability	25	50	9	83
Survival	19	23	36	78
Total	91	97	57	245

Table 3: Summary of results

	C1 Sustained performance	C2 Stability	C3 Survival
Practice-based learning	–	+	+
Proximal learning	+	–	+
Distal learning	+	+	–
Learning orientation	+	+	–
Proactive posture	+ (initially) then –	- (initially) then +	–
Firm age	–	+	+
Firm size	+ (initially)	+ (initially)	– (initially)
Education	– initially then + then –	– initially then +	+ initially then – then +

Figure 1: Conceptual model

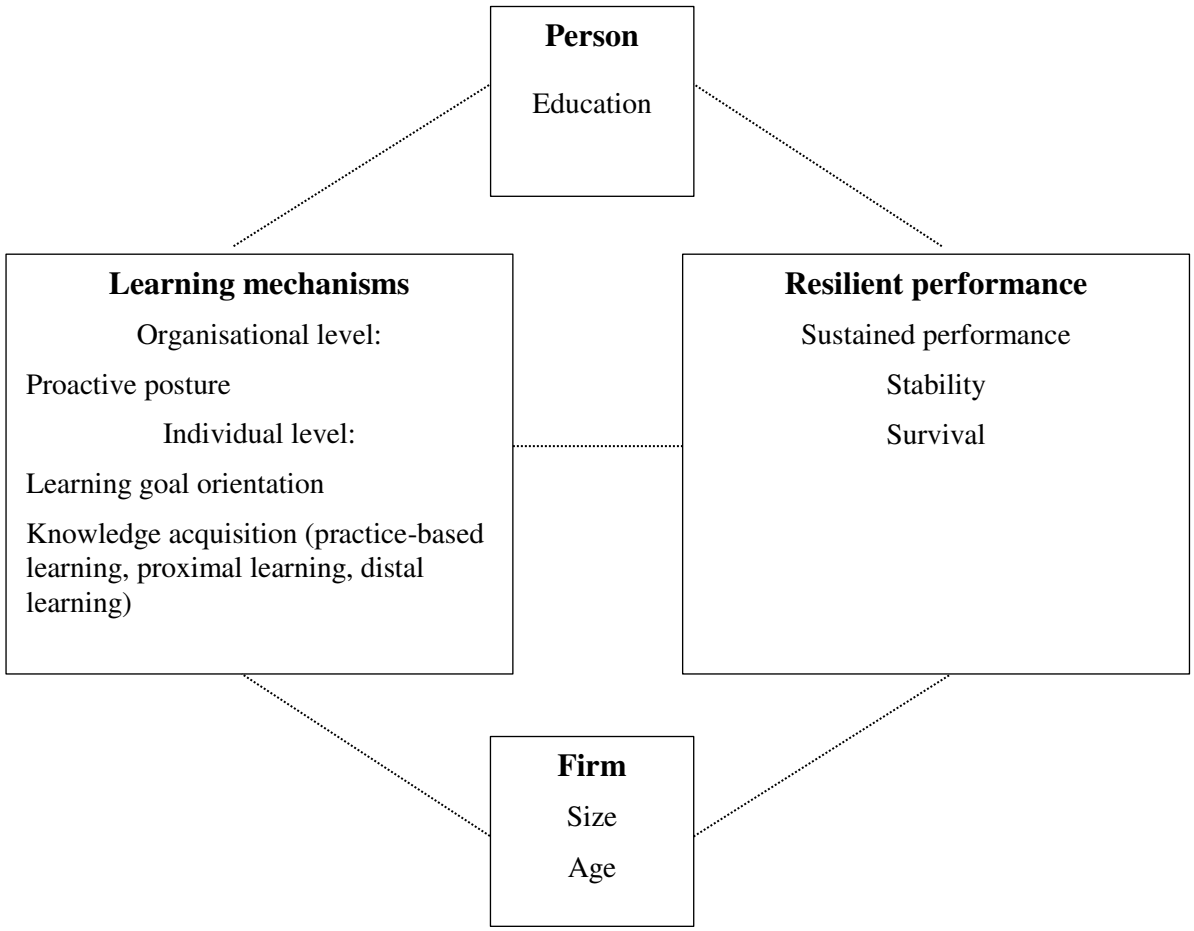


Figure 2. Description of clusters based on constituent mean values of five performance factors for groups of firms majority associated with clusters

