Schumpeterian endogenous growth and dynamic capabilities: an under-researched nexus?

Tim Ng

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Abstract

Recent developments in endogenous growth research are improving our understanding of how economic growth can arise in general equilibrium when innovation drives Schumpeterian processes of creative destruction. However, this – mainly economics-oriented – literature appears largely to abstract from intentional processes in the minds of entrepreneurs and managers motivating action in innovating firms. Much of the economic modelling is instead concerned with the nature of equilibria and how they are influenced by firms' external conditions and innovation opportunities. By contrast, the intentionality involved in innovation as a competitive and uncertainty-laden process, and the constructs operative in managers' and entrepreneurs' minds, are much more to the fore in the rapidly growing "dynamic capabilities" literature in the strategic management field – which for its part tends to stop short of exploring the whole-economy, equilibrium implications of different expressions of dynamic capabilities. The disjunct appears also to be reflected in the limited empirical treatment of dynamic capabilities as an influence on economic performance using nationally-representative samples. This paper contributes to addressing this disjunct by presenting preliminary factor-model-based measures of dynamic capabilities for New Zealand firms derived from StatsNZ's Business Operations Survey. I present some questions that deserve testing using these measures as part of assessing the relevance or otherwise of dynamic capabilities theory to understanding endogenous growth in New Zealand.

Keywords: Schumpeterian endogenous growth, dynamic capabilities, Business Operations Survey

JEL classification: L26, M21, O31, O47

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Disclaimers

These results are not official statistics. They have been created for research purposes from the Longitudinal Business Database (LBD) which is carefully managed by Stats NZ. For more information about the LBD please visit
`https://www.stats.govt.nz/integrated-data/`.

Access to the data used in this study was provided by Stats NZ under conditions designed to give effect to the security and confidentiality provisions of the Statistics Act 1975. The results presented in this study are the work of the author, not Stats NZ or individual data suppliers.

This paper is not policy advice. The views, opinions, findings, recommendations, and conclusions expressed in this paper are those of the author and they do not necessarily reflect the views of the New Zealand Treasury or the New Zealand Government. The New Zealand Treasury and the New Zealand Government take no responsibility for any errors or omissions in, or for the correctness of, the information contained in this paper.

Contents

List of Tables

List of Figures

1 Introduction

This paper presents preliminary work exploring the potential for the recently developed theory of firm "dynamic capabilities" (Teece et al. (1997), Eisenhardt and Martin (2000), Winter (2003), Teece (2007), Barreto (2010)) to contribute to understanding endogenous economic growth driven by innovation. Understanding growth, innovation, productivity and their determinants is one of the most important economic problems, because growth opens the door to higher material living standards, and widens the set of politically feasible choices available to policymakers seeking to enhance justice and social welfare more generally. The problem is especially relevant in New Zealand, with its disappointing productivity performance in recent decades (see e.g. Nolan et al. (2018), Conway (2018)), which has also been seen in the UK (e.g. Valero and Van Reenen (2019)).

Recognising these issues, governments often implement various policies intended to support innovation by firms. Such policies might include direct subsidies to certain types of firm or entrepreneurial activity (for example, R&D tax credits or providing services to young firms, sometimes sectorally targeted) or setting "framework" conditions such as competition and intellectual property regimes.

Recent developments in endogenous growth research are improving our understanding of these influences on growth and its general equilibrium characteristics. Some of the models incorporate "Schumpeterian" processes of creative destruction. Creative destruction is characterised by firms using old and relatively inefficient technology being competed out of business. Such models are able to replicate many of the stylised facts of business dynamics that other types of growth models can struggle with (Aghion (2017)).

However, most of this economics-oriented literature focuses on the nature of growth equilibria and the structural determinants of the average firm innovation (and hence economic growth) rate. It generally employs highly stylised representations of firm behaviour, few margins of choice and simple treatment of uncertainty and firm heterogeneity. These features help with tractability towards the goal of understanding general equilibrium characteristics in the models. However, in so doing, they abstract from the diverse attitudes and business practices through which entrepreneurs actually position their firms to detect, create and exploit innovation opportunities.

By contrast, managers' and entrepreneurs' intentionality regarding innovation as a competitive and risky process is much more to the fore in the dynamic capabilities (DC) literature. DC thinking also draws inspiration from Schumpeterian thought and concepts of creative destruction. This rapidly growing field, centred in the strategic management discipline, emphasises the heterogeneity of competitive attitudes and practices across firms as a framing for whether or not a firm pursuing a particular set of practices will be persistently successful or unsuccessful at innovating, and more generally maintaining a competitive edge amidst uncertainty and change. Much DC literature develops constructs or mental models to describe sense-making by entrepreneurs contemplating and exploiting innovation opportunities.

For its part, and perhaps reflecting the field's normative focus on what *firms* should do (as opposed to, say, policymakers), and on firm behaviour rather than whole-economy equilibrium behaviour, the DC literature to date has largely not ventured to exploring the whole-economy, equilibrium implications of various mental models that might drive firm innovation behaviour. Consistent with this focus on the firm as the main object of interest, there also appears to be relatively little empirical work using nationally-representative samples. Such samples are necessary to address questions of the significance of firm DC for economic growth and dynamics. These questions include whether or how DC may mediate or moderate a firm's (or industry's) responses to macroeconomic or other external influences and shocks, for example through investments in human or physical capital.

