Business practices, dynamic capabilities and firm performance in New Zealand: unpacking the black box of innovation

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Abstract

What is really inside the black box of firm innovation, and how does it relate to firm performance and economic growth? This study summarises, via factor analysis, a wide range of reported business practices into a handful of key areas, which I interpret in terms of the "dynamic capabilities" view of innovation as a source of enduring business success. As theoretically predicted, I find a positive statistical association between a number of these areas of business practice and performance measures such as sales per employee and firm longevity. This finding sets the stage for the investigation of the causal mechanisms that could underlie these empirical associations. I discuss theoretical connections to firm responses to shocks and how these connections might be taken to the data.

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1 Introduction

The flowering in recent decades of endogenous growth modelling and associated empirical research leaves no doubt that innovation, and the new ideas and know-how it generates, are key to sustained economic growth, broadened policy choice sets and higher living standards. But innovation as a *process* remains mysterious. Which innovation practices matter most for firm and economic performance? Under what circumstances? How do such practices relate to performance measures such as sales growth, profitability, productivity and firm longevity?

These questions are of keen interest not just to researchers and firms, but to policymakers also. When new ideas and know-how can be appropriated by competitors, firms may tend to underinvest in innovation activities relative to the socially optimal level (Nelson (1959), Arrow (1962b)) or act to protect the economic rents gained from unique knowledge, inhibiting its socially desirable diffusion to other firms (Dinopoulos and Syropoulos (2007), Levin et al. (1987)). The spillovers from innovation activity can be quite large in practice (e.g. Jaffe (1986), Shu et al. (2012)).

Governments therefore commonly implement policies and programmes expressly intended to boost firm innovation. They often provide substantial direct support for innovation activities, and set "framework" policies such as competition and intellectual property rules with a view to sharpening innovation incentives.[1]

In this paper, I provide evidence from New Zealand on the relation between a diverse set of business practices and a range of firm and economic performance outcomes. This addresses the gap in understanding what is inside the "black box" of innovation, that is left largely unopened by leading models of endogenous growth.

Building on previous work documented in Ng (2021), I use the recently developed "dynamic capabilities" framework (Teece et al. (1997), Eisenhardt and Martin (2000), Winter (2003), Teece (2007), Barreto (2010)) to select over a hundred specific and granular business practices and attitudes relating to innovation, adaptation, change-making and operational efficiency from Stats NZ's Business Operations Survey (BOS), a high-quality, nationally representative, periodic survey of around 5-7,000 firms. Using factor analysis, I model numerous dynamic-capabilities-

[1]The New Zealand government, for example, provides research and development (R&D) tax credits worth around NZ$40m per annum (OECD (2021)) and directly supports "ambitious" and "innovative" firms to the tune of around $200m per annum in the case of New Zealand Trade and Enterprise, and $300m per annum in the case of Callaghan Innovation. These funds are used to provide financial and in-kind support for firm innovation and growth via a range of programmes, generally involving intensive engagement with a firm's innovation and growth activities. Yet a range of New Zealand studies has linked New Zealand's disappointing productivity performance in part to weak innovation (e.g. Nolan et al. (2018), Conway (2018)).

related practices and attitudes reported by the firms four-yearly from 2005 to 2017 as observable expressions of a handful of underlying (latent) dynamic capabilities factors. I link these factors to broad areas of business activity (marketing, collaboration, environmental scanning, etc.) representing particular capabilities. I then use firm "scores" on each of the capability factors as explanatory variables in panel regression models of a range of short-term firm performance measures, and in firm survival models.

I find a parsimonious and statistically satisfactory 5-factor model can capture the correlations among 87 BOS items selected as expressions of dynamic capabilities. Rotation of the model's item loading matrix to produce a "simple" loading pattern across the factors suggests that there exists a latent capability factor underlying external cooperation practices, one underlying marketing innovation supported by internal restructuring, one underlying situational awareness practices, and one underlying exporting and other cross-border activities supported by access to external expertise. Loadings on the fifth factor under that rotation less clearly suggest an obvious theme or recognisable coherent business function. The high loadings for this factor were on activities relating to health and safety, environmental impact and internal efficiency.

From the panel regression and survival modelling, I find evidence for a positive association between all of the dynamic capabilities factors and sales and employment growth. The "Exporting + expertise-seeking" factor is positively associated with sales per employee, average wages and longevity. The "Situational awareness" factor appears particularly strongly associated with longevity. I find these associations in the presence of controls for industry, year, firm age, size, foreign ownership, the capital/labour ratio, and firm scores on factors extracted from BOS items to represent firm "ordinary capabilities" (internal quality control systems and the like). The associations are generally robust to a variety of specification changes and estimation choices. These findings suggest that it is indeed possible to identify systematically successful innovation practices inside the black box.

The rest of this paper proceeds as follows. In Section 2, I briefly review the endogenous growth literature, which deals abstractly with the general-equilibrium interplay between innovation and steady state economic dynamics. I counterpose that literature with the dynamic capabilities framework, from the strategic management literature, which interrogates specific business practices and guides my empirical strategy to open up the black box. In Section 3, I set out the empirical methods in detail. Section 4 describes the data. Section 5 presents the results of factor modelling of the selected BOS items, the panel regressions and the survival modelling. Section 6 concludes with a discussion of further potential work to explore the causal mechanisms that may be at play in the associations documented here.

2 Existing theory and evidence

In Ng (2021) I argued that, notwithstanding the success of endogenous growth modelling in advancing new theoretical machinery for the study of long-run growth, this modelling had given very limited attention to the actual process of innovation and how new ideas and knowledge come to be. I discussed the recent field of dynamic capabilities research as a way to characterise the innovation process and how it contributes to firm and economic success, and presented some preliminary "proof of concept" measures of dynamic capabilities for further empirical testing.

In this section, as a framing for the empirical application in the rest of the paper, I review the main elements of endogenous growth theory, and show how it can be connected formally to the dynamic capabilities literature. I note the production function parameters capturing the fruits of innovation and the idea "arrival process" in a benchmark endogenous growth model. These are the black boxes to be unpacked in terms of innovation practices. This work thus represents a further response to Teece (2017)'s call for more "intellectual exchange between strategic management and economics" (p.1).

The economics of innovation, knowledge and ideas, and their intimate connection with long-run growth dynamics, has developed substantially since the 1980s to the point where the centrality of innovation as a driving force for prosperity can hardly be challenged. Jones (2019), writing of the "renaissance" (p. 879) in the field of economic growth since then, celebrates the growth model with endogenous technological change of Romer (1990), setting it as a watershed that brought together earlier ideas about the importance of knowledge and ideas for sustaining growth (e.g. Arrow (1962a), Lucas (1988)). Earlier (also seminal) "neoclassical" growth models of Solow (1956), Solow (1957), Swan (1956), Ramsey (1928), Cass (1965) and Koopmans (1963) had demonstrated that capital accumulation would eventually "peter out" as a source of growth. The models stimulated by Romer (1990), including Grossman and Helpman (1991) and Aghion and Howitt (1992), provide a compelling answer to the question of how growth could persist in the steady state (but possibly in a non-welfare-maximising manner), based on the key concepts of the non-rivalry of ideas and monopoly rents incentivising firms to invest in searching for new ideas.

2.1 Schumpeterian endogenous growth modelling

This paper draws most closely from the "Schumpeterian" endogenous growth modelling strand developed by Aghion and Howitt (1992) and Grossman and Helpman (1991). This strand is distinguished by its focus on increasing product quality generating the possibility of obsolescence ("creative destruction"), and innovation being motivated by a desire to stay ahead of competitors in terms of quality. Schumpeterian endogenous growth models can account for a range of stylised facts about firm dynamics, size and age distributions and the relationship between competition and innovation that other growth modelling approaches struggle with (Aghion, 2017).

Barro and Sala-i-Martin (2004, ch. 7) provide a simple production function capturing the essence of one approach to incorporating improving quality and obsolescence, the "quality ladder", which nests an even simpler production function that enables growth to arise endogenously through increasing "product variety", the other major strand of endogenous growth modelling.

They specify firm i's production function as:

$$Y_i = AL_i^{1-\alpha} \cdot \sum_{j=1}^{N} (q^{\kappa_j} X_{ij})^{\alpha} \tag{2.1}$$

where

Y_i = output
L_i = labour input
X_{ij} = the quantity of the jth type of specialised intermediate good employed
q^{κ_j} = the quality level ("ladder rung") of intermediate good j with $q > 1$
N = the number of varieties of intermediate goods

and $0 < \alpha < 1$.

In this model, "innovations" (i.e. the flow of new ideas) take the form of random increases in κ_j, and have a Poisson arrival rate given by the probability per unit time of a successful innovation in the sector producing intermediate good j when the best quality in that sector is κ_j,

$$P(\kappa_j) = Z(\kappa_j)\phi(\kappa_j), \tag{2.2}$$

where $Z(\kappa_j)$ is investment in R&D in the sector producing intermediate good j when the best quality is at level κ_j, and $\phi(\kappa_j)$ is a function that allows the impact of R&D to depend on that level.

In quality-ladder models, growth comes from $P(\kappa_j) > 0$ in equilibrium. Within this framework, the key question for the present paper is how business practices and dynamic capabilities affect $Z(\kappa_j)$ and $\phi(\kappa_j)$.[2]

These models pay little attention to the specifics of the innovation process, that is, the firm behaviours, attitudes and practices that are the

[2] Setting $q^{\kappa_j} = 1$ provides the product variety model, wherein growth results from increasing N in the production function, which becomes

$$Y_i = AL_i^{1-\alpha} \cdot \sum_{j=1}^{N} X_{ij}^{\alpha}.$$

observable expressions of a firm's desire to innovate. The present work helps unpack $Z(\kappa_j)$ and $\phi(\kappa_j)$ in 2.2. To do so, I use concepts from the dynamic capabilities framework to empirically assess the relevance of a large number of business practices to firm success, from which may be inferred what lies behind those two key parameters that drive steady state growth in Schumpeterian endogenous growth models of the above ilk.

2.2 The dynamic capabilities framework

The dynamic capabilities literature claims that dynamic capabilities are the essential source of persistent business success (Teece (2007), Eisenhardt and Martin (2000), Zollo and Winter (2002)). In this view, dynamic capabilities are used by successful firms to sense and seize new business opportunities, and to transform their "ordinary" capabilities to make the most of the detected opportunities, for the ultimate purpose of creating and sustaining competitive advantage over time.

The framework draws explicit inspiration from essentially the same Schumpeterian story as the endogenous growth theory sketched above. It grew out of earlier work on the "resource-based view" of the firm stimulated by works such as Penrose (1959) and Nelson and Winter (1973).

In this view, firms are motivated to chase rents and avoid obsolescence. The framework also recognises the role of knowledge and ideas as firm resources, analogously to the role of q^{κ_j} in equation 2.1). In the dynamic capabilities framework, the accumulation of resources over time, which may be deliberately steered by the firm as well as resulting from changes in the firm's external environment, gives the firm options to pursue new strategies and products.

The framework makes a key distinction between ordinary capabilities ("doing things right") and dynamic capabilities ("doing the right things"). The latter includes changing focus to keep up as "the right things" change, or indeed influencing what the right things are, given market opportunities. Most applied literature on business practices does not make this distinction sharply. For example, Bloom and Van Reenen (2007) examine the impact of management practices on firm performance, but tend to focus on operational (plant-level) management, which would be considered mostly an "ordinary" capability. Bertrand and Schoar (2003) look a little closer at strategic (enterprise-level) management, including elements of innovation. There is some empirical literature on management practices and their dynamics in New Zealand (e.g. Green et al. (2010), Sanderson (2022)). But these studies tend not to clearly distinguish the two capability concepts distinctly within the same empirical model to test the relative importance of each in terms of performance.

In product variety models, increasing N may be explained as a function of R&D cost η, which provides another potential black box of innovation to open up.

Such an integration is a key contribution of the present work. The dynamic capabilities literature claims that there is a difference between firms with high dynamic capabilities and those with high capability generally. This work tests this claim directly, making the project conceptually distinct from studies that look at the performance and economic impacts of management capability generally.

The dynamic capabilities literature and broader resource-based view of firm behaviour provides a rich and intuitively appealing narrative about the innovation process, as distinct from innovation products (new knowledge and ideas). But it seldom involves formal modelling, and even less so welfare analysis, which help meet the scientific need to understand the enduring sources of long-run growth performance, and the policy interest in why market-led investment in innovation might be different to the social optimum in dynamic equilibrium. This interest includes how policy interventions might shift the equilibrium closer to the optimum.

There is thus the potential for endogenous growth modelling and its impact to be enhanced by more specificity about the innovation process. In the next section, I explain how I go about using the dynamic capabilities framework to guide the empirical approach to gaining more specificity. I also set out the specific hypotheses related to particular parameters in the empirical models.

3 Empirical methods

The unit of analysis for this study is the firm.

I choose the study sample of firms with the objective of representing New Zealand firms broadly, subject to their practices relating to innovation being measurable in some detail. Reflecting that constraint, I base the sample of firms on that in Stats NZ's Business Operations Survey (BOS). I describe the BOS and the sample in more detail in section 4.

This approach to the firm sample contrasts with much of the empirical dynamic capabilities literature, which often is limited in scope to firms from certain industries (often manufacturing, or "high tech"), or of certain sizes (e.g. large, complex firms) or ages (e.g. startups). Sampling strategies are often accordingly based on sampling frames that may or may not be intended to represent broad populations of firms, or be statistically sufficiently well-founded for findings to be generalisable beyond the sample.

The intent of the present work is to go beyond such "convenience" samples, and take a broad and general view of firm innovation, reflecting the general (e.g. industry-agnostic) approach of the endogenous growth literature. I test for the relevance of innovation-related business practices to firm success irrespective of industry, age, size and other firm characteristics. In part this is to reflect that New Zealand, being a small country, has mostly small firms by international standards, and so the innovation dynamics relevant to, say, large multinationals would be unlikely to be relevant to the bulk of firms in New Zealand.

3.1 Methodological overview

There are two parts to the empirical work reported here, as follows:

1. I select a large number of specific business practices relating to innovation, and use factor modelling to obtain a manageable number of measured aspects (factors) of dynamic and ordinary capabilities.

2. I test for association of the dynamic and ordinary capabilities factors with firm performance measures, using panel regression and survival models.

The first part is an extension and application of the approach documented in Ng (2021). In that work, I used factor analysis on the same sample of firms as used here, but a smaller set of BOS items, and focused on dynamic capabilities only rather than both dynamic and ordinary capabilities. In that earlier work, I found that a factor model with a manageably small number of factors could represent the correlation structure among the BOS items, chosen as observable expressions of dynamic capabilities, in a statistically satisfactory manner. The pattern of estimated factor scores across different subsamples of firms by size and industry was consistent with the predictions of the dynamic capabilities literature. Building on that "proof of concept" in terms of the factor-analytic approach to measuring capabilities, the current work extends the factor model approach to substantially more BOS items, as well as to the task of measuring ordinary capabilities.

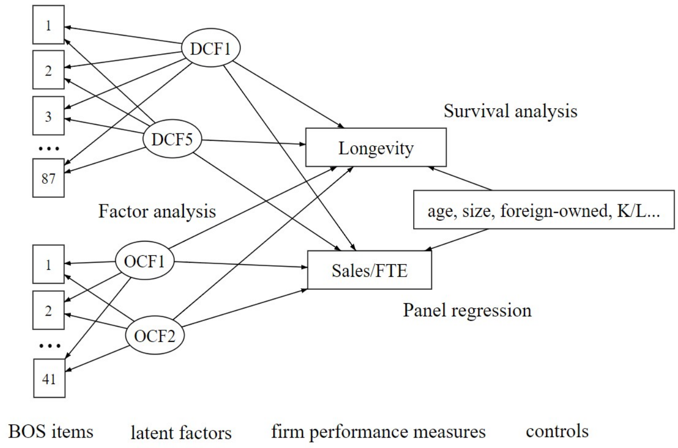
The second part can be viewed as a substantive validity test of the measures created in the first part. In order to be substantively valid the measures need to have some (statistical) explanatory power for firm and economic performance.

There is a third part to this project, which follows from the findings documented here that the dynamic and ordinary capabilities factors do have statistical explanatory power for a range of firm success measures. The third part is to test for causal mechanisms that may underlie the finding of a statistical association between the capabilities factors and firm success. Such testing in a formal framework with careful identification is needed because there are a range of reasons why capabilities might be correlated with success. Although this paper does not report findings in relation to the third part, in section 6 I discuss some potential empirical approaches to the potential mechanisms.

Figure 3.1 shows how the two parts of the empirical work fit together.

Moving from left to right in the figure, the left hand side of the figure shows the BOS items (answers to questions about specific business practices, activities and attitudes) I select for the factor analysis. There

Figure 3.1: Empirical model structure



are in the order of a hundred items, which I interpret as observable manifestations of a much smaller number of underlying (latent) dynamic and ordinary capabilities factors. The latent factors underlying each item group are assumed to be mutually orthogonal, for ease of interpretation. I interpret the firms' estimated "scores" on the factors as measures of their levels of dynamic and ordinary capabilities, which are allowed to vary over time. I then use the factor scores as explanatory variables in panel regression models of a range of firm performance measures, and in firm survival models, alongside a range of control variables.

I set out the principles of each of these empirical modelling elements in the following subsections. The data sources are described in Section 4.

3.2 Factor modelling

3.2.1 Selection of BOS items

I judgementally select BOS items for factor modelling based on the descriptions of dynamic and ordinary capabilities in the dynamic capabilities literature. I classify items as potential manifestations of dynamic capabilities, ordinary capabilities, or both, prior to estimation of separate factor models for each type of capability.

Items were selected into the "dynamic capabilities" group if they were broadly about "doing the right things" in a dynamic sense, or dynamic efficiency in economics terms. The dynamic capabilities literature explains this strategic management objective as comprising "sensing", "seizing" and "transforming" functions. Based on this description, items were selected into the dynamic capabilities group if they explicitly mentioned "innovation" or otherwise conveyed a sense of responding to or creating external change, or planning for the future. Items that described activities that could reasonably be interpreted as adjuncts to sensing, seizing and transforming activities, such as internal reorganisation and restructuring, were also selected into the group. Appendix A shows the items selected into the dynamic capabilities group.

Items were selected into the "ordinary capabilities" group if, on their face, they were broadly about "doing things right", or static efficiency in economics terms. Although this category of practices and activities was not the main focus on this work, the dynamic capabilities framework distinguishes between ordinary and dynamic capabilities, and hence it is important to control for ordinary capabilities in the empirical work.

Some items were selected into both groups, reflecting that it is possible for a particular practice to be motivated both by static and dynamic efficiency considerations. For example, practices or activities relating to internal change or the flow of information within the firm could in principle be motivated by either or both.

As in Ng (2021), I take an inclusive approach to the selection of items into each group. This recognises that the dynamic capabilities framework is rather broad and non-specific in the activities it discusses as being related to sensing, seizing and transforming. Indeed, the framework has been criticized on this point as being vague or even tautological (e.g. Williamson (1999)).

Factor modelling is a technique particularly suited to handling this situation, in that in principle it can achieve dimension reduction over an arbitrarily large number of items, including items that are in reality hardly relevant or not relevant.[3] Although prescreening the items at some coarse level, if it eliminates irrelevant items (those with true factor loadings of zero), should result in more efficient factor model estimates, in this work I err towards including more items rather than less, since the purpose is to explore the potential relevance of a wide range of practices. Those that turn out to be irrelevant are in effect defined as such through small loadings in the factor models.

The selection of items into a group for factor modelling can be constrained by the statistical properties of the resulting group. Factor analysis by maximum likelihood, my preferred approach because it is statistically better founded than other methods, requires the correlation matrix to be invertible. This constraint is binding in my selection process for the dynamic capabilities group. In the first pass of selecting items for this group, I identified 102 candidate items for the group. However, the tetrachoric correlation matrix (described below) estimated for this group was

[3] Factor modelling is, in mathematical terms, closely related to principal components analysis (PCA), which can also achieve dimension reduction and a partitioning of total item variance into a common component and an idiosyncratic component. Factor modelling differs in that it is founded explicitly on an assumed causal relationship between items and factors. For the reasons explained in Ng (2021), I prefer the factor modelling approach in this work. Experimentation with common components estimated with PCA in the regression modelling produced very similar results.

not invertible, indicating there were items which, if included in the analysis, would imply collinear correlation patterns across the item group. I therefore reduced the selection of items until an invertible correlation matrix was achieved, which required omitting about 15% of the items.

This selection process results in 87 items selected into the dynamic capabilities group and 41 items into the ordinary capabilities group, on which I base the rest of the analysis.

The finding that including some variables beyond the 87 finally selected generates collinearity in the correlation matrix indicates that caution is needed in interpreting exactly what the factors represent based on the question texts for the underlying items, because collinearity implies that the excluded items are able to substitute for some of the included items with little statistical effect.

3.2.2 Processing the BOS item data

All of the selected BOS items are discrete variables. Some are in the form of "Yes" (the firm held the attitude or executed the practice asked about) or "No" (the firm did not) responses, while others offer several points in an ordinal scale as response options (e.g. Very important/Quite important/Not very important/Not important). As in Ng (2021), for Yes/No questions I code "Yes" as 1 and "No" (and "Don't Know" or "Not applicable" where applicable) as 0. I code all responses to multi-point scales as 1 for responses in the upper half or middle of the scale, and 0 for responses in the lower half. So, all items entering the factor modelling step enter as dichotomous variables.

The item data are described in more detail in Section 4.

3.2.3 The factor model

In a factor model, the observed variables $\mathbf{w}$ (a p dimensional vector of BOS items in this case, with e.g. $p = 87$ for the dynamic capabilities group of items) are viewed as manifestations of k underlying (latent) factors such that

$$\mathbf{w} = \mathbf{\Lambda f} + \eta \tag{3.1}$$

where

$\mathbf{\Lambda}$ = factor loadings ($p \times k$)
$\mathbf{f}$ = orthogonal common factors ($k \times 1$)
η = unique components ($p \times 1$), assumed uncorrelated with $\mathbf{f}$

$\mathbf{\Lambda\Lambda}'$ is the "common component" of the item covariance matrix $\mathbf{R}$, with $\mathbf{\Psi}$ the (diagonal) covariance matrix of η:

$$\mathbf{R} = \mathbf{\Lambda\Lambda}' + \mathbf{\Psi}$$

In the present application, $\mathbf{R}$, which is $p \times p$, is the tetrachoric correlation matrix estimated from the n firm-year observations on the p BOS items, as described below.

The number of factors k for a group of items is chosen to produce the "best" factor model representation of $\mathbf{R}$. The factor model partitions the variance of each item into a common component explained by the k factors and p item loadings on the factors, which are the correlations of the items with the factors, and an idiosyncratic component uncorrelated with the common component and with the other idiosyncratic components.

One objective of factor modelling in the current setting is to find a $k \ll p$, so that dimension reduction is achieved, since $p = 87$ and $p = 41$ items are far too many to include directly in a regression model where the aim is to interpret the coefficients.

A statistically best-fitting k may be found simultaneously with the loading matrix and other parameters of interest as the solution to a maximum likelihood (ML) problem. k may also be chosen less formally via the iterated principal factors (IPF) method of performing an eigenvalue-eigenvector decomposition of the correlation matrix, and then selecting k on the basis of inspecting the scree plot of the eigenvalues ordered by size. In this work I use both potential sources of information.

Factor modelling is able to identify the $p \times k$ loading matrix $\mathbf{\Lambda}$ up to a rotation only. The researcher may then decide, as I do here, to find a rotation of $\mathbf{\Lambda}$ subsequently, to facilitate substantive interpretation of the factors.

3.2.4 Factor modelling as applied here

In applications in which the items are continuous variables, the modelled correlation matrix $\mathbf{R}$ typically contains Pearson product-moment correlation coefficients. With discrete ordinal variables, Pearson correlations may be subject to potentially sizeable error when calculated using categorical data (Pearson (1913), Bollen and Barb (1981)). Hence, in this work I use tetrachoric pairwise correlations in the modelled correlation matrix, which treat the dichotomous observed data as discrete realisations of latent bivariate normally distributed continuous variables.[4]

For each group of items, I estimate $\mathbf{\Lambda}$ by ML, imposing k based on inspection of the scree plot from the IPF solution to the factor model. Because I am interested in interpreting the factors substantively in terms of broad business functions and linking them to the dynamic capabilities framework, I search for a loading matrix $\mathbf{\Lambda}_R$, an orthogonal rotation of

[4]This "limited information" approach has been shown in factor modelling settings to produce estimates with statistical properties close to theoretically superior "full information" approaches that model the discrete responses directly, but are more computationally intensive especially in complex model settings (multiple factors such as in the present case, exogenous variables etc.; Christoffersson (1975), Forero and Maydeu-Olivares (2009)).

the unrotated solution $\mathbf{\Lambda}_{NR}$, that is simple and facilitates the substantive interpretation ("naming") of the factors.

To form the set of candidate rotations, I use rotation criteria commonly used in the literature to find simple loading matrices: quartimax, varimax, equamax, parsimax (which are all members of the same family specified by Crawford and Ferguson (1970)), minimisation of the entropy of the squared loadings (Jennrich (2004)), and the "tandem" criteria of Comrey (1967), which use the correlation matrix to find loading patterns where highly correlated items have high loadings on the same factor and lowly correlated items do not have high loadings on the same factor. Across the rotations found by these criteria, and including the non-rotated loading matrix in the assessment, I judge a rotation to be simple if the spread of high loadings is even across the factors and if there are few negative loadings and cross-loadings (high loadings on more than one factor).

I then name each factor from the simplest rotated loading matrix to correspond to a broad business function which appears judgementally to best capture the items with the highest loadings on that factor. Statistically, the items that load highly on one factor are the ones that "move together" with that factor in the sample. Substantively, I interpret them as practices that tend to be undertaken by firms expressing a dynamic capability in a particular broad business function (say, "external collaboration", "marketing", "environmental scanning" etc.). I interpret these named factors as the substantive, orthogonal dimensions corresponding to major areas of variation in dynamic or ordinary capabilities exhibited by the sample firms. For dynamic capabilities in particular, this step gives substantive colour to the business functions that, empirically, appear to constitute sensing, seizing and transforming functions in the sample.

Finally, for use in my tests for the empirical importance of the capability factors in business and economic performance, I use the factor models with the chosen "simple" rotated loading matrices to derive factor score estimates of the levels of dynamic and ordinary capabilities factors for each firm-year in the sample. [5] The factor score estimates are included as explanatory variables in the panel regression and survival models described in the next two subsections.

[5] Two factor score estimation methods are common, the Thomson or "regression" method and the Bartlett method. In this work I use the Bartlett method on the basis that it produces unbiased estimates and is more suitable for providing estimates of the factor scores for a particular observation unit (a firm-year in this case; Bartholomew et al. (2009)). Repeating the analysis using the regression method produces very little difference in the results.

3.3 Defining and modelling firm performance

I define firm "success" using the following range of outcome variables: margins, sales, sales per full-time equivalent (FTE) employee, total factor productivity, average wages, FTE employment and longevity. These variables cover a number of aspects of profitability, a fundamental measure of firm success. Growth and expansion as measured by changes in certain of these variables are obvious markers of firm dynamism, which is a central part of the dynamic capabilities narrative. Sales/FTE is a proxy for labour productivity.

Although labour productivity, TFP, average wages and FTE employment are less direct measures of firm success compared to profitability and growth, they are of interest for economic performance, and one of the aims of this work is to test for the relevance of the dynamic capabilities framework for overall economic as well as firm performance.

Finally, longevity is perhaps the ultimate measure of a firm's ability to continue successfully operating over time. Firm survival is also a less ambiguous measure of firm performance than the other measures, since the investments in dynamic capabilities (like other firm actions) may take time to pay off, or even result in short-term dips in the other measures, before a long-term overall payoff becomes apparent. Firm survival as a success measure abstracts from these dynamic or over-time effects, which may require careful dynamic modelling to resolve in terms of the other success measures.

I use a range of variables to control for other influences on firm performance. I variously control for firm age, size, industry, foreign control and the capital/labour ratio (which is of particular relevance to average wages and sales/FTE), as well as for reference year, which picks up effects common to all firms in a given year such as macroeconomic conditions. I test different specifications in which age and size, and industry and year, are interacted to allow for broad-ranging heterogeneity in the influences on firm success (for example, interacting industry and year allows the industry fixed effects to vary by year).

Controlling for these variables makes it more tenable to interpret the estimates as measuring the association of dynamic capabilities (and ordinary capabilities) as a success factor of general relevance to all firms, rather than as something specific to, say, large or high-tech firms.

For all success measures except longevity, I use a panel regression approach to test for the explanatory power of the dynamic capabilities factors. For longevity, I estimate survival models. I set out these two methods below.

3.3.1 Panel regression models

I estimate panel regression models of the form

$$X_{it} = \alpha + \sum_{r=1}^{k^{DC}} \beta_r F_{r,it}^{DC} + \sum_{s=1}^{k^{OC}} \gamma_s F_{s,it}^{OC} + \sum_{j=1}^{J} \delta_j Z_{j,it} + \epsilon_{it} \tag{3.2}$$

where, for firm i in year t:

X_{it}	= outcome variable of interest, in levels and changes or growth rates for margins, sales/FTE, TFP and average wages, and growth rates for sales and employment.
$F_{r,it}^{DC}$	= dynamic capabilities factor j
$F_{s,it}^{OC}$	= ordinary capabilities factor j
$Z_{j,it}$	= control variable j
$\alpha, \beta_r, \gamma_s, \delta_j$	= parameters to be estimated
ϵ_{it}	= a random error term.

with $t = 2005, 2009, 2013, 2017$, reflecting the reference years for the four BOS waves from which I derive the measures of capabilities. (Changes or growth rates of the dependent variables, where applicable, are still calculated as annual movements, i.e. from year $t-1$ to t.)

Both dynamic capabilities and ordinary capabilities factors enter as explanatory variables in the regression model 3.2. This recognises that the dynamic capabilities framework discusses both doing things right, and doing the right thing (over time), are important for performance.

The parameters of interest in this equation are the β_j and, to a lesser extent, the γ_j. The dynamic capabilities framework predicts that the β_j and the γ_j are all positive, i.e. that firms with higher levels of dynamic or ordinary capabilities should be more successful, all else equal.

In the analysis and interpretation, I follow typical practice and assume that the error process

$$\epsilon_{it} = a_i + u_{it} \tag{3.3}$$

where

a_i	= a time-invariant, unobserved influence on performance allowed to vary across firms
u_{it}	= a random error term assumed to be distributed $N(0, \Omega)$.

I alternately use random-effects (RE), fixed-effects (FE) and between-effects (BE) estimators to estimate the parameters of the model 3.2, and interpret them based on whether or not a_i is assumed to be correlated with the observed explanatory variables. I assume u_{it} to be uncorrelated over time (I include year dummies in all panel regressions). In all panel regressions, I discard the top and bottom 1% of dependent variable observations, to reduce the effect of extreme observations. These are present for some firm years due to phenomena such as sales or employment changing around a very low base, or possible discontinuities such events as mergers, acquisitions or branch closures.

I impose structure on Ω to allow for standard errors clustered by firm to account for the repeated measures of the firms, but otherwise restrict the between-firm correlations of u_{it} to be zero.

3.3.2 Survival models

I model firm longevity using survival models, in which the instantaneous rate of failure at time t after birth

$$h(t) = \frac{f(t)}{S(t)} \tag{3.4}$$

where $S(t)$ is the probability of survival beyond t and $f(t)$ is the PDF of $F(t) = 1 - S(t)$, the probability of not surviving beyond t. $h(t)$ is often modelled in "proportional hazard" form, which corresponds to

$$h(t) = h_0(t)e^{\nu+X} \tag{3.5}$$

where in the present case

$$X = \sum_{r=1}^{k^{DC}} \eta_r F_{r,it}^{DC} + \sum_{s=1}^{k^{OC}} \zeta_s F_{s,it}^{OC} + \sum_{j=1}^{J} \omega_j Z_{j,it} \tag{3.6}$$

h_0 is the "baseline" hazard and is scaled by the same variables in X as in the panel regression models. When the model is written in hazard ratio form as above, the dynamic capabilities framework predicts that the $\eta_r < 1$ (and that the $\zeta_s < 1$), i.e. that a firm with high dynamic capabilities faces a lower hazard, all else equal.

Survival models in hazard ratio form are often estimated using Cox regression, which is convenient because it does not require any assumption about the underlying probability of survival function $S(t)$. I use Cox regression as well as parametric hazard ratio models alternately assuming exponential, Weibull and Gompertz survival probability distributions. I also use survival models alternately based on the lognormal, loglog and generalised gamma survival probability distributions, which produce results in the accelerated failure time metric. This metric measures the effect of the conditioning variables on the expected time to failure, which provides a more intuitive scale against which to look at the magnitude of the effects. The dynamic capabilities framework predicts that a firm with high dynamic and ordinary capabilities will exhibit a decelerated expected time to failure.

4 Data

4.1 Study sample

The study sample is based on firms surveyed by Stats NZ's Business Operations Survey (BOS), an official, compulsory, nationally representative annual survey of firm activities. The survey is modular, with different modules or topics that typically change each year, and some that are repeated at particular frequencies.[6]

Reflecting the focus of this study on activities related to innovation as described broadly by the dynamic capabilities framework, the BOS modules of interest are "Business Operations" (run annually), "Innovation" (two-yearly), and "Business Practices" (four-yearly), all of which contain items relating to the study focus. My sample is all firms sampled in the BOS in the years 2005, 2009, 2013 and 2017, which are, to date, all the available years in which all three modules were run.

The sample frame for those years was all private enterprises with more than NZ$30,000 in annual sales and more than 5 employees, that have been operating for more than one year. For the BOS waves that I use, the population of firms within the sample frame was around 35,000. Each sample year that I use contains 5,000 - 7,000 firms.

Some of the firms are re-sampled by chance in different BOS waves, and larger firms are deliberately given a higher probability than chance of being re-sampled by Stats NZ's sampling procedures, to bolster the longitudinal content in the BOS data (Fabling and Sanderson (2016)).

The use of these four BOS waves results in an unbalanced panel structure, with around 14,000 firms sampled up to four times for a total of around 25,000 firm-year observations.

4.2 BOS items

As outlined in Section 3, I select around 120 BOS items for this study. All items appeared in some form in all four BOS waves used. [7] The essential wordings for the items selected into the dynamic capabilities group, which is the focus of this study, are shown in Appendix A, expressed for brevity in the form of statements, in some cases slightly summarized. Looking at the text of the items shows that the survey mostly asks about very specific activities, many of which are variations within a larger theme or business function. That granularity motivates aggregation in some form, such as factor analysis as set out here, to draw out more generalisable patterns.

[6]The Stats NZ website, www.stats.govt.nz, describes the BOS methodology in more detail.

[7]The vast majority had the same question text, but some had minor wording changes.

The table also shows item question numbers for the 2017 wave, with the alpha digit alongside indicating the module from which the question is drawn. [8] Roughly three quarters of the dynamic capabilities items are from the Business Practices module (B), roughly one quarter from Innovation (C), and a handful from Business Operations (A).

The distribution of reported number of practices and attitudes across both groups features an implausibly large spike of 336 observations (1.3% of the sample) reporting zero practices and attitudes. I treat these observations as unusable, reducing the maximum sample size for all subsequent quantitative work reported here to 25,230.[9] [10]

Using this slightly reduced sample of observations on the individual BOS items, on the whole, practices and attitudes in the dynamic capabilities group tended to be expressed (i.e. coded as 1) less frequently than those in the ordinary capabilities group. Median expression rates are about a quarter and two thirds respectively (Table 4.1).[11]. The variances of expression rates are similar, while the skews indicate a long right-hand tail of expression rates of dynamic capabilities items, and a long left-hand tail for ordinary capabilities items.

Table 4.1: Prevalence of practices and attitudes

	No. items	Mean	Std. dev.	Skewness
Dyn. cap. items	87	0.27	0.15	0.57
Ord. cap. items	41	0.61	0.17	-0.74

Table 4.2 shows the dynamic capabilities practices and attitudes expressed most and least often in the sample. The most frequently expressed practices and attitudes tended to be enduring practices and attitudes, while the least frequent tended to refer to activities conducted within particular reference periods.

4.3 Firm performance and control variables

I obtain all firm performance and control variable data from the Longitudinal Business Database (IBULDD 2019). All time series variables are available at the annual frequency and are as constructed and documented by Fabling and Maré (2019), except for the age, size and foreign

[8]The modules are consistent across waves, but in a small number of cases the question numbers are different.

[9]This count and the previous one, and all other firm-year and firm counts in this paper, have been randomly rounded to base 3 in accordance with Stats NZ confidentiality procedures.

[10]These observations could reflect the respondent marking “No” or “N/A” for all questions in an attempt to complete the compulsory survey as quickly as possible.

[11]The table shows descriptive statistics calculated over all firm-year observations, excluding the 336 observations in which zero practices or attitudes were reported. All observation counts have been random rounded to base 3.

Table 4.2: Most and least prevalent dynamic capabilities practices and attitudes

Item	**Preval. (%)**
Top 5	
C0203 Views flexibility as important for strategy	88
C3400 Actively encourages non-managerial staff to suggest improvements	85
C1800 Has formal information management system	84
C2302 Identifies risks/opportunities from changes in market conditions	80
C0601 Often incorporates customer requirements in developing goals	78
Bottom 5	
B2341 Had cooperative relationship with NZ research institute in last 2 yrs	3
B2511 Engaged in cooperative arrangements for other reasons in last 2 yrs	3
B2508 Engaged in cooperative arrangements to access finance in last 2 yrs	2
C2104 Systematically compared perf. with diff-ind. bus. x-NZ last 2 yrs	1
B2342 Had coop. relationship with overseas research institute in last 2 yr	1

ownership dummy variables. The time series and longevity variables are defined as follows, with Fabling and Maré (2019)'s variable names in *italics*, except where indicated.

$$\textbf{Sales} = go\_nom$$

$$\textbf{FTE employment} = fte$$

$$\textbf{Average wages} = \frac{total\_gross\_earn}{e^{lnL}}$$

$$\textbf{Margins} = \frac{go\_nom}{total\_gross\_earn + M\_nom + K\_nom}$$

$$\textbf{Total factor productivity (TFP)} = mfp\_go\_cd, mfp\_go\_tl.$$

$$\textbf{Capital/labour ratio} = lnK - lnL.$$

Dummies and other categorical variables are defined as follows.

Age: dummies for startup (<2 years old), young (2-10), mid-age (10-20) and old (20+), derived from *birth_date* in the Longitudinal Business Frame.

Size: dummies for small (6-19 rolling mean employment (RME)), medium (20-99 RME) and large (100+ RME), derived from *rme* in the Business Operations Survey.

Industry: ANZSIC06 industry as recorded in the Business Operations Survey.

Foreign-owned: dummy = 1 if Question A1201 in the 2017 BOS or equivalent question in other waves, about the foreign-ownership percentage, was answered 50% or greater.

For **Longevity**, survival data are derived from *birth_date* and *cease_date* from the Longitudinal Business Frame. For the survival analysis, I align the episodes of firm experience (within which firms may die or not die) with the four-yearly frequency of measurement of the BOS items and dynamic capabilities factors derived therefrom. Each firm's observation values for the conditioning variables from a given BOS measurement year are set to persist for the period following that year until the next available BOS measurement year for that firm.

All data analysis was run in Stata 16.

5 Results

5.1 Factor modelling

Analysis of the item tetrachoric correlation matrices for the dynamic capabilities and ordinary capabilities items suggests that both groups of items are at least moderately suitable for factor modelling, with the ordinary capabilities group a little more suitable. Overall Kaiser-Meyer-Olkin (KMO) statistics are 0.64 and 0.84, respectively (Table 5.1).

Table 5.1: Suitability of item groups for factor analysis

	Median	mean	std. dev.
Dynamic capabilities (p=87)			
Tetrachoric correlations	0.30	0.32	0.16
Squared multiple correlation coefficients	0.84	0.81	0.15
Anti-image absolute correlations	0.16		
Kaiser-Meyer-Olkin statistic: 0.64			
Ordinary capabilities (p=41)			
Tetrachoric correlations	0.25	0.27	0.17
Squared multiple correlation coefficients	0.68	0.64	0.17
Anti-image absolute correlations	0.05		
Kaiser-Meyer-Olkin statistic: 0.84			

Pairwise item tetrachoric correlations are centered around 0.3 for both groups.[12] The dynamic capabilities group shows fairly high squared multiple correlation coefficients centred on about 0.8, indicating that the items are able to explain a substantial amount of each other's variance (less so for the ordinary capabilities group, at 0.6). However, the dynamic capabilities group shows mostly higher anti-image correlations (median 0.16 vs. 0.05), which is consistent with the lower overall KMO statistic for that group.

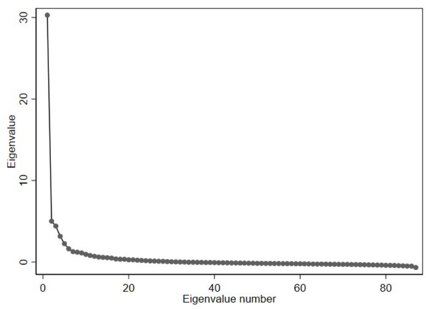
[12]For each group, most tetrachoric correlations are about 0.1 to 0.2 higher than the corresponding Pearson correlations.

5.1.1 Choosing k

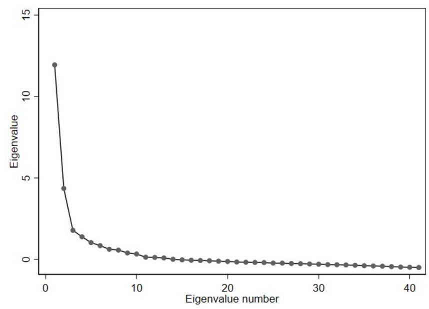
The kinks in the scree plots derived from modelling of the correlation matrices using the iterated principal factors (IPF) method suggest a 5-factor model for the dynamic capabilities group and a 2-factor model for the ordinary capabilities group (Figure 5.1).

Figure 5.1: Scree plots

(a) Dynamic capabilities group



(b) Ordinary capabilities group



I also tried to solve for k using ML in each case, but did not find an interior maximum across k in the dynamic capabilities group. The ML solution algorithm finds unacceptable Heywood cases[13] for $k > 5$ and lower likelihood values for $k < 5$ in the dynamic capabilities group. On this basis, I set $k = 5$ and $k = 2$ for the dynamic and ordinary capabilities factor models respectively.

Examining the eigenvalues shown in Figure 5.1 also shows that the factor models achieve very substantial dimension reduction. The five dynamic capabilities factors explain over 50% of the total variance in the 87 items[14] in the dynamic capabilities group, and the two ordinary capabilities factors explain almost 40% of that in the 41 items in the ordinary capabilities group.[15]

The bulk of estimated item idiosyncratic variance proportions ("uniqueness") lie between about a third and two thirds for the dynamic capabilities items, and between a half and four fifths for the ordinary capabilities items. The 5- and 2- factor models for the two item groups appear statistically satisfactory, on the basis of small residuals associated with the modelled correlation matrices (Table 5.2).

[13]Heywood cases are boundary solutions likely indicating some violation of the distributional assumptions needed for ML estimation.

[14]strictly speaking, the variance in the latent distributions assumed by the tetrachoric correlation estimation procedure to generate the 0/1 item realisations I derive from the actual BOS measures - see section 3.2

[15]The respective proportions of total variance explained by the first five principal components of the dynamic capabilities group, and the first two principal components of the ordinary capabilities group, are very similar.

Table 5.2: Factor models: residuals and item uniqueness

	LQ	Median	UQ
Dynamic capabilities group			
Correlation matrix model residuals	0.01	0.02	0.04
Item uniqueness	0.34	0.44	0.65
Ordinary capabilities group			
Correlation matrix model residuals	0.02	0.04	0.07
Item uniqueness	0.52	0.60	0.79

The dynamic capabilities factor model suggests that practices related to cooperation and innovation relating to improvements to internal efficiency are particularly strongly correlated with the other items in the group (i.e. they have high communality). The ordinary capabilities factor model attributes high communality to less specific practices and attitudes; the top five items by communality are difficult to disagree with as markers of "good" management practice (Table 5.3).

5.1.2 Choosing a rotation

Defining a loading greater than 0.4 in absolute value to be "high", the high-loading patterns across the factors under various rotations of the respective factor loading matrices suggest that the parsimax and varimax rotations produce the "simplest" loading patterns, in terms of the overall numbers of high loadings (desirably high), high cross-loadings (desirably low), and high negative loadings (desirably low). All other rotations involve a number of high negative loadings, which I place a high negative weight on, because a negative loading is difficult to interpret when the dynamic capabilities framework clearly suggests positive loadings on the factors. The minimum number of high loadings across the factors under the parsimax rotation is greater than that under the varimax rotation; on the other hand, the parsimax rotation also features a greater number of cross-loadings (Table 5.4).

On the basis that the difference on minimum number of high loadings is greater than that on number of cross-loadings, I choose the parsimax rotation in the analysis that follows.

5.1.3 Interpreting the (rotated) factors

Table 5.5 shows the top 10 loadings by factor under the parsimax rotation.

The first factor appears to capture external cooperation activities as a general functional area or dimension underlying the common variance of the items, given that all of the items in the top 10 by loading are about cooperation of various sorts. I therefore name this factor the "Cooperation" factor.

Table 5.3: Highest and lowest communality items

Item	Communality (%)
Dynamic capabilities practices and attitudes	
Top 5	
B1903 Innovated to reduce costs last 2y	84
B2505 Engaged in coop. arrangements to access mgmt. skills last 2y	83
B2507 Engaged in coop. arrangements to access work practices last 2y	83
B2405 Cooperated on training last 2y	82
B1904 Innovated to improve customer responsiveness last 2y	82
B1907 Innovated to improve safety last 2y	81
B2503 Engaged in coop. arrangements to access R&D last 2y	81
B1905 Innovated to increase mkt share last 2y	79
B1909 Innovated to reduce environmental impact last 2y	76
B1908 Innovated to reduce energy consumption last 2y	76
Bottom 5	
C0400 Plans 2 or more years ahead	23
A2400 Business's technology changed a lot in last year	23
C1800 Has formal information management system	22
C2103 Systematically compared perf. w/ diff.-ind. businesses last 2y	20
A0800 Invested in expansion in last year	19
C1100 Non-sales/marketing staff have contact with major custs	17
C1200 Measures customer satisfaction twice-yearly or more	17
C2104 Systematically compared perf. w/ diff.-ind. o/seas firms last 2y	16
C2901 Most staff participated in technical training in last yr	12
A2900 Acquired s/holding in or merged w/ NZ or o/seas firm in last yr	8
Ordinary capabilities practices and attitudes	
5 highest communality items	
C0202 Views quality as important for strategy	98
C0204 Views delivery as important for strategy	83
C0201 Views pricing as important for strategy	80
C2001 Focused on financial measures in assessing performance last 2y	58
C0902 Regularly communicates with employees about goals	53
5 lowest communality items	
C2700 Most staff are on a performance pay scheme	14
C3700 Has measures to reduce environmental impact	13
C1600 Non-managerial staff have contact with major suppliers	12
A2500 Equipment is technologically up to date	11
C0302 Focused on existing export markets last 2y	10

Table 5.4: Numbers of high loadings by rotation

	Dyn. cap. factor model			Ord. cap. factor model		
Rotation	Cross	x-Factor min.	Neg.	Cross	x-Factor min.	Neg.
parsimax	18	16	0	3	9	0
varimax	12	8	0	3	9	0
quartimax	23	3	0	3	7	1
equamax	21	16	0	7	14	0
unrotated	7	0	12	8	18	0
entropy	23	3	0	3	5	1
tandem1	21	3	0	0	0	4
tandem2	21	16	0	7	14	0

Table 5.5: Dynamic capabilities factor model: Top 10 loadings by factor, parsimax rotation

Item	Loading
Dynamic capabilities items	
Factor 1	
B2507 Engaged in cooperative arrangements to access work practices last 2y	0.85
B2505 Engaged in cooperative arrangements to access management skills in last 2	0.84
B2405 Cooperated on training last 2y	0.84
B2501 Engaged in cooperative arrangements to share costs in last 2 yrs	0.76
B2508 Engaged in cooperative arrangements to access finance in last 2 yrs	0.74
B2510 Cooperated for access to new suppliers last 2y	0.70
B2504 Engaged in cooperative arrangements to access production processes last 2y	0.69
B2502 Engaged in cooperative arrangements to spread risk in last 2 yrs	0.68
B2503 Engaged in cooperative arrangements to access R&D in last 2 yrs	0.64
B2402 Cooperated on production last 2y	0.64
Factor 2	
B1409 Changed marketing strategies to support innovation in last 2 yrs	0.71
B1404 Implemented new strategy or management to support innovation last 2y	0.71
B1405 Restructured organisation to support innovation in last 2 yrs	0.67
B1200 Introduced new sales/marketing methods to increase product appeal in last	0.64
B1407 Marketed introduction of new products to support innovation last 2y	0.63
B1410 Trained employees to support innovation last 2y	0.61
B1000 Introduced new organisational/managerial processes in last 2 yrs	0.59
B1402 Acquired IT to support innovation last 2y	0.58
B1408 Did market research to support innovation last 2y	0.58
B1904 Innovated to improve customer responsiveness in last 2 yrs	0.57
Factor 3	
B1907 Innovated to improve safety last 2y	0.85
B1908 Innovated to reduce energy consumption last 2y	0.83
B1909 Innovated to reduce environmental impact last 2y	0.81
B1903 Innovated to reduce costs last 2y	0.74
B2009 Found industry organisations an important source of information/ideas for	0.61
B1904 Innovated to improve customer responsiveness in last 2 yrs	0.58
B2004 Found suppliers an important source of information/ideas for innovation in	0.57
B2006 Found advisors/consultants/banks/accountants an important source of inform	0.53
B2008 Found conferences an important source of information/ideas for innovation	0.53
B2007 Found books/internet an important source of information/ideas for innovati	0.51
Factor 4	
A0900 Did R&D in last yr	0.71
A2300 Entered new export markets in last yr	0.66
B0300 Introduced new products last 2y	0.62
B1701 Started but didn't finish a new product development in last 2 yrs	0.62
C0304 Focused on new export market last 2y	0.60
B2404 Cooperated on prototyping last 2y	0.60
B2503 Engaged in cooperative arrangements to access R&D in last 2 yrs	0.59
B2312 Had cooperative relationships with overseas suppliers in last 2 yrs	0.54
B1906 Innovated to exploit new market opportunities in last 2 yrs	0.53
B2341 Had cooperative relationship with NZ research institute last 2y	0.50
Factor 5	
C2302 Identifies risks/opportunities from changes in market conditions	0.83
C2304 Identifies risks/opportunities from changes in competitors	0.79
C2303 Identifies risks/opportunities from changes in skill availability	0.68
C2301 Identifies risks/opportunities from technology	0.68
C2200 Monitors competitors' products closely	0.64
C2305 Identifies risks/opportunities from changes in regulations	0.62
C2005 Innovation was a focus of business performance assessment last 2y	0.55
C0601 Often incorporates customer requirements in developing goals	0.55
C3400 Actively encourages non-managerial staff to suggest improvements	0.53
C0203 Views flexibility as important for strategy	0.51

Half of the second factor's top 10 highest-loading items are about marketing, with another three and arguably the remaining two relating to internal restructuring to support innovation. I name the second factor "Marketing+restructuring".

The third factor does not seem to have a clear theme, but appears to be about internal efficiency and attention to environmental and health and safety issues, if the items measuring openness to information from suppliers, banks and conferences are interpreted as relating to operational improvements. I name the third factor "ESG + internal efficiency", noting that there is no item relating to governance in the top 10 (and indeed governance practices are hardly examined in the BOS).

The top 10 highest-loading items in the fourth factor clearly relate to exporting and other international activities, as well as to the seeking of expertise in the form of R&D, new product development and interaction with research institutions. I name the fourth factor "Exporting and expertise-seeking".

The fifth factor's top 10 highest-loading items seem related to environmental scanning, with at least five of the items about risks and opportunities and external monitoring. I name this factor "Situational awareness".

The parsimax rotation of the loading matrix for the ordinary capabilities factor model also seems reasonably interpretable in terms of broad business functions (Table 5.6). The first factor appears to be about HR management, while the second factor seems most related to operational or process quality. I name them accordingly.

The five dynamic capabilities factors appear about equally important in capturing the common variance in the respective items (Table 5.7). Of the ordinary capabilities factors, the human capital management factor explains somewhat more of the common variance in the respective items than the process management factor.

Naming and interpreting the factors is obviously a somewhat subjective exercise and requires the judgemental extraction of "themes" from the text of the high-loading items. That caveat noted, the named dynamic capabilities factors in the present work, and their expressions in the form of specific business activities, can be linked substantively to the broader concepts of "sensing", "seizing" and "transforming" discussed in the dynamic capabilities framework as essential components of dynamic capabilities. For example, situational awareness is clearly related to sensing, while cooperation, marketing and expertise-seeking are about seizing, and restructuring is part of transformation. The emergence of the more specific underlying functions - which are orthogonal by construction - from the factor analysis suggests that the dynamic capabilities framework has some relevance to the way in which business activities at the most granular level are organised in practice.

The dynamic capabilities framework discusses dynamic capabilities as a resource that firms can develop over time. In my sample, about a third of the variance of the factor score estimates derived from the factor models is variance within firms (i.e. over time) and two-thirds between firms (i.e. across firms).

5.2 Dynamic and ordinary capabilities, and firm success

Of all the success measures, whether in contemporaneous levels or in growth rate/change terms and all entered contemporaneously, the dynamic capabilities factors had the most convincing explanatory power for sales growth and employment growth. In panel regression models of these two dependent variables, coefficients on all five dynamic capabilities factors were statistically significant, with the positive sign predicted by the dynamic capabilities framework. This result was consistent across most of the estimators and specifications I used.

Looking first at sales growth, as a fairly straightforward measure of firm success, Table 5.8 shows the estimates across a range of estimators for the sales growth regression model. The fourth column in Table 5.8 shows OLS estimates of the regression model 3.2 shown in Section 3. The OLS estimator is consistent if the unobserved time-invariant firm-specific effect a_i in the error process equation 3.3 is zero. Because this condition is unlikely to be true, I use random effects (RE), fixed effects (FE) and between effects (BE) estimators also. The third column shows the RE estimates with the same set of dummies as the fourth column. The estimates are very similar to the OLS estimates. RE estimates are consistent and more efficient than OLS if the a_i are uncorrelated with the included variables, given the other assumptions about the terms in equation 3.2.

The first and second columns show the effect on the RE estimates if the age-size or foreign ownership dummies are excluded. The estimates are again very similar.

The fifth column shows the estimates using the FE estimator, which uses the within-firm (across time) variation in the data only and hence is not dependent on the properties of the a_i for consistency, though there is a loss of efficiency from ignoring the across-firm variation. Using the FE estimator, the dynamic capabilities factors have no explanatory power for contemporaneous sales growth. This could reflect that there are lags before changes in dynamic capabilities for a given firm have detectable positive effects on sales growth, as argued in Section 3.

Finally, the sixth column shows the estimates using the BE estimator. This estimator performs a least-squares regression using the time-averages of the observations for each firm, reducing the regression model in effect to a pure cross-section across firms. The BE estimates are of higher magnitudes than the RE estimates, suggesting that the within-firm variation in this setting may simply be adding noise, consistent with the insignificant FE estimates. The BE estimates of the coefficients on the dynamic capabilities factors are quite substantial, at 1-2 percentage points higher annual sales growth for every 1 standard deviation increase in factor scores. Similarly to the RE estimator though, the BE estimator will be inconsistent if the a_i are correlated with the included explanatory variables.

A Hausman specification test for difference between the RE and FE estimates strongly rejects the null that there is no difference. This is evidence that the a_i are correlated with the included variables, which would mean the RE and BE estimators are inconsistent. This places a clear caveat on the apparently strong significance and substantial coefficient estimates obtained using across-firm variance.

Table 5.6: Ordinary capabilities factor model: Top 10 loadings by factor, parsimax rotation

Item	Loading
Factor 1	
C0902 Regularly communicates with employees about goals	0.70
C0700 Has clear vision for the future	0.69
C2006 Focused on HR measures in assessing performance last 2y	0.68
C2600 Conducted performance review for most employees last year	0.68
C2500 Evaluated job satisfaction for most employees last yr	0.67
C3000 Systematically assesses training needs	0.65
C0800 Promotes company values to employees	0.62
C0901 Regularly communicates with employees about plans	0.62
C1900 Regularly assesses achievement of goals	0.59
C0501 Plans are developed through formal process	0.58
Factor 2	
C0202 Views quality as important for strategy	0.98
C0204 Views delivery as important for strategy	0.90
C0201 Views pricing as important for strategy	0.89
C0301 Focused on existing domestic markets last 2y	0.64
C3200 Assesses quality of goods before delivery	0.61
C2001 Focused on financial measures in assessing performance last 2y	0.58
C3300 Non-manager staff are encouraged to identify problems in goods or processe	0.57
C2002 Focused on costs in assessing performance last 2y	0.47
C2004 Focused on quality in assessing performance last 2y	0.44
C2003 Focused on operational measures in assessing performance last 2y	0.40

Table 5.7: Proportion of common variance explained by each factor

	Proportion
Dynamic capabilities	
Factor	
"Cooperation"	0.22
"Marketing+Restructuring"	0.22
"ESG+Internal efficiency"	0.20
"Exporting+Expertise-seeking"	0.19
"Situational awareness"	0.17
Ordinary capabilities	
Factor	
"Human capital management"	0.58
"Process management"	0.42

Table 5.8: Dep. var.: Annual change in log sales

Explanatory variable	RE	RE	RE	OLS	FE	BE
	Estimator					
Dynamic capabilities factor score						
“Cooperation”	0.008***	0.007**	0.007**	0.007***	0.000	0.014***
“Marketing+restructuring”	0.013***	0.010***	0.010***	0.011***	0.001	0.016***
“ESG+Internal efficiency”	0.008***	0.007**	0.007**	0.007**	0.002	0.011***
“Exports/expertise-seeking”	0.006*	0.006**	0.006**	0.006**	0.000	0.009**
“Situational awareness”	0.006*	0.007*	0.007*	0.007*	0.001	0.011**
Ordinary capabilities factor score						
“Human capital management”	0.002	0.000	0.001	0.000	0.004	-0.003
“Process management”	0.001	0.001	0.001	0.000	0.003	-0.001
capital/labour ratio	-0.003	0.002	0.002	0.002	-0.004	0.003
Dummy variables						
Industry-year (19x4)	Yes	Yes	Yes	Yes	Yes	Yes
Age-size (4x3)		Yes	Yes	Yes	Yes	Yes
Foreign-owned			-0.014*	-0.018**	0.024	-0.024**
N			15507			
R^2	0.036	0.078	0.079	0.079	0.069	0.109

Results for the FTE employment growth regression model were just as strong as for sales growth (Table 5.9). For brevity I show only the models with all dummies, estimated by RE, FE and BE estimators. The RE and BE coefficient estimates for the dynamic capabilities factors are significant and substantial (1-3 percentage points higher employment growth for every 1 standard deviation increase in factor scores). Interestingly, the FE estimates of the coefficients on the "Marketing+restructuring" and the "Exports+Expertise-seeking" factors are significant, but less so than the RE and BE estimates, and of smaller magnitude.

Table 5.9: Dependent variable: annual change in log FTE employment

	Estimator		
Explanatory variable	RE	FE	BE
Dynamic capabilities factor score			
"Cooperation"	0.005**	0.000	0.012***
"Marketing+restructuring"	0.016***	0.008**	0.024***
"ESG+Internal efficiency"	0.006***	0.000	0.013***
"Exports+expertise-seeking"	0.009***	0.006*	0.013***
"Situational awareness"	0.006*	0.000	0.013***
Ordinary capabilities factor score			
"Human capital management"	-0.001	0.003	-0.007*
"Process management"	0.002	0.007*	-0.005
capital/labour ratio	-0.002	-0.026***	0.001
Dummy variables			
Industry-year	Yes	Yes	Yes
Age-size	Yes	Yes	Yes
Foreign-owned	Yes	Yes	Yes
Constant	Yes	Yes	Yes
N	15489	15489	15489
R^2	0.116	0.101	0.154

The positive association of the dynamic capabilities factors with sales growth raises the question of the mechanism underlying the association. The positive association with employment growth suggests that sales growth through adding labour is one of the relevant mechanisms. The other two possibilities are increased productivity and higher prices. The results for growth in sales per FTE (Table 5.10), which should capture productivity and pricing effects, suggest that they are not part of the story. The coefficient on the "Marketing+restructuring" factor is the only one significant, and it has the wrong sign.[16]

The dynamic capabilities coefficient estimates (not shown) from regressions models of the changes in margins and in total factor productivity (both the Cobb-Douglas and the translog measures constructed

[16]Participants at the VUW School of Government and School of Economics and Finance brown bag seminars where I presented work-in-progress for this paper will have seen panel regression model results for "growth in sales/FTE" that showed significant coefficients on the dynamic capabilities factors. These results involved a coding mistake such that what I showed was actually results for growth in sales, as reported here.

Table 5.10: Dependent variable: annual change in log sales/FTE

	Estimator		
Explanatory variable	RE	FE	BE
Dynamic capabilities factor score			
“Cooperation”	-0.002	-0.003	0.000
“Marketing+restructuring”	-0.008***	-0.007*	-0.009***
“ESG+Internal efficiency”	-0.001	0.001	-0.003
“Exports+expertise-seeking”	-0.004*	-0.005	-0.004
“Situational awareness”	-0.002	0.001	-0.004
Ordinary capabilities factor score			
“Human capital management”	0.003	0.002	0.005
“Process management”	0.001	0.000	0.003
capital/labour ratio	0.005*	0.022**	0.005*
Dummy variables			
Industry-year	Yes	Yes	Yes
Age-size	Yes	Yes	Yes
Foreign-owned	Yes	Yes	Yes
Constant	Yes	Yes	Yes
N	15447	15447	15447
R^2	0.021	0.03	0.032

by Fabling and Maré (2019)) are also not significant, suggesting more directly that increased productivity and better pricing are not a major part of the mechanism by which dynamic capabilities are associated with sales growth in the sample.

Although I do not find evidence for an association between the dynamic capabilities factors and growth in sales/FTE, the RE and BE estimated coefficients on the “Exports+expertise-seeking” and (less so) the “Situational awareness” factors are positively significant in the regression model of the *level* of sales/FTE (Table 5.11). Estimated coefficients on the dynamic capabilities factors are not significant in the model of the level of margins, suggesting that the association with the level of sales/FTE is related to productivity rather than pricing. Having said that, estimates of the model for the level of TFP (not shown) did not suggest any relationship with the dynamic capabilities factors.

Consistent with the productivity (level) channel being relevant, the RE and BE estimates of the coefficient on the “Exports+expertise-seeking” factor are positive and significant in the model of average wages (Table 5.12). RE and BE estimates of the coefficient on the “Marketing+restructuring” factor are also positive and significant, although curiously the BE estimate of the coefficient on “ESG+internal efficiency” is significant with the wrong sign.

Finally, in the survival models, the “Situational awareness”, “Exporting + expertise-seeking” and “Cooperation” dynamic capabilities factors were significantly associated with a reduction in the instantaneous rate of failure. The hazard ratios associated with these factors were significantly

Table 5.11: Dependent variable: log sales/FTE

	Estimator		
Explanatory variable	RE	FE	BE
Dynamic capabilities factor score			
"Cooperation"	0.002	0.000	0.001
"Marketing+restructuring"	-0.005	-0.008	-0.007
"ESG+Internal efficiency"	0.003	0.005	-0.010
"Exports/expertise-seeking"	0.016***	-0.002	0.042***
"Situational awareness"	0.010*	0.001	0.020*
Ordinary capabilities factor score			
"Human capital management"	0.026***	0.010	0.042***
"Process management"	0.007	0.008	-0.003
capital/labour ratio	0.277***	0.183***	0.310***
Dummy variables			
Industry-year (19x4)	Yes	Yes	Yes
Age-size (4x3)	Yes	Yes	Yes
Foreign-owned	0.137***	0.004	0.202***
N		17187	
R^2	0.447	0.209	0.467

Table 5.12: Dependent variable: log average wages

	Estimator		
Explanatory variable	RE	FE	BE
Dynamic capabilities factor score			
"Cooperation"	0.002	0.002	-0.002
"Marketing+restructuring"	0.006***	0.003	0.013***
"ESG+Internal efficiency"	-0.001	0.000	-0.012***
"Exports/expertise-seeking"	0.008***	0.000	0.030***
"Situational awareness"	0.002	-0.001	0.004
Ordinary capabilities factor score			
"Human capital management"	0.014***	0.003	0.041***
"Process management"	0.000	0.000	-0.009*
capital/labour ratio	0.053***	0.022***	0.073***
Dummy variables			
Industry-year (19x4)	Yes	Yes	Yes
Age-size (4x3)	Yes	Yes	Yes
Foreign-owned	0.076***	0.000	0.179***
N		17223	
R^2	0.492	0.751	0.517

below 1, and the time ratios significantly greater than 1 (Table 5.13). [17]

The coefficient magnitudes are meaningful, representing an increase in expected time to failure of 6-8% depending on the factor. The median longevity in the sample is around 40 years, so that increase in the expected time to failure is equivalent to about two or three years for the median firm.

Results were very similar using the Weibull, Gompertz, loglog, lognormal and generalised gamma distributions for the probability of survival (not shown).

Table 5.13: Survival models

	Cox	Exponential	
	Hazard ratios		Time ratios
Explanatory variable	(1)	(2)	(3)
Dynamic capabilities factor score			
"Cooperation"	0.945*	0.943*	1.060*
"Marketing+restructuring"	1.003	0.991	1.009
"ESG+Internal efficiency"	0.962	0.958	1.044
"Exporting+Expertise-seeking"	0.925**	0.924***	1.082***
"Situational awareness"	0.919**	0.921**	1.086**
Ordinary capabilities factor score			
"Human capital management"	1.018	1.014	0.986
"Process management"	1.012	1.013	0.987
capital/labour ratio	0.835***	0.849***	1.177***
Dummy variables			
Foreign owned	0.914	0.908	1.101
Size	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Constant	No	Yes	Yes
Observations N		27645[a]	
Firms		9966	
Failures		2787	

[a]All counts have been independently randomly rounded to base 3 (RR3).

6 Discussion

In the work documented in this paper, I set out to open up the black box of firm innovation, with the aim of better understanding the relation of innovation and related practices to firm and economic performance. I used the recently established "dynamic capabilities" framework to guide the selection of data on over a hundred highly specific practices related to innovation and efficiency. Using factor analysis, I modelled the practices as observable manifestations of a smaller number of latent, broader business dynamic and ordinary capabilities, which I named based on the

[17]According to the Grambsch and Therneau (1994) global test, the proportional-hazard assumption is acceptable for the models.

specific practices with the highest loadings on the latent factors. I then used the modelled dynamic and ordinary capabilities factors as explanatory variables in panel regression and survival models of a range of firm and economic success measures. The work used a large dataset from a comprehensive, high-quality, nationally representative survey of firms, going beyond previous studies both methologically and conceptually.

6.1 Overall findings

I find reasonably compelling evidence overall that there is a non-trivial association between certain specific business practices relating to dynamic capabilities, and firm and economic performance measures. Factor models are able to represent the common component of the variance of the specific practice items in a highly parsimonious and statistically satisfactory manner. Rotation of the item loading matrix is able to produce a simple factor structure with orthogonal factors related to the broad business functions of external collaboration; marketing and internal restructuring; ESG and internal efficiency; exports and expertise-seeking; and situational awareness. These functions can in turn be mapped onto the key broader concepts of sensing, seizing and transformation in the dynamic capabilities framework, which are claimed by the framework to be critical determinants of persistent business success.

The econometric results suggest that, although the five dynamic capabilities factors explain roughly equal amounts of the total variance in the observable practice items, their explanatory power varies considerably across the firm success measures examined. They are all relevant for sales and employment growth, but none explains changes or growth rates in margins, sales per FTE or TFP. This suggests that the relationship of the dynamic capabilities factors, taken as a whole, with firm success in terms of dynamism and growth is to do with expansion driven by labour addition, rather than productivity improvement or better pricing.

Having said that, the results also suggest roles for particular factors in a more static sense of firm success and high performance. The "Exporting + expertise seeking" factor is relevant for the levels of sales per FTE and average wages, and for longevity also. The importance of exporting and international activities capabilities as a factor associated with a number of aspects of high performance is consistent with previous studies on exporting, skills, productivity, and international connections among New Zealand firms (e.g. Fabling and Sanderson (2013), Sin et al. (2014)).

The "Situational awareness" factor is strongly associated with greater longevity and, to a lesser extent, sales per FTE. This perhaps points to the sensing capability, in terms of the dynamic capabilities framework, as being the most general success factor of the three. Most, if not all, firms face demands to sense and react to external events even if they are not in the habit of changing their business models substantially in response.

Situations presenting the opportunity to seize and transform in order to shape markets proactively may be rarer, and relevant only to particular subclasses of firms.

The dynamic capabilities factors have the explanatory power outlined above in the presence of controls for ordinary capabilities factors, size, industry, foreign ownership and the capital/labour ratio, and where applicable, age and year. The pattern of findings was also robust to various changes in specification within both the factor modelling and the firm performance modelling steps. The significant positive association is found for both contemporaneous period-by-period success measures as modelled in the panel regressions, and for the over-time success measure of longevity.

This suggests that the dynamic capabilities framework has relevance to firms in general, even in a small country such as New Zealand with mostly small firms by global standards. The dynamic capabilities factors in general have stronger explanatory power for the success measures than the ordinary capabilities measures, consistent with the claim of the dynamic capabilities framework that it is dynamic, not ordinary, capabilities that are more important for enduring success.

The present work thus shows the relevance to business success of the sorts of innovation-related business practices examined by the dynamic capabilities literature. The findings provide clues to what may be inside the innovation black box typically invoked by endogenous growth models, particularly of the Schumpeterian variety. The findings could therefore strengthen endogenous growth modelling, taking it towards an explicit treatment of the complex territory of entrepreneurship and strategic management.

6.2 Limitations and further work

A limitation of the present work worth drawing out is that the panel regression results are based on estimators that use across-firm variance. The fixed effects (FE) estimator, that uses across-time (within-firm) variance only, did not detect any significant association between dynamic capabilities and contemporaneous performance variables, with the exception of a small and only mildly significant within-firm association between the "Marketing" and "Exports+expertise-seeking" factors and employment growth.

Notwithstanding the finding of significant, positive relationships across a number of firm success measures, which are generally robust to different model specifications that use the across-firm variance, the reliance on across-firm variance raises a concern about the consistency of the estimators, which relies on any excluded firm-level influences on performance being uncorrelated with the included explanatory variables. Hausman specification tests indicate that this assumption is questionable for the panel regression specifications used here, warranting caution in interpreting the magnitudes and significance levels. Consistency of the survival model estimators is likely also dependent on assumptions about the correlation between the included and excluded influences on longevity.

This underscores the point that inference about any causal mechanisms underlying the observed relationship between the dynamic and ordinary capabilities factors and firm performance requires careful use of credibly independent sources of variation in a regression designed to identify the parameters of interest.

Business practices, and hence the dynamic capabilities factors generated here, are almost certainly co-determined with firm performance, by a wide range of potential influences. A credible instrument for estimating the direct causal effect of dynamic capabilities on performance may thus be hard to find.

A causal role for dynamic capabilities in moderating firm responses to exogenous shocks may be easier to test for with observational data. Dynamic capabilities may strengthen firms' resilience to shocks arising from, for example, macroeconomic or sectoral fluctuations or natural disasters. They may also position firms to take better advantage of emerging positive opportunities, such as encountered during economic booms, to shape and create markets. The connection between ideas as a source of sustained growth, adaptation and business cycles is thus another relatively underdeveloped area of economics that may benefit from exploration through the lens of business practices and dynamic capabilities. Further work could fruitfully pick up this thread.

A moderation mechanism for dynamic capabilities suggests an econometric specification in which dynamic capabilities factors are interacted with a shock variable (say, global demand, world oil prices, etc.). If the shock variable is exogenous, then under certain conditions, the coefficients on the interaction terms may be consistently estimated by OLS or certain IV techniques (Bun and Harrison (2019), Nizalova and Murtazashvili (2016)). Further work could fruitfully pick up this thread.

Appendix A BOS items selected for dynamic capabilities group

Table A.1: BOS items selected for dynamic capabilities group

Dynamic capabilities items
A0800 Invested in expansion in last year
A0900 Did R&D in last yr
A2200 Developed new products or operational, managerial or organisational processes in last yr
A2300 Entered new export markets in last yr
A2400 Business's technology changed a lot in last year
A2900 Acquired shareholding in or merged with another NZ or overseas business in last yr
B0300 Introduced new products in last 2 yr
B0700 Introduced new operational processes in last 2 yr
B1000 Introduced new organisational/managerial processes in last 2 yr
B1200 Introduced new sales/marketing methods to increase product appeal in last 2 yr
B1401 Acquired machinery to support innovation in last 2 yr
B1402 Acquired IT to support innovation in last 2 yr
B1403 Acquired knowledge to support innovation in last 2 ys
B1404 Implemented new strategy or management to support innovation in last 2 yr
B1405 Restructured organisation to support innovation in last 2 yr
B1406 Designed to support innovation in last 2 yr
B1407 Marketed introduction of new products to support innovation in last 2 yr
B1408 Did market research to support innovation in last 2 yr
B1409 Changed marketing strategies to support innovation in last 2 yr
B1410 Trained employees to support innovation in last 2 yr
(continued)

Table A.1: (continued)

Dynamic capabilities items (continued)
B1601 Abandoned a new product development in last 2 yr
B1602 Abandoned a new operational process development in last 2 yr
B1603 Abandoned a new organisational process development in last 2 yr
B1604 Abandoned a new marketing development in last 2 yr
B1701 Started but didn't finish a new product development in last 2 yr
B1703 Started but didn't finish a new organisational process development in last 2 yr
B1704 Started but didn't finish a new marketing development in last 2 yr
B1903 Innovated to reduce costs in last 2 yr
B1904 Innovated to improve customer responsiveness in last 2 yr
B1905 Innovated to increase mkt share in last 2 yr
B1906 Innovated to exploit new market opportunities in last 2 yr
B1907 Innovated to improve safety in last 2 yr
B1908 Innovated to reduce energy consumption in last 2 yr
B1909 Innovated to reduce environmental impact in last 2 yr
B1910 Innovated to replace an obsolete product in last 2 yr
B2001 Found new staff an important source of info/ideas for innovation in last 2 yr
B2003 Found customers an important source of information/ideas for innovation in last 2 yr
B2004 Found suppliers an important source of information/ideas for innovation in last 2 yr
B2005 Found other businesses an important source of information/ideas for innovation in last 2 yr
B2006 Found advisors/consultants/banks/accountants an important source of information/ideas for innovation in last 2 yr
B2007 Found books/internet an important source of information/ideas for innovation in last 2 yr
B2008 Found conferences an important source of information/ideas for innovation in last 2 yr
B2009 Found industry organisations an important source of information/ideas for innovation in last 2 yr

(continued)

Table A.1: (continued)

Dynamic capabilities items (continued)
B2010 Found universities/polytechs an important source of information/ideas for innovation in last 2 yr
B2012 Found govt agencies an important source of information/ideas for innovation in last 2 yr
B2312 Had cooperative relationships with overseas suppliers in last 2 yr
B2322 Had cooperative relationships w/ other o/seas business in last 2 yr
B2341 Had cooperative relationship with NZ research institute in last 2 yr
B2342 Had cooperative relationship with overseas research institute in last 2 yr
B2402 Cooperated on production in last 2 yr
B2404 Cooperated on prototyping in last 2 yr
B2405 Cooperated on training in last 2 yr
B2501 Engaged in cooperative arrangements to share costs in last 2 yr
B2502 Engaged in cooperative arrangements to spread risk in last 2 yr
B2503 Engaged in cooperative arrangements to access R&D in last 2 yr
B2504 Engaged in cooperative arrangements to access production processes in last 2 yr
B2505 Engaged in cooperative arrangements to access management skills in last 2 yr
B2506 Cooperated for access to distribution channels in last 2 yr
B2507 Engaged in cooperative arrangements to access work practices in last 2 yr
B2508 Engaged in cooperative arrangements to access finance in last 2 yr
B2509 Cooperated for access to new markets in last 2 yr
B2510 Cooperated for access to new suppliers in last 2 yr
B2511 Engaged in cooperative arrangements for other reasons in last 2 yr
C0203 Views flexibility as important for strategy
C0205 Views innovation as important for strategy
C0303 Focused on new domestic market last 2 years
(continued)

Table A.1: (continued)

Dynamic capabilities items (continued)
C0304 Focused on new export market in last 2 yr
C0400 Plans 2 or more years ahead
C0601 Often incorporates customer requirements in developing goals
C0602 Often incorporates supplier requirements in developing goals
C1100 Non-sales/marketing staff have contact with major customers
C1200 Measures customer satisfaction twice-yearly or more
C1300 Works closely with customers to improve product
C1800 Has formal information management system
C2005 Innovation was a focus of business performance assessment in last 2 yr
C2101 Systematically compared performance with same-industry businesses in NZ in last 2 yr
C2102 Systematically compared performance with same-industry-businesses outside NZ in last 2 yr
C2103 Systematically compared performance with different-industry businesses in NZ in last 2 yr
C2104 Systematically compared performance with different-industry businesses outside NZ in last 2 yr
C2200 Monitors competitors' products closely
C2301 Identifies risks/opportunities from technology
C2302 Identifies risks/opportunities from changes in market conditions
C2303 Identifies risks/opportunities from changes in skill availability
C2304 Identifies risks/opportunities from changes in competitors
C2305 Identifies risks/opportunities from changes in regulations
C2901 Most staff participated in technical training in last yr

References

Aghion, P. (2017). Entrepreneurship and growth: Lessons from an intellectual journey. *Small Business Economics*, *48*(1), 9–24.

Aghion, P., & Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, *60*(2), 323–351.

Arrow, K. J. (1962a). The economic implications of learning by doing. *The Review of Economic Studies*, *29*(3), 155–173.

Arrow, K. J. (1962b). Economic welfare and the allocation of resources for invention. *The rate and direction of inventive activity: Economic and social factors* (pp. 609–626). Princeton University Press.

Barreto, I. (2010). Dynamic capabilities: A review of past research and an agenda for the future. *Journal of Management*, *36*(1), 256–280.

Barro, R. J., & Sala-i-Martin, X. (2004). *Economic growth, second ed.* MIT Press.

Bartholomew, D. J., Deary, I. J., & Lawn, M. (2009). The origin of factor scores: Spearman, Thomson and Bartlett. *British Journal of Mathematical and Statistical Psychology*, *62*(3), 569–582.

Bertrand, M., & Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, *118*(4), 1169–1208.

Bloom, N., & Van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *The Quarterly Journal of Economics*, *122*(4), 1351–1408.

Bollen, K. A., & Barb, K. H. (1981). Pearson's r and coarsely categorized measures. *American Sociological Review*, 232–239.

Bun, M. J., & Harrison, T. D. (2019). OLS and IV estimation of regression models including endogenous interaction terms. *Econometric Reviews*, *38*(7), 814–827.

Cass, D. (1965). Optimum growth in an aggregative model of capital accumulation. *The Review of Economic Studies*, *32*(3), 233–240.

Christoffersson, A. (1975). Factor analysis of dichotomized variables. *Psychometrika*, *40*(1), 5–32.

Comrey, A. L. (1967). Tandem criteria for analytic rotation in factor analysis. *Psychometrika*, *32*(2), 143–154.

Conway, P. (2018). Can the Kiwi fly? Achieving productivity lift-off in New Zealand. *International Productivity Monitor*, (34), 40–63.

Crawford, C. B., & Ferguson, G. A. (1970). A general rotation criterion and its use in orthogonal rotation. *Psychometrika*, *35*(3), 321–332.

Dinopoulos, E., & Syropoulos, C. (2007). Rent protection as a barrier to innovation and growth. *Economic Theory*, *32*(2), 309–332.

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: What are they? *Strategic Management Journal*, *21*(10-11), 1105–1121.

Fabling, R., & Maré, D. C. (2019). *Improved productivity measurement in new zealand's longitudinal business database*. Motu Working Paper 19-03.

Fabling, R., & Sanderson, L. (2013). Exporting and firm performance: Market entry, investment and expansion. *Journal of International Economics*, *89*(2), 422–431.

Fabling, R., & Sanderson, L. (2016). *A rough guide to New Zealand's Longitudinal Business Database*. Motu Working Paper 16-3.

Forero, C. G., & Maydeu-Olivares, A. (2009). Estimation of IRT graded response models: Limited versus full information methods. *Psychological Methods*, *14*(3), 275.

Grambsch, P. M., & Therneau, T. M. (1994). Proportional hazards tests and diagnostics based on weighted residuals. *Biometrika*, *81*(3), 515–526.

Green, R., Agarwal, R., Brown, P., Tan, H., & Randhawa, K. (2010). *Management matters: How does manufacturing measure up?* Ministry of Economic Development, New Zealand.

Grossman, G. M., & Helpman, E. (1991). Quality ladders in the theory of growth. *The Review of Economic Studies*, *58*(1), 43–61.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *The American Economic Review*, 984–1001.

Jennrich, R. I. (2004). Rotation to simple loadings using component loss functions: The orthogonal case. *Psychometrika*, *69*(2), 257–273.

Jones, C. I. (2019). Paul Romer: Ideas, nonrivalry, and endogenous growth. *The Scandinavian Journal of Economics*, *121*(3), 859–883.

Koopmans, T. C. (1963). On the concept of optimal economic growth. *Cowles Foundation Discussion Paper No. 163*.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R., & Griliches, Z. (1987). Appropriating the returns from industrial research and development. *Brookings Papers on Economic Activity*, *1987*(3), 783–831.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3–42.

Nelson, R. R. (1959). The simple economics of basic scientific research. *Journal of political economy*, *67*(3), 297–306.

Nelson, R. R., & Winter, S. G. (1973). Toward an evolutionary theory of economic capabilities. *The American Economic Review*, *63*(2), 440–449.

Ng, T. (2021). *Schumpeterian endogenous growth and dynamic capabilities: An under-researched nexus?* Paper prepared for New Zealand Association of Economists annual conference, June.

Nizalova, O. Y., & Murtazashvili, I. (2016). Exogenous treatment and endogenous factors: Vanishing of omitted variable bias on the interaction term. *Journal of Econometric Methods*, *5*(1), 71–77.

Nolan, P., Fraser, H., & Conway, P. (2018). Moving on from New Zealand's productivity paradox. *Policy Quarterly*, *14*(3), 3–9.

OECD. (2021). *R&d tax incentives: New zealand, 2021*. OECD.

Pearson, K. (1913). On the probable error of a coefficient of correlation as found from a fourfold table. *Biometrika*, *9*(1/2), 22–33.

Penrose, E. T. (1959). *The theory of the growth of the firm*. Oxford: Blackwell.

Ramsey, F. P. (1928). A mathematical theory of saving. *The Economic Journal*, *38*(152), 543–559.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5, Part 2), S71–S102.

Sanderson, L. (2022). *The evolution of management practices in New Zealand*. CEU Working Paper 22/03, MBIE, March.

Shu, P., Acemoglu, D., Stern, S., Romano, R., & Snover, L. (2012). *The long-term impact of business cycles on innovation: Evidence from the Massachusetts Institute of Technology*. MIT Working Paper.

Sin, I., Fabling, R., Jaffe, A., Maré, D., & Sanderson, L. (2014). *Exporting, innovation and the role of immigrants* (tech. rep.). Motu Economic and Public Policy Research.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*(1), 65–94.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312–320.

Swan, T. W. (1956). Economic growth and capital accumulation. *Economic Record*, *32*(2), 334–361.

Teece, D. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, *28*(13), 1319–1350.

Teece, D. (2017). Towards a capability theory of (innovating) firms: Implications for management and policy. *Cambridge Journal of Economics*, *41*(3), 693–720.

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533.

Williamson, O. E. (1999). Strategy research: Governance and competence perspectives. *Strategic Management Journal*, *20*(12), 1087–1108.

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic Management Journal*, *24*(10), 991–995.

Zollo, M., & Winter, S. G. (2002). Deliberate learning and the evolution of dynamic capabilities. *Organization Science*, *13*(3), 339–351.