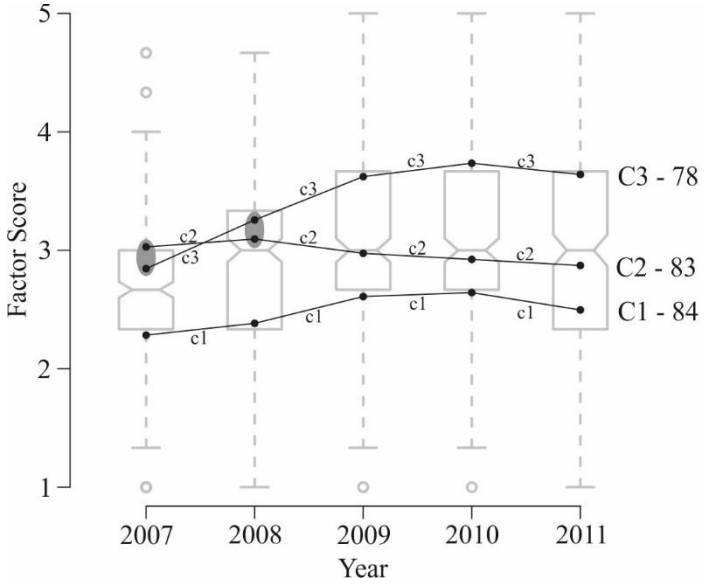


Figure 3. Simplex plot based representation of 245 small firms in terms of their fuzzy membership score-based associations to each of the established three clusters in three-cluster solution (triplet of values summing to one)

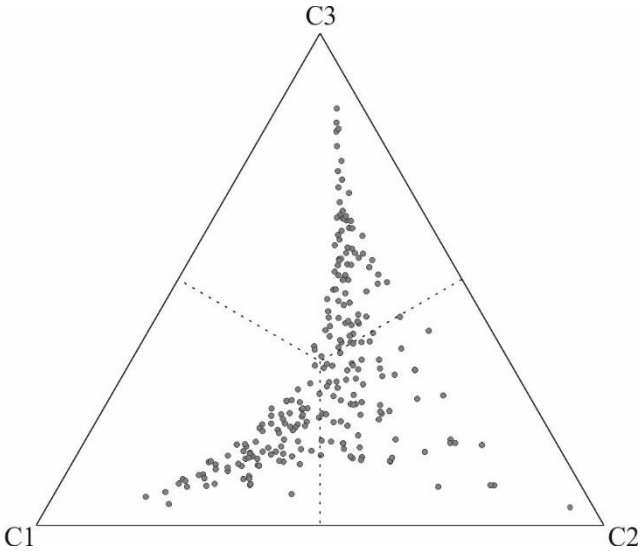


Figure 4. Simplex plot based representation of predicted outcome (triplets of $BetP_i(\cdot)$ values), partitioned based on known majority associations to clusters C1, C2 and C3

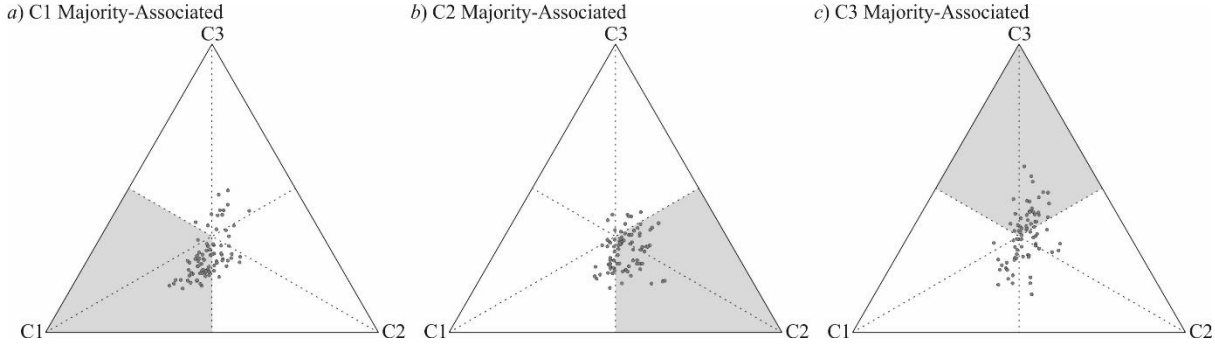
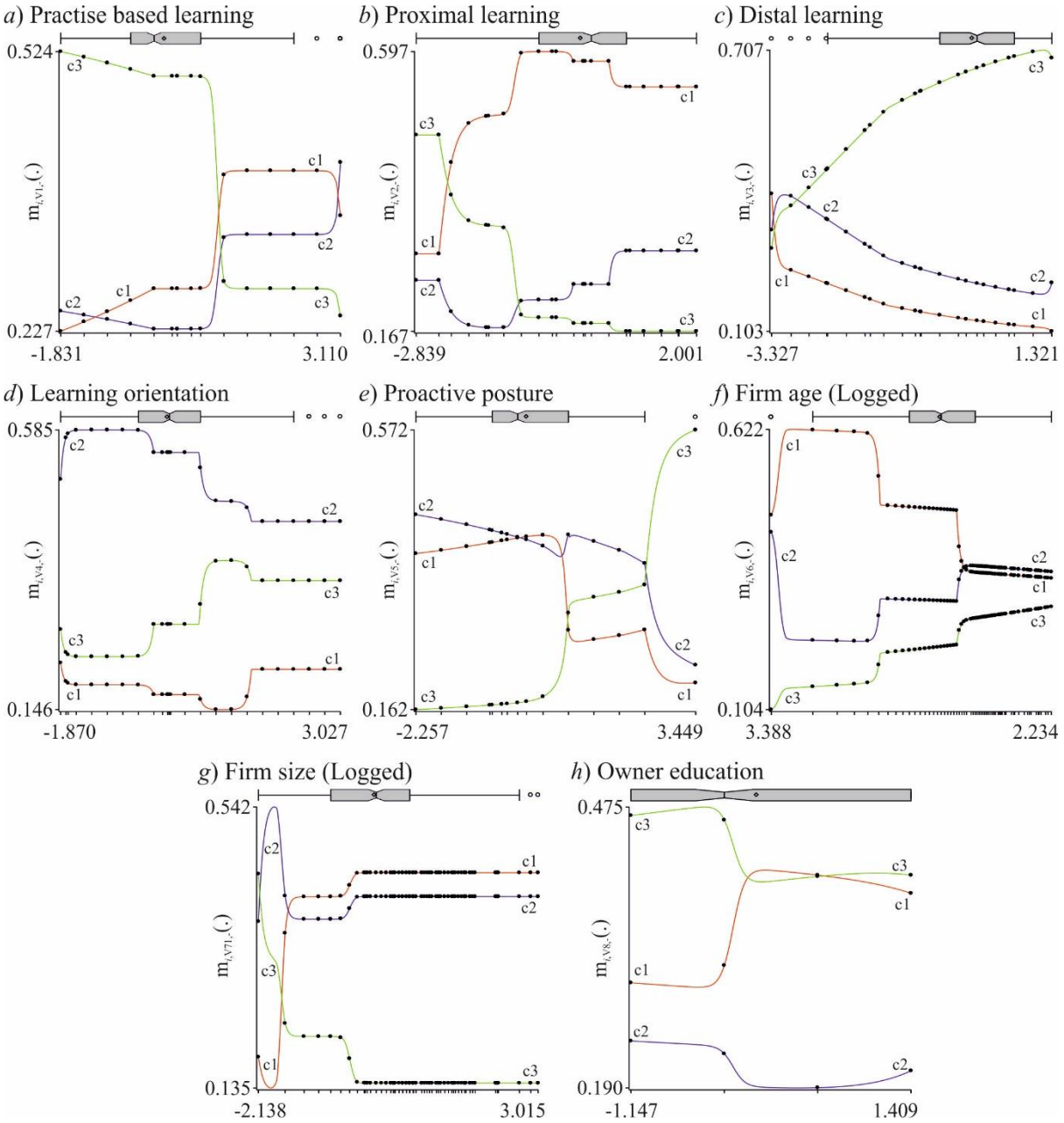


Figure 5: Graphical elucidation of characteristic variables (lines connecting points are to signify the internal structure of going from one possible set of pignistic probability values to another) a) Practice-based learning, b) Proximal learning, c) Distal learning, d) Learning orientation, e) Proactive posture, f) Firm age (logged) g) Firm size (logged) and h) Owner education.



Appendix A: Measures

Constructs and Indicators	Standardised Factor Loadings
	α = .82
Practice-based learning (ave = .74)	*CRC=.89*
Carrying out every day managerial work activities	.89
Reviewing what I did and thinking about how to do it better	.87
Discovering what does and does not work (trial and error)	.82
	α = .76
Proximal learning (ave = .58)	*CRC=.85*
Learning from suppliers or customers	.75
Getting advice from an accountant/bank manager	.83
Learning from other people running a business	.78
Learning from family and/or friends	.68
	α = .76
Distal learning (ave = .58)	*CRC=.85*
Attending occasional off-site management training courses, seminars and workshops	.78
Being mentored or coached	.70
Getting information from business events	.78
Getting information from Chambers of Commerce, economic development agencies, and professional and industry associations	.78
	α = .87
Learning orientation (ave = .60)	*CRC=.90*
I often read materials related to my work to improve my ability	.65
I am willing to select a challenging task that I can learn a lot from	.85
I often look for opportunities to develop new skills and knowledge	.85
I enjoy challenging and difficult tasks where I'll learn new skills	.83
Development of my ability is important enough to take risks	.75
I prefer to work in situations that require a high level of ability and talent	.70
	α = .72
Proactive posture (ave = .65)	*CRC=.85*
We are able to shift rapidly from business-as-usual mode to respond to a crisis	.85
We are focused on being able to respond to the unexpected	.90
Whenever we suffer a close call, we use it as a trigger for self-evaluation rather than confirmation of success	.65

Legend:
AVE – average variance extracted
α – Cronbach's alpha
CRC – composite reliability coefficient