1.1 This paper's contribution

This paper argues that the potential relevance of DC theory to Schumpeterian endogenous growth theory is an under-researched topic, and that filling this gap would enrich endogenous growth research. Both fields emphasise a key role for creative destruction and the deliberate act of innovation as a market-shaping mechanism. Better articulating the firm practices and attitudes regarding innovation in the nexus between individual firm success and economic dynamics would support further research on the empirical relevance, or otherwise, of DC to economic performance and growth. In this sense, the paper can be seen as a response to the call in Teece (2017) for more intellectual exchange between strategic management and economics .

This paper contributes to filling the gap as follows. I derive firm-level measures of DC for New Zealand firms, based on factor modelling of firm-year observations on 39 innovation- or DC-related items that appear in each of the 2005, 2009, 2013 and 2017 waves of StatsNZ's Business Operations Survey (BOS). The BOS asks a nationally-representative sample of New Zealand firms a diverse range of questions about their business operations, practices and innovation, among other topics. I judgementally select the 39 items on the basis that they represent, on their face, various aspects of DC discussed in the DC literature. While various earlier studies have used the BOS to study more specific firm activities and practices, to my knowledge this is the first study using the BOS to address the topic of DC.

The factor modelling suggests the existence of two or three latent factors that can together explain almost half the total variance in the sample. Preliminary analysis of factor score estimates for the first factor suggests that large firms exhibit relatively strong scores compared to small firms. If the first factor indeed represents a general DC construct, that pattern is consistent with the predictions of DC theory and Schumpeterian endogenous growth theory. It is also consistent with other evidence that suggests large firms are both better able and more likely to find it worthwhile to invest in sophisticated innovation-oriented capabilities.

I find relatively high first factor score estimates for firms from the Professional, Scientific and Technology Services broad industry grouping (ANZSIC Division) also, which is consistent with the idea from DC thinking that firms from industries featuring a high rate of technological change stand to benefit more from investments. Firms from the Construction sector had relatively low scores, which may reflect the prevalence of small building firms in NZ. Splitting the scores into a 2005/09 group and a 2013/17 group did not show any evidence of differences in DC in the periods pre- and post- the GFC and earthquakes in New Zealand.

Together, these preliminary and high-level results are consistent with the existence of some underlying higher level capability resembling DC in New Zealand firms, with a small number of dimensions (two or three based on the results presented here), associated with the selected innovation-related practices and attitudes. This finding is a necessary first step prior to more substantive modelling and hypothesis testing of the relevance of the DC concept to firm performance and economic dynamics in New Zealand.

1.2 The exploratory nature of this work

The work reported here is preliminary and exploratory in nature, and intended to be a first step in a more extensive project. Further internal and external validity testing of the measures is needed, to establish how strongly one might claim that they really are measuring the concept of DC. Then, if that claim is in fact valid, questions of relevance to understanding economic growth in New Zealand through a DC-inspired firm-innovation lens can be asked econometrically. Such questions could include, for example, how firm DC are influenced by external conditions such as industry competitive intensity, technological dynamism and volatility, and how a firm's DC may mediate or moderate its response to shocks. All of these questions are relevant to endogenous growth theory also.

The rest of the paper proceeds as follows. In Section 2, I outline the key features of the innovation process as represented in a reference Schumpeterian endogenous growth model. I draw links to other strands of endogenous growth research, and show how the DC construct can be located within this reference model. Section 3 explains the selection of DC-related items and firm populations of interest from the BOS. Section 4 outlines the factor modelling strategy. Section 5 presents the factor modelling results. Section 6 concludes by discussing how the measures developed here might be used for testing substantive questions of interest about firm performance in the context of innovation and endogenous growth, which are tougher tests of the potential value of DC research to understanding economic dynamics.

2 Schumpeterian endogenous growth theory and dynamic capabilities

2.1 A reference Schumpeterian endogenous growth model

Paul Romer's work beginning in the 1980s and his classic paper (Romer (1990)) are widely cited (including by the Nobel Prize Committee) as laying the foundations for the advancement of endogenous growth research in recent decades. The key insights brought together by Romer were the non-rivalry of ideas, imperfect competition incentivising firms to search for new ideas from which they could earn above-normal profits (rents), and an adaptation of the differential equation for steady state growth from earlier "AK" models (e.g. Rebelo (1991)) to the production function for ideas Jones (2019). A range of modelling approaches followed, developing different mechanisms for how new ideas influence production, consumption and whole-economy dynamics.

Aghion and Howitt (2009) categorise the subsequent development of the field into two major branches, with the first being the "product variety" mechanism in Romer (1990) itself, in which new ideas take the form of new input technologies, and the second being the "Schumpeterian" branch in which a key difference is that quality-improving innovations result in the obsolescence and replacement of old products. It is the second branch (cited by Jones (2019), p. 871 as the "most important") that is the main focus of this paper, because of the explicit connection to the Schumpeterian perspective shared with DC research. The connection means that the core narratives in each field of research about the motivations for, and impacts of, innovation can be relatively easily related to each other. This creates the potential for the richer description of entrepreneurial practices and mindsets in the DC literature to enhance the realism and applicability of endogenous growth modelling.

An early and influential Schumpeterian endogenous growth (SEG) model is Aghion and Howitt (1992). In this model, growth results from innovation in the form of the discovery of a new intermediate good that improves productive efficiency. The arrival of the new intermediate good renders the previous one obsolete, since any firm using it for production will be uncompetitive (creative destruction). The current intermediate good is produced by a firm that enjoys a monopoly position through a patent on the intermediate good, until the next intermediate good is discovered through research and patented, at which point the firm that discovered it becomes the new monopolist. The prospect of earning monopoly rents provides the incentive for firms to do research (as in the other branch of endogenous growth research). Firms' key decision is the amount of labour to employ for research, which has an uncertain payoff in terms of how long it will take for an innovation to be discovered, and how long the firm might be able to enjoy a monopoly position if it is successful at innovating. The creative destruction aspect adds the property that the firm's expected payoff from research depends on the likelihood that a successful innovation will subsequently be superceded.

While this core story is obviously highly stylised, it contains sufficient scaffolding for many of the elements of DC thinking to add richness in terms of innovating firms' business practices, as I argue in the next subsection.

2.2 Unpacking the innovation process: dynamic capabilities theory

A widely cited early paper in the DC field, Teece and Pisano (1994), defines DC as follows: "Dynamic capabilities are the subset of the competences/capabilities which allow the firm to create new products and processes, and respond to changing market circumstances" (p.541). Alternative definitions and elaborations on this basic idea develop concepts of organisational and strategic routines (Eisenhardt and Martin (2000)) and learned patterns of collective activity (Zollo and Winter (2002)) as expressions of DC. The common conceptual core appears to be that DC are persistent business practices used deliberately to change or reconfigure internal firm resources in pursuit of new sources of competitive advantage (Ambrosini and Bowman (2009)). The DC view can be seen as an extension of the older "resource-based view" of the firm (Penrose (1959), Wernerfelt (1984), Barney (1991)), but with a stronger emphasis on intentional action. That is, to be persistently successful a firm needs not only to possess resources but to use them effectively. This includes the key act of recombining and transforming existing resources ("ordinary capabilities") to suit changing circumstances (Teece et al. (1997)). As noted earlier, researchers in the DC field also routinely cite Schumpeter as a key influence on DC thinking.

The functional essence of routines constituting DC is further elaborated in Teece (2007), with a disaggregation into three main categories: "(1) to sense and shape opportunities and threats, (2) to seize opportunities, and (3) to maintain competitiveness through enhancing, combining, protecting, and, when necessary, reconfiguring the business enterprise's intangible and tangible assets" (p. 1319). Further disaggregations are provided in Teece (2017). That paper also considers the implications of DC theory for understanding innovating firms. (Lockett and Thompson (2001) provide some earlier discussion of the implications of the resource-based view of the firm for innovation dynamics). Eisenhardt and Martin (2000) provide some examples of business practices, such as cross-functional R&D teams, new product development routines and quality control routines, that they see as important elements of DC.

While the language used in these examples from the DC literature cited above is obviously different to that typically used in the SEG literature, it seems clear that there are common underlying concepts and a relatively simple translation from one language to the other. For example, consider the Aghion and Howitt (1992) reference model outlined above. "Sensing" in the DC terminology can be understood as a firm (whether the incumbent monopolist or one seeking to displace the incumbent) contemplating the stochastic process of innovation arrival times. "Seizing" would be the firm deciding to invest in research to attempt innovation, given that stochastic process. Finally, "transforming" would be the firm reconfiguring its resources (skilled and specialised labour deployments in the reference model) to capture monopoly rents in the event it successfully innovates.

A key scientific question is then whether DC theory is able to predict the specific observable business practices that influence the probability of ongoing innovation success. These practices could then be used to "unpack" various parameters and representations of firm behaviour governing the innovation process in SEG models such as that outlined above. By so doing, the equilibrium implications of different DC choices by firms would be more amenable to research.

3 Data sources and preparation

I adopt a factor modelling strategy for the empirical part of this work, as follows. I treat firm DC as a superordinate construct in the sense of Edwards (2001), i.e. as a latent construct that causes variance in a larger (by an order of magnitude) number of observable variables. The construct may have a handful of dimensions (such as sensing, seizing and transforming). In essence, the strategy is to infer, on the basis of the comovements in BOS items selected as potential manifestations of the underlying construct, the existence of DC as a small set of unobservable, proximate causal influences on a range of observable innovation-related firm practices and attitudes. I then use the estimated construct to produce DC estimates at the firm-year observation level.

I use the descriptions and explications of DC in the papers cited in the previous section as the main basis for the judgemental selection of BOS items. Reflecting the exploratory nature of this work, I take an inclusive approach to the selection of items. I also note that the DC literature has been criticised for a "proliferation of definitions" (Barreto (2010), p. 257). Unclear definitional boundaries present some operationalisation issues (Eriksson (2013)). Given this criticism it seems appropriate to be inclusive, rather than impose a strict definition of DC for the selection of questions.

3.1 The New Zealand Business Operations Survey

The BOS suits the research objectives of this work because it is a high-coverage, statistically well-founded, nationally representative survey. These properties support generalisability of the results to the populations of interest. The BOS has a substantial longitudinal component (Fabling and Sanderson (2016)) and is one of a number of national surveys of innovation now running regularly in several countries.

The BOS is modular, with an annual module on business operations and characteristics, a two-yearly module on innovation aligned to the international Oslo Manual guidance on measuring innovation (OECD (2018)), a four-yearly module on business practices, recurrent modules on other topics, and ad hoc modules. As well as the rich longitudinal detail provided by the BOS itself, it is also linked through common enterprise identifiers to other business-related longitudinal data from other survey and administrative sources (Hong et al. (2012)).

Various modules from the BOS, which began running in 2005, or its predecessor surveys from a few years earlier, have been used previously for a range of work studying various aspects of firm behaviour and performance in New Zealand. Examples include Harris and Le (2019) on absorptive capacity, Fabling and Grimes (2010) on HR practices, Hong et al. (2016) on firm size and innovation, and Fabling and Grimes (2007) on a range of business practices.

For this study I used all BOS years in which both the innovation module and the business practices module were run, which are the four years 2005, 2009, 2013 and 2017. This is because both modules contain items that, on their face, are potential aspects of DC for inclusion in the factor modelling. The four BOS years provide a time span of 12 years. Firm-level BOS data were obtained from StatsNZ's Longitudinal Business Database (IBULDD 2019 version).

3.2 BOS items of interest

I chose BOS items for analysis judgementally and based mainly on face validity of the question text, in light of the narratives cited in the previous section about what DC are, and are not. I used the key functions of sensing, seizing and transforming in particular to screen for items related to these functions as described in the DC literature. Given the focus on innovation in this study, I also looked in particular for items relating to firm responses to change and the future. In marginal cases I tended to include items because this study is exploratory and later refinement may motivate subsequent exclusions. However, one aspect of DC thinking that is quite clear in the literature is that DC are distinct from "ordinary" capabilities relating to static efficiency. To recognise this distinction, I excluded from the analysis items that appeared to be mostly or entirely about static efficiency.

This process of filtering items is of course subjective. At this point, it is based solely on my interpretation of the question texts and their relevance for measuring the concept of DC, also as interpreted by me. More transparent approaches that reduce subjectivity in the selection process, such as using a panel of DC experts to score questions for relevance, as well as sensitivity analysis of the effect of edge cases on the results, are reserved for further work.

The process of filtering resulted in the selection of 39 BOS items that appear in all four of the BOS years used. Some questions have different questionnaire codes in different BOS years, and 11 questions have very slight wording changes, that do not affect the substance of the question. The questionnaire codes from the 2017 BOS identifying the selected questions are shown in Appendix Table A1.

3.3 Firm populations of interest

The unit of analysis in this study is the firm, reflecting that that is also the object of interest in the reference SEG model. In the largest sample of firm-year observations, I combine the data from the four BOS years. I use the following subgroups also in the analysis:

- observations pooled across the 2005 and 2009 BOS years
- observations pooled across the 2013 and 2017 BOS years
- firm size groups by rolling mean employment (RME)
- selected industries represented by ANZSIC Divisions C (Manufacturing), E (Construction), F (Wholesale Trade) and M (Professional, Scientific and Technical Services). These industries were chosen because they are represented in the BOS by the greatest numbers of firms and because their activities are most often the subject of overseas surveys and studies.

Table 1 shows the numbers of firm-year observations for the whole sample as well as for the firm size and industry subgroups. The firm-year observation counts in the table are not the same as firm counts, because some firms appear in more than one year.

Table 1: Number of BOS firm-year observations

All firm-years		25566
By firm size (RME)	6-19	9564
	20-29	3189
	30-49	2808
	50+	10008
By industry (ANZSIC Division)	C Manufacturing	5898
	E Construction	1437
	F Wholesale Trade	2160
	M Prof/Sci/Tech	1818

Note. All counts including total have been indepedently randomly rounded to base 3 (RR3), hence disaggregates may not sum to total.

In this preliminary work, I ignore the fact that some, but not all, firms appear in more than one BOS year (i.e. ignoring issues of survivorship bias). In effect, for most of the analysis, the observation period is 12 years. This is a rather long period in that changes in, for example, the macroeconomic environment might be relevant over such a timeframe.

Firms that appear in more than one BOS year are of econometric interest also because repeated observations allow the researcher to ask questions about changes in DC over time, as well as about lags and dynamics in shock responses. This may support identification strategies. I discuss these issues in more detail in the final section on further work.

3.4 Data cleaning and processing

Not all selected BOS questions offered respondents the same response choices. 4 questions offered Yes/No, 16 offered Yes/No/Don't Know, 16 offered a four-point ordinal scale and Don't Know, and 2 offered a five-point ordinal scale and Don't Know.

In the dataset for this study, items were coded as either 0 or 1, noting that this procedure discards information in the ordinal responses. Coding rules were as follows. All Yes responses were coded as 1 and No or Don't Know responses as 0. For questions with ordinal responses offered, responses strictly in the upper half of the ordinal scales were coded as 1 and all other responses as 0 (including the middle response for the two five-point ordinal scales). In effect all questions were coded to represent a binary variable measuring whether a business practice is done or not, or an attitude held or not.

All variables were checked for missing observations and codings in the source database other than 0 or 1. All variables were "clean" in this sense. I assume that, for any missing data in returned questionnaires for the BOS data used in this study, StatsNZ used the same imputation method as documented in StatsNZ (2011) for the 2010 BOS, i.e. nearest neighbour imputation (all data in this study are categoric) for respondent units that answered at least 60 percent of the questions.

4 A factor modelling approach to measuring dynamic capabilities

As noted earlier, the empirical strategy in this study is to use factor modelling or factor analysis (FA) to extract and analyse a measure of DC for the firm-years in the sample. DC is treated as a latent construct or trait of the firms in the sample that causes variance in the 39 BOS items, which were selected judgementally on the basis that they potentially reflect elements of DC as described in the DC literature. The purpose of factor modelling is to use the observed statistical associations between the items to infer the existence and level of the latent DC construct, and to relate the construct back to the items themselves. This provides information about which kinds of practices both tend to go together, and tend to be most characteristic of DC in the sample.

Principal components analysis (PCA), which is also often used as a dimension-reduction technique when one is interested in one or more common components of variance in a (typically large) number of items, is mathematically a special case of factor analysis. PCA allocates the variance in the n observations of p variables into p components, which are orthogonal linear combinations of the p variables defined such that the first component is the linear combination that explains the maximum proportion possible of the total variance, the second explains the maximum proportion of the remaining variance, and so on. PCA is a restricted form of FA in that, in PCA, the total variance is by construction allocated entirely across the p components, whereas in FA, in addition to the variance explained by the (up to p) orthogonal factors (similarly ordered to explain decreasing successive amounts of variance), residual idiosyncratic variance in each of the variables is also allowed.

In practice, the researcher might expect on the basis of theory that a (much) smaller number $k << p$ of factors explains a large fraction of the variance, with the remainder being idiosyncratic. Methodological guidance (e.g. Bandalos and Finney (2018), Costello and Osborne (2005)) suggests that if researchers have a theoretical k in mind, and/or if they do not have a good reason to defend the restriction of zero idiosyncratic variance in PCA, they should use FA. Among other things, the estimates of idiosyncratic variance in FA are informative about the statistical validity of the factor model approach, whereas PCA does not provide such information because idiosyncratic variance is assumed to be zero.

In the present case, the DC literature speaks of DC as a single construct, with potentially a handful of dimensions (e.g. sensing, seizing and transforming). I do not have a strong reason to assume that the BOS items do not contain idiosyncratic variance. Together, these conditions suggest an FA approach rather than PCA. In the Results section, I report the results of both techniques. In practice, there is little substantive difference in the key results, although the results of FA provide some additional comfort about the statistical validity of the latent factor approach.

5 Results

This section first looks in a little more detail at the prevalence of various DC-related practices and attitudes. I then present the results of the factor modelling of the correlation pattern among the items. This indicates those items that appear to be most important as part of a group of DC-related practices - whether or not the practices are done by relatively many or relatively few firms.

5.1 Prevalence of practices and attitudes

Table 2 shows the top ten and bottom ten items of the 39, ranked by the proportion of firms responding “Yes” or in the upper half of an ordinal response scale. Rankings for the same questions are reported by size group and by the four selected ANZSIC Division industries.

Notably, there is little difference in the practices and attitudes that turn up as most prevalent across the different subgroups shown. The prevalence pattern in the total sample is very similar to that for small (RME 6-19) firms and, to a lesser extent, Manufacturing firms. There are more noticeable differences in the rankings of certain highly prevalent practices for large (RME 50+) firms and for Professional, Scientific and Technical Services firms.

The bottom 10 practices and attitudes show even less variation across the subgroups. This suggests that these practices are not particularly informative in discriminating among the firms in the BOS sample.

The information in this Table is intended to be illustrative only. It should be noted that these are rankings, and absolute levels of prevalence are not shown. I reserve for future work analysis of the distributions of prevalence of practices and attitudes, and formal statistical testing for differences among the prevalence rankings.

Table 2: Incidence rankings of practices and attitudes (summarised BOS questions)

	All firm-years	By firm size (RME)		By industry (ANZSIC Div.)	
		6-19	50+	C: Mfg	M: P/S/T
	n=25566	n=9564	n=10008	n=5898	n=1818
Top 10					
Flexibility is important to strategies	1	1	1	1	2
Non-managers encouraged to suggest improvements	2	2	4	2	3
Has formal information system	3	3	2	3	1
Identifies risks/opps. from changes in mkt. conditions	4	4	3	4	4
Incorporates customers' requirements in developing goals	5	5	5	7	6
Innovation is important to strategies	6	6	6	5	8
Works closely with customers to improve products	7	7	8	6	9
Identifies risks/opportunities from changes in competitors	8	10	6	8	11
Non-sales staff have contact with major customers	9	8	13	15	6
Identifies risks/opportunities from changes in tech	10	11	10	9	5
Bottom 10					
Industry orgs. were important source of info last 2y	30	30	30	31	33
Focused on new export markets last 2y	31	32	32	24	32
Did market research to support innovation last 2y	32	31	33	32	34
Compared perf. w/ same-industry o'seas firms last 2y	33	34	31	34	31
Did R&D last year	34	33	34	30	30
Government was important source of info last 2y	35	35	36	37	36
Universities were important source of info last 2y	36	36	35	35	35
CRIs were important source of info last 2y	37	37	37	36	37
Compared performance w/ diff.-industry NZ firms last 2y	38	38	38	38	38
Compared performance w/ diff.-industry o'seas firms last 2y	39	39	39	39	39

Note. All observation counts shown have been randomly rounded to base 3.

5.2 Factor modelling results

Factor modelling models the pairwise correlation matrix of the p variables. A first step therefore is to get a sense of these correlations, or the extent to which the items move together.

At this point, the fact that the data studied here are all categorical deserves some attention. Pearson (1913) showed that his familiar r correlation coefficient is subject to potentially sizeable error when calculated on pairs of categorical data. Hence, I use the tetrachoric pairwise correlation matrix (a special case of polychoric correlation when both variables are dichotomous, as is the case here) in the factor modelling work. (Bollen and Barb (1981) suggest that Pearson's r should only be used with ordinal data if it has 5 or more categories, which is not the case in the present study.)

Table 3 reports the maximum, upper quartile, median, lower quartile and minimum off-diagonal absolute pairwise correlation coefficients calculated as both Pearson's r and as tetrachoric correlations. Pairwise absolute correlations were calculated on the full sample of firm-year observations.

Table 3: Item absolute pairwise correlation coefficients

All firm-year observations (n=25566; 39 items)		
	Pearson's r	Tetrachoric
Minimum	0.00	0.01
Lower quartile	0.10	0.21
Median	0.14	0.29
Upper quartile	0.22	0.39
Maximum	0.62	0.85

Note. Observation count has been randomly rounded to base 3.

The distribution of tetrachoric correlations has substantially higher summary statistics than that of Pearson's r, e.g. by about 0.15-0.20 in the upper halves of the distributions. About a quarter of the tetrachoric correlations are 0.4 or greater, consistent with the existence of a moderate degree of common variance.

5.3 Factor-analytic measures of dynamic capabilities for New Zealand firms

Table 4 shows key results from FA (and PCA for comparison) of the tetrachoric correlation matrix calculated on the full sample of firm-year observations. The first, second and third columns of the upper panel show the ten largest eigenvalues and cumulative variance explained under PCA of the correlation matrix, and the fourth, fifth and sixth columns show the same for FA. (Note that these statistics are calculated for unrotated factors, so they should be interpreted as only one possible partitioning of the total variance - the one that maximises the shares of explained variance in successive factor order.) The results for PCA and FA are very similar for the first three or four eigenvalues, after which the cumulative variance explained tails off noticeably more quickly under FA, consistent with there being nontrivial idiosyncratic variance in at least some of the items. Hereon I refer exclusively to the FA results, for the reasons explained in the previous section.

The upper panel of Table 4 shows that the first factor explains a high proportion of the total variance (35%), and the second explains a further 10%, in the sample. These results suggest a fairly strong factor structure in the data, i.e. they are consistent with a latent construct with a small number of dimensions (exactly how many discussed below) causing common variance in a large number of items.

The lower panel of Table 4 shows the five items loading most highly on the first factor (which were the same for the first principal component), meaning the items with the highest coefficients in the eigenvector representing the factor. The uniqueness statistics for these items is also shown, which are the proportions of item variance not explained by the estimated factors. For the highest-loading items, the uniqueness statistics are in the "low" range (Costello and Osborne (2005)), again supporting the idea of a reasonably strong factor structure in the data.

Turning to the substance, what is striking about looking at the lower panel of Table 4 together with Table 2 on the prevalence of practices is that there is zero overlap between the highest-loading items and the most prevalent items. The 5 highest-loading items are all time-bound items about things the respondent firms **did**, mostly in the last two years, whereas the 10 most prevalent items are attitudes or practices without a reference period. Also interesting is that the least prevalent items are all time-period-referenced.

Also notable from the highest-loading items for the first factor shown in Table 4 is that four of the five are about the importance of particular sources of information ("sensing" functions in the Teece (2007) taxonomy). These variables are all sourced from a single BOS question on importance of information that presents a checklist of sources which the respondent is asked to score. This raises a concern that the variables' high loadings may reflect respondents ticking the same score for each information source out of form-filling expedience, inflating the correlation above its true level. This possibility needs to be investigated further, with some robustness testing.

Table 4: Principal components and factor modelling results, tetrachoric correlation matrix

All firm-year observations (n=25566)					
Principal components			Factor model, iterated principal factor method		
Top 10 eigenvalues	Prop. variance explained	Cum. prop. variance explained	Top 10 eigenvalues	Prop. variance explained	Cum. prop. variance explained
13.9	0.36	0.36	13.6	0.35	0.35
4.3	0.11	0.47	4.0	0.10	0.45
2.0	0.05	0.52	1.6	0.04	0.49
1.8	0.04	0.56	1.3	0.03	0.53
1.5	0.04	0.60	1.1	0.03	0.55
1.2	0.03	0.63	0.8	0.02	0.58
1.2	0.03	0.66	0.8	0.02	0.60
1.0	0.03	0.69	0.6	0.02	0.61
0.9	0.02	0.71	0.4	0.01	0.62
0.9	0.02	0.73	0.4	0.01	0.63

5 highest-loading items	Principal components	Factor model it. principal factor estimation	
	1st comp. loading	1st fact. loading	Uniqueness
Existing staff important source of info last 2y	0.22	0.84	0.06
Custs. important source of info last 2y	0.22	0.81	0.14
Innovated to inc. responsiveness to custs. last 2y	0.21	0.79	0.17
Conferences important source of info last 2y	0.21	0.76	0.23
New staff important source of info last 2y	0.20	0.75	0.22

Note. Observation count has been randomly rounded to base 3.

A next question is what the factor model suggests about the number of factors (latent constructs or dimensions of a single latent construct) in the data. Figure 1 shows a scree plot of the eigenvalues from the factor model. The scree plot is a workhorse tool to assist with the choice of number of factors. A distinct "kink" in the scree plot at the third eigenvalue is evident, suggesting either two or three factors are present.

Further analysis of the loading patterns (including after rotation of the factors, discussed below) in light of theory is needed for a more informed judgement about exactly how many factors to retain for analysis. In this study, I concentrate on the first (unrotated) factor, which is clearly a major driver of the common variance.

Figure 1: Scree plot, factor model

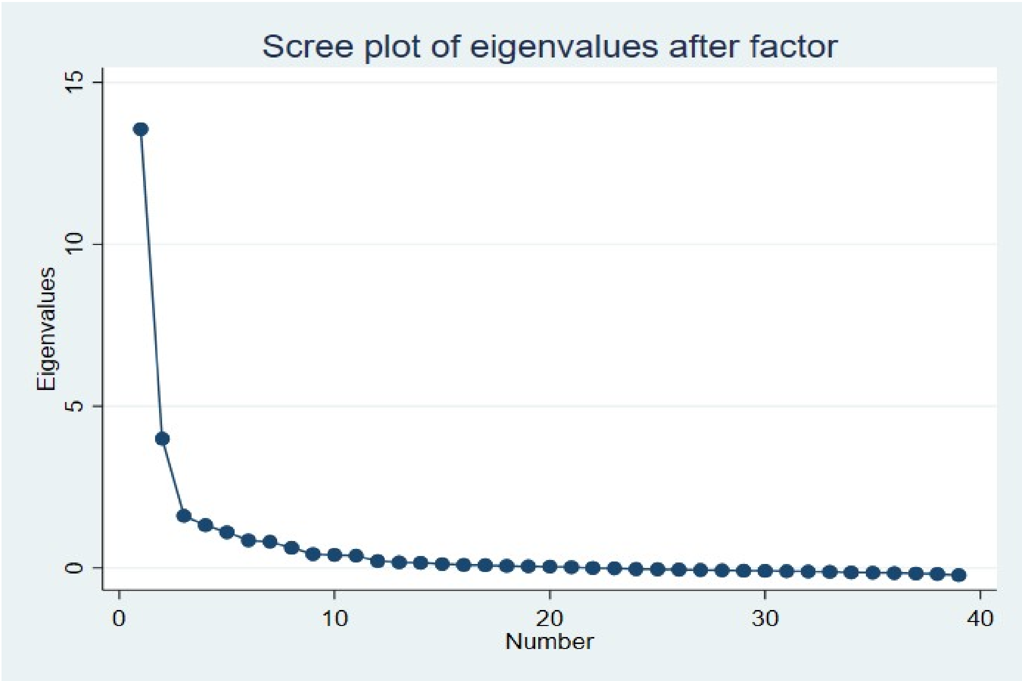
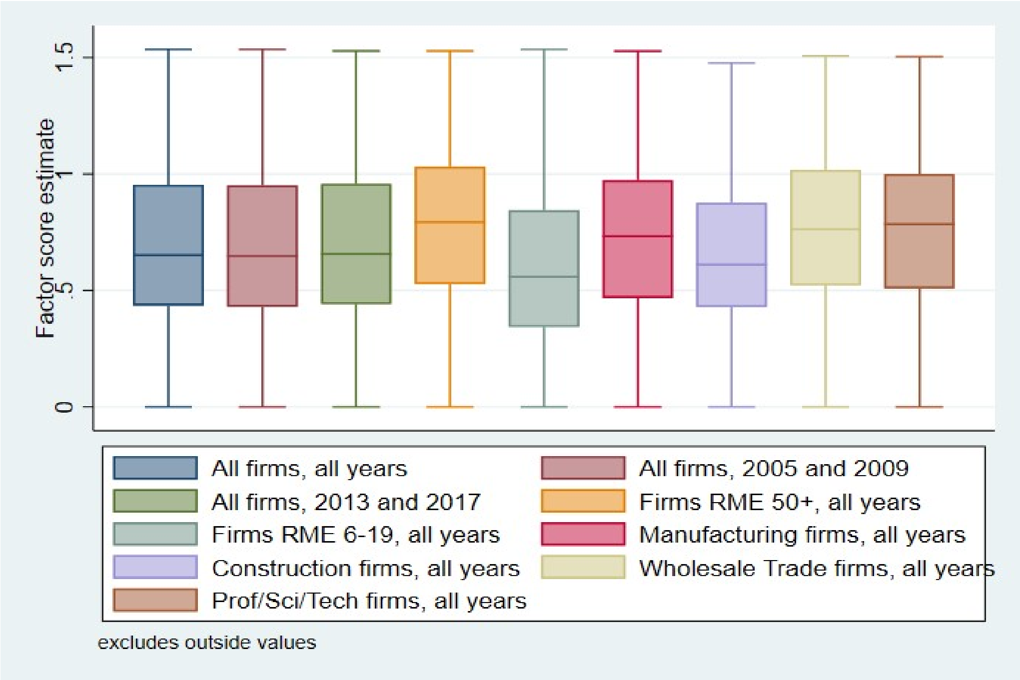


Figure 2 shows box-whisker plots (with outliers suppressed) of the distributions of factor score estimates (using the regression method) produced using the first factor from the factor model. The factor score estimates provide an indicator of the component of the observations predicted by the first factor. To the extent that the first factor is interpreted as representing DC or a dimension of DC, the factor score estimates indicate the level of DC evident in each firm-year observation.

From left to right are plots for the whole sample of firm-year observations, the pooled 2005 and 2009 BOS years, the pooled 2013 and 2017 years, large and small firms, and firms by industry.

Eyeballing Figure 2 suggests clearly higher first factor score estimates for large compared to small firms, which would be consistent with the factor representing an underlying capability that draws together different innovation and competitive practices and attitudes described by DC theory. A wealth of evidence suggests large firms are better able, and are likely to find it more worthwhile, to invest

Figure 2: Factor score estimates, 3-factor model



in sophisticated rent-seeking capabilities of the sort contemplated by DC theory. Relatively high capability in Professional, Scientific and Technical Services firms also seems unsurprising. Relatively low dynamic capability in Construction firms may be consistent with the prevalence of small building firms in New Zealand.

Manufacturing and Wholesale firms also show relatively high first factor score estimates. Further interpretation for these sectors requires further exploration, as one might expect them to be quite heterogeneous in the capability dimension. One strategy would be to form subgroups that are more homogeneous.

There is little evidence on the face of Figure 2 for any change in capability between 2005/09 and 2013/17, i.e. the pre- and post-GFC and earthquakes period.

Finally, an interesting aspect of Figure 2 is that the within-group variances in the factor score estimates are much greater than the between-group variances. This pattern is consistent with the stylised fact of wide intra-class variance in firm performance emphasised by the DC literature and attributed to substantial differences in firm capabilities.

6 Discussion

6.1 Main findings and limitations

This study set out to construct preliminary measures of dynamic capabilities for New Zealand firms. Subject to refinement, these measures are intended for eventual use in substantive testing for relevance in explaining or causing firm performance differences and economic dynamics. I used factor analysis of selected items from the BOS and found that there indeed appears to be a strong factor structure in the selected items. Some basic results from applying the factor model to subgroups of observations are consistent with broad predictions of DC theory, such as that large firms and Professional/Scientific/Technical Services firms tend to exhibit higher capability.

It is worth being cautious before making strong claims about exactly what the estimated factor(s) from this preliminary work represent. Specifically, in light of the purposes of this study, further work is needed on the facgtor modelling to test any claim that the estimated factor(s) represent DC as described in the literature and in a discriminating manner across firms.

First, as noted in the Results section, the results are based on unrotated factors. FA involves an indeterminacy in that there is an infinite number of rotations of the factors that are just as valid as each other in the sense that they are all equally consistent with the correlation matrix. Yet different rotations imply different patterns of loadings and partitions of the total variance across the factors, whose validity needs to be judged against theoretical priors and other evidence.

A second indeterminacy in FA is in the factor score estimation, which can be done in a variety of ways and, depending on the strength of the factor structure, different estimation methods can result in materially different factor score estimates (Di Stefano et al. (2010)).

More generally, the internal and external validity of the statistical FA-based DC measure needs to be assessed more rigorously, with formal statistical testing and reference to other evidence. Robustness to different choices of edge cases in the item selection and to changes in subsamples are examples of sensitivity testing that is needed to test the fragility of the results presented here.

Beyond the BOS work cited above, there is at least one unofficial survey of New Zealand business practices (Ministry of Economic Development (2010)), and New Zealand is included in a large cross-country survey of management practices in manufacturers (Bloom et al. (2016)). As well, MBIE (2019) conducted an in-depth interview-based study of 30 businesses drawn from the 2017 BOS sample, which provides some related data. These data sources and studies using them provide a useful avenue for testing consistency and external validity.

6.2 Future research directions

The focus of this paper is on measuring the construct of dynamic capabilities in New Zealand. Preliminary results are encouraging. The next step is to use the measures (further refined and tested along the lines suggested above) in econometric work to test for impacts on outcome variables related to firm and economic performance, such as profitability, productivity, employment and real wages. Evidence of predictive power and the involvement of DC in broader firm performance and economic dynamics of interest is needed to support external validity of the measures. It is also needed to strengthen the possibility that the DC construct can enhance the relevance of DC theory to Schumpeterian endogenous growth theory, and to enrich the realism and applicability of SEG theory.

Some examples of questions, with associated hypotheses, that deserve testing in this vein include the following:

- Do high levels of DC demonstrably improve firms' chances of successfully innovating, anticipating or exploiting the arrival of a profitable innovation, in a manner akin to the conceptions of Schumpeterian growth theory?
- Is DC a mediator or a moderator, or both, for other influences on firm and economic performance?
- Do DC affect a firm's success at acquiring or developing ordinary capabilities (skilled staff, multi-purpose technologies, etc.), and are these related to innovation or simply static efficiency?
- Are there key complementary investments that enhance the impact of DC on firm and economic performance?
- How do investments in DC manifest in hiring and staff development practices related to innovation?
- Can DC mechanisms help distinguish which of the two branches of endogenous growth theory is more important empirically?

Appendices

Appendix A BOS items selected for analysis

Questionnaire code from 2017 BOS		
A0900	B2010	C2005
B1408_01	B2011	C2101
B1410_01	B2012	C2102
B1904	C0203	C2103
B2001	C0205	C2104
B2002	C0303	C2200
B2003	C0304	C2301
B2004	C0601	C2302
B2005	C0602	C2303
B2006	C1100	C2304
B2007	C1200	C2305
B2008	C1300	C2901
B2009	C1800	C3400

Exact question texts corresponding to these codes are available from the author on request.

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