Dynamic capabilities and firm resilience in the 2011 earthquake in Christchurch, New Zealand

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Abstract

I use firm-level data from New Zealand's official Business Operations Survey linked to administrative data to test whether firm "dynamic capabilities" – behaviours and practices related to change – improve firm adaptation and resilience in the face of a large shock, in the form of the devastating February 2011 Christchurch earthquake. I find that dynamic marketing and internal improvement capability factors helped construction sector firms outperform their peers in terms of sales and employment for some years after the earthquake, and that a dynamic marketing capability factor helped retailers outperform. These findings accord with the theoretical view that dynamic capabilities support long-term firm performance in situations of rapid change. This study goes beyond previous work by using a much larger, highly-granular sample representing the whole economy, focusing on longer-term impacts of dynamic capabilities on firm performance, and identifying dynamic capabilities effects using a natural experiment.

Keywords: dynamic capabilities, business practices, natural disasters

JEL Codes: D22, Q54, M21, O31

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1 Introduction

Large natural disasters present sudden, major business challenges to exposed firms (Tierney, 1997). Some businesses are able to cope with or exploit the disruption, swiftly resuming operations or repositioning themselves to take advantage of newly created opportunities, while others struggle or permanently close.

An effective business sector response to disasters is key to limiting the damage to lives and livelihoods and setting the foundations for recovery. A range of studies have examined business impacts and responses in the immediate months following major disasters, when the threat to economic security is most acute (e.g. Battisti and Deakins, 2017; Fabling et al., 2019). However, less attention has been paid to the specific organisational capabilities that enable firm survival and adaptation over the longer term (Cole et al., 2013; Uchida et al., 2014), perhaps because of the need to track firms over some years, which may be prohibitively costly. Yet sustained business sector recovery is necessary for the economy, and life in general, to return durably to normal.[1] It is worth knowing (both for firms and policymakers) if certain organisational capabilities make a difference to performance following a disaster, and if so, how.

In this paper, I address these questions by investigating the contribution of organisational "dynamic capabilities" (Eisenhardt and Martin, 2000; Teece et al., 1997) to longer-term firm performance outcomes following a major natural disaster in New Zealand. Following the literature, I define dynamic capabilities as capabilities relating to change (as opposed to "ordinary capabilities", which are related to the pursuit of static efficiency predicated on unchanging business circumstances). I measure dynamic capabilities at the firm level using the factor model strategy documented in Chapter 3 of Ng (2024). The factor model maps onto five underlying dimensions (latent factors) the co-movements in 87 observed diverse and granular business practices related to change, measured via an official survey of a nationally representive sample of firms, spanning 12 years from 2005 to 2017. I treat the factors as distinct dynamic capabilities in which the sample firms vary, and interpret the capabilities substantively on the basis of their correlation patterns (factor loadings) across the 87 practices.

Results reported in Chapter 4 of Ng (2024) showed that dynamic capabilities measured in this way are significantly positively associated with various measures of firm performance,

[1] An example of a study of medium-term firm performance following a typhoon is Okubo and Strobl (2021), which looked at industry, but not management capabilities, as the conditioning variable for post-shock firm performance. Basker and Miranda (2018) looked at firm survival following a hurricane, focusing on the role of financing conditions.

including survival, sales and employment growth, sales per employee and average wages paid. The associations could reflect either that dynamic capabilities cause better performance on these measures (the claim underlying the dynamic capabilities literature) or the reverse, that successful firms invest more in dynamic capabilities – or both. The first possibility is obviously a stronger basis on which to advocate investment in dynamic capabilities. In order to focus on that possibility, in this paper I exploit the natural experiment of the major earthquake in February 2011 that devastated the New Zealand city of Christchurch, with an accompanying large government response in the weeks and months immediately following. (Hereafter for brevity, I refer to the combination of events in the first few months following February 2011 as "the earthquake shock", treating the earthquakes themselves and the subsequent government response as a single shock.)

Many studies have looked at the immediate aftermath of impacts on firms and their responses in the months after a natural disaster (Basker and Miranda, 2018; Leiter et al., 2009), including the Christchurch earthquake (e.g. Fabling et al., 2019; Potter et al., 2015). Like the present study, Battisti and Deakins, 2017 looked at the earthquake's consequences for firms with explicit dynamic capabilities framing.[2] However, most of the studies in the disaster/firm literature tend to focus on a single sector, or use small, non-representative samples, over a relatively short period of a few months.[3] Often the literature examines specific business decisions such as reopening (e.g. LeSage et al., 2011). In contrast, I investigate performance on a range of dimensions, using nationally representative samples of firms from the construction/infrastructure (CI), manufacturing (MFG) and distribution/retail (DR) sectors, hundreds of which were exposed to the earthquake and which experienced the disruption in different ways.

Exploiting the longitudinal firm-level data available in New Zealand's Longitudinal Business Database (LBD), I compare by industry the longer-term performance of firms exposed to the earthquake shock to that of a matched group of unexposed firms. I test whether the level of any of the five dynamic capabilities in exposed firms made a difference to their performance after the earthquake. Separately for each industry, I measure performance in

[2] While there are a few studies that look explicitly at dynamic capabilities and responses to disasters, most are based on qualitative approaches taken with very small samples of firms from particular sectors or particular types (e.g. Mahto et al., 2022; Martinelli et al., 2018. Eriksson (2013)'s review of empirical research on dynamic capabilities generally found widespread methodological issues, including heavy reliance on data gathered from interviews with little attention to random sampling from a defined population of firms. Although such approaches may help develop concepts and ideas, the generalisability of findings based on such data is limited. Echoing this assessment, Arend and Bromiley (2009) and Harris and Yan (2019) argue for greater use of large representative samples and longitudinal data to help overcome these inferential limitations, as in this study.

[3] Dietch and Corey (2011) is one of the few looking at recovery over several years.

terms of survival probability, sales, employment and other outcomes for up to eight years following the earthquake.

The earthquake shock – a large, acute and localised event – provides a good test case for the investigating the causal role of dynamic capabilities in performance, for two reasons. First, many firms were affected at the same time, facing either sudden disruption or sudden opportunity, or both. Second, exposure to the shock can be reasonably presumed to be uncorrelated with time-varying variables that are relevant to performance but omitted. The exogeneity of the exposure allows more confident identification of the shock's effects on performance and whether they depend on dynamic capabilities, even if dynamic capabilities themselves are correlated with omitted variables (Bun and Harrison, 2019; Nizalova and Murtazashvili, 2016). The econometric results can therefore address effectively the question of whether the positive association of dynamic capabilities with performance reflects at least partly a causal mechanism running in the direction predicted by the dynamic capabilities perspective, that better capabilities help firms perform better after shocks.

The econometric model allows the post-shock performance of exposed firms to depend on their levels of pre-shock dynamic capabilities, up to 8 years (for survival) and 5 years (for other performance outcomes) after the shock. I estimate the models on a sample of firms with either 100% presence in Christchurch, or in one of four other major New Zealand cities ("100% single-city-only" firms). The Christchurch firms are defined as exposed and the others non-exposed. I match the groups of exposed and non-exposed firms so that the groups roughly match in terms of age and size distributions. The groupwise matching sharpens the contrast between the exposed and non-exposed groups of firms, thereby improving the likelihood of good estimates.[4]

I find that exposed CI firms with high levels of capability for *internal improvement* and *marketing strategy adjustment* immediately before the shock enjoyed substantially and persistently higher sales after the shock, compared to their exposed-firm peers. The effect magnitudes are not trivial. Exposed CI firms with 1 standard deviation higher-than-mean *internal improvement* capability had 57% higher sales in 2015, five years after the earthquake. Exposed CI firms with 1 standard deviation higher *marketing strategy adjustment* capability had 28% higher sales in 2015. CI firms with 1 standard deviation higher *external cooperation* capability had 32% higher employment in 2015.

[4]Fabling et al. (2019) is perhaps the most closely related study to this one, in that it used a similar difference-in-difference approach with careful matching, but looked at only the short term of five months and resolved dynamics at the monthly frequency. It did not include the influence of dynamic or ordinary capabilities.

Exposed DR firms with higher *marketing strategy adjustment* capability also performed better after the earthquake (27% higher sales in 2015 per 1 standard deviation higher capability).

I find little evidence that dynamic capabilities made a difference to performance outcomes for exposed MFG firms. Nor do I find evidence that dynamic capabilities affected the survival probability of exposed firms in any of the three industries. The latter result may reflect low statistical power, as there were few firm failures in either the exposed or unexposed groups in the post-shock period.

The paper's findings offer important insights for theory development in organisational resilience and adaptive capacity. They also provide useful evidence for firms and policymakers on the sorts of regular change-related business practices that can enhance business preparedness for disasters and recovery capacity after an event.

The rest of the paper proceeds as follows. Section 2 briefly discusses the dynamic capabilities framework, its connection to resilience and adaptation, and the background to the Christchurch earthquake. Section 3 describes the data sources and sample definition. Section 4 sets out the performance modelling and results. Section 5 discusses and concludes.

2 Dynamic capabilities and the Christchurch earthquake

2.1 Dynamic capabilities

A growing body of evidence suggests that management practices and capabilities are important influences on economic growth, and should therefore be included in "mainstream" views of production (Winter, 2012).[5] Much of this literature focuses on human resources practices (e.g. Fabling and Grimes, 2007; Ichniowski et al., 1997; Lazear and Shaw, 2007; Shearer, 2004). The body of economic literature investigating management formally as part of a production function, especially in connection with productivity, is small but also growing (e.g. Bertrand and Schoar, 2003; Bloom and Van Reenen, 2007; Bloom et al., 2015, 2016, 2019).

The "dynamic" subset of firm capabilities refers to capabilities oriented towards change. The dynamic capabilities literature (Eisenhardt and Martin, 2000; Teece and Pisano, 1994; Zollo and Winter, 2002) draws a distinction between "ordinary" capabilities – those used to maximise efficiency given an unchanging environment – and dynamic capabilities which are deployed when circumstances change, or when an opportunity to develop or shape markets

[5]The importance of management to production was recognised in the empirical literature as early as 1944 (Tintner, 1944).

and earn economic rents is detected (DiStefano et al., 2009; Laaksonen and Peltoniemi, 2018). One claim is that dynamic capabilities are especially relevant to industries or firm circumstances involving a high degree of dynamism, competition or volatility (Barreto, 2010; Eisenhardt and Martin, 2000; Teece et al., 1997). In this view, firms invest in capabilities as a survival strategy, accumulating resources over time if they succeed (Nelson and Winter, 2002).[6]

The literature emphasises that its logic is most relevant for understanding long-term firm performance, whether in relation to innovation or adaptation.[7] The latter perspective on firm capabilities strongly resembles the idea of "resilience" from the disaster recovery and business continuity management literatures (e.g. Buzzao and Rizzi, 2023; Duchek, 2020; Herbane et al., 2004; Rose, 2004). Those literatures distinguish "anticipatory" from "reactive" capabilities (McKnight and Linnenluecke, 2019). Both sorts are claimed to be key for firms to take advantage of sudden demand shifts and the incapacitation of competitors, or to absorb productively an influx of government financial or in-kind support, all of which occurred during the earthquake shock.

2.2 The Christchurch earthquake and aftermath

The 6.3-magnitude that hit the Christchurch CBD in February 2011 earthquake was preceded by a large, 7.1-magnitude earthquake on 4 September 2010, centred about 30km away. The first earthquake did not cause loss of life, but it did injure about 100 people, and structurally weakened buildings and infrastructure in the city itself. This weakening likely exacerbated the damage and loss of life when the far more destructive and deadly second earthquake hit, killing 185 people (Potter et al., 2015). Around a hundred thousand stone and brick buildings were damaged, and thousands were subsequently demolished and re-built (Potter et al., 2015; Sapeciay et al., 2017; Thornley et al., 2015). A large-scale financial and logistical government response followed (Greater Christchurch Group, 2017).

According to official estimates produced shortly after the second earthquake, the cumulative financial loss due to the two earthquakes was around NZ$15 billion (about 8% of New Zealand GDP and 2.5% of the nation's capital stock at the time; The Treasury, 2011). Immediately after the second earthquake, the government provided direct financial assistance to local employers and employees at an estimated cost of NZ$0.5 billion, most of which was forecast

[6] The links between capabilities, growth and responses to change are discussed at length in Chapter 2 of Ng (2024).

[7] Although the bulk of the dynamic capabilities literature seems to have focused on innovation, there are also studies looking at adaptation as a related aspect of change (e.g. Meeus and Oerlemans, 2000).

to be disbursed in the first half of 2011. The Reserve Bank of New Zealand cut the official interest rate by 0.5 percentage points to 2.5%, citing the disruption to business activity and the likely deterioration in business and consumer confidence (Reserve Bank of New Zealand, 2011). The rebuild and recovery expenditure facing the government was estimated at that time to be almost $9 billion, the vast majority of which was forecast to be spent by the end of 2015 (The Treasury, 2011). Estimates of total public and private rebuild expenditure (including betterment) from various sources were much larger than this figure (Parker and Steenkamp, 2012).

The earthquakes induced a very substantial public and private sector response to repair the damage, support lives and livelihoods, and rebuild Christchurch. Market opportunities were probably also created during the recovery by the authorities' stated intent to address a number of pre-existing issues of perceived poor urban form (Rodrigo and Wilkinson, 2020). The confluence of adverse and stimulatory events in the shock created both opportunities and threats for exposed firms, as is common following disasters (Akinboye and Morrish, 2022; Gregg et al., 2022). Although many industries faced supply chain disruptions due to damaged buildings and infrastructure, construction-related industries experienced a very sudden and large increase in demand, exceeding existing capacity in many cases (Boiser et al., 2011; Y. Chang et al., 2012). Industries dependent on foot traffic such as retail and hospitality, as well as passenger transport, saw the opposite (Parker and Steenkamp, 2012; Potter et al., 2015). Overall activity in manufacturing was less affected overall. This cross-industry impact pattern has been observed in other major earthquake events, such as Nisqually, Seattle (2001; S. Chang and Falit-Baiamonte, 2002), Loma Prieta, San Francisco (1989; Kroll et al., 1990) and Northridge, Los Angeles/Santa Monica (1994; Tierney, 1997).

Heterogeneity at the industry level was likely compounded at the firm level by the spatial lumpiness of impacts, on both the demand and supply sides. The overall impact on an individual firm's operating environment might have been negative or positive. Some firms may well have been in the position of suddenly having to respond to an operational disruption while at the same time trying to take advantage of new opportunities, including due to competitors failing or departing and thus presenting opportunities to grow market share, even in the face of a decline in overall industry demand.

Strategic adjustments by the many firms exposed in different ways to such a profound shifts are likely to have played out over several years. The claim tested in this paper is that firms with higher dynamic capabilities made better such adjustments and hence outperformed in the years following the earthquake, regardless of whether the particular shifts they faced were overall positive (in which case, theory would predict their more effective gearing up to take advantage of the opportunity) or negative (in which case, better adaptation of their operations to cope and limit losses).

3 Data sources and the sample

3.1 The data

LBD codes for all source data, formulae for all derived variables and other details about the construction of the dataset for this paper are shown in Appendix A.

3.1.1 Dynamic capabilities

As noted, I measure dynamic capabilities in this study using the factor model-based measures (factor score estimates) documented in Chapter 3 of Ng (2024). Factor modelling as an empirical operationalisation approach is motivated by the lack of specificity in the dynamic capabilities literature as to exactly what the capabilities are and are not. A teleological description defines them at the highest level as capabilities supporting the purposeful reconfiguration of ordinary capabilities (Arend and Bromiley, 2009). Beyond that, key sources distinguish subclasses of related behaviour including "sensing", "seizing", "building" (Teece, 2007), "learning", "knowledge articulation", "knowledge codification" (Zollo and Winter, 2002) and "creation, evolution and recombination" (Eisenhardt and Martin, 2000). Some authors provide a little more specificity in naming business activities at the next level down, such as developing new products and processes, discovering opportunities, designing and implementing viable business models, internal and external technology transfer (Teece, 2007), acquisition and shedding of resources, making strategic decisions, "alliancing", restructuring to match shifting customer demand, assembling cross-functional teams (Eisenhardt and Martin, 2000), post-acquisition integration, re-engineering, process R&D, testing and prototyping (Zollo and Winter, 2002). Capabilities can include attitudes as well as behaviours (e.g. Helfat and Peteraf, 2015).

Relatively tangible business processes, activities and attitudes are needed for empirical operationalisation of the dynamic capabilities concept, but evidently, a very wide variety of practices could in principle constitute dynamic capabilities, so long as they are related to reconfiguration in some way (Kump et al., 2019). The factor model solves this problem of high dimensionality by mapping a large number of measured change-related business practices and attitudes to a level of aggregation where specific practices are statistically clustered together into a (much) smaller number of thematic activity classes that capture the bulk of the observed variance in the practices. The empirical fact of clustering presumably reflects that the practices are complementary (Helfat, 1997; Helfat and Peteraf, 2003; Laaksonen and Peltoniemi, 2018).

For the factor model, I draw business practices data on 14,146 firms from the New Zealand Business Operations Survey (BOS), an official, nationally representative survey run regularly from 2005 to 2017. I select the BOS business practices and attitudes for factor modelling judgementally using the dynamic capabilities literature as a guide. From 87 practices selected for dynamic capabilities modelling and 41 selected for ordinary capabilities modelling, the factor models produce factor score estimates for the firms along five dynamic capabilities dimensions and two ordinary capabilities dimensions. The thematic activities corresponding to the dynamic capabilities dimensions are *external cooperation*, *marketing strategy adjustment*, *internal improvement*, *internationalisation* and *situational awareness and responsiveness*. All the thematic activities feature in the dynamic capabilities literature as mechanisms or channels relevant to firm reconfiguration. Chapter 2 of Ng (2024) has full details of the construction of the dynamic capabilities measures, including tables showing the top business practices by factor loading for each of the factors, from which I derived the thematic interpretations reflected in the factor names.

3.1.2 Firm performance

The large literature on firm performance makes clear that researchers have in mind many aspects of performance that are likely to interact in complex ways. Financial measures (e.g. profitability, return on assets) and product market performance (e.g. market share, sales growth, pricing margins achieved) are often studied, while more "ultimate" measures of shareholder value such as survival feature in the literature (and especially in the dynamic capabilities theoretical literature) but are less commonly investigated (Capon et al., 1990; Richard et al., 2009). Finally, policymakers may consider outcomes with wider social importance as relevant "performance" outcomes of firm activity, such as employment, productivity and wages paid, even though such outcomes may be viewed by the firms themselves as purely instrumental to profitability and survival.

In this study, I use survival probability, sales and employment growth, margins, sales per employee, multi-factor productivity (MFP) and average wages paid as performance outcome variables, measured as follows.

Survival data are derived from records of commencing and ceasing activity as defined for the purposes of the Longitudinal Business Frame (LBF). The LBF is the longitudinal statistical register of "economically significant" New Zealand businesses (legal entities). A firm birth (cessation) is recorded when a business becomes (ceases to be) economically significant (Stats NZ, 2021). Although recorded cessations can occur due to a firm's deregistration following an acquisition, even if in economic substance the firm's operations continue, the vast majority of LBF cessations appear to be economic cessations, as I treat them here.[8] I discard the small number of firms that had either missing birth dates, or reported cease dates before their apparent observation in the 2009 BOS. I track all firms on the LBF until 31 March 2019 (the "right-censoring" date for survival modelling).

All other outcome variables are measured in annual terms and sourced or derived from the firm-level productivity dataset developed by Richard Fabling and Dave Maré (Fabling, 2011; Fabling and Maré, 2015a, 2015b; Fabling and Maré, 2019). The year-end in that dataset is 31 March.[9]

I source **sales growth**, full-time equivalent (FTE) **employment growth** and the translog measure of **MFP** estimated without firm fixed effects directly from the Fabling/Maré dataset. Growth measures are defined as growth from the year before the reference BOS year to the reference year (i.e. $t-1$ to t, e.g. from 2008 to 2009 for the 2009 growth observation). **Margins** are defined as in Fabling and Maré (2015b) and calculated as nominal sales divided by operating costs, defined as the sum of wages and the costs of capital services and materials. I define **sales per employee** as annual nominal sales divided by FTE employment, and **average wages** as annual wages divided by FTE employment.

3.1.3 Earthquake exposure

I define a firm's exposure to the earthquake shock as the proportion of the firm's employment located in the Christchurch Territorial Authority (TA), the epicentre of the February 2011 earthquake.[10] Data on the Christchurch TA proportion of employees is sourced from the data on employment by firm "geographic unit" in the Longitudinal Business Frame (LBF).

[8] To investigate the issue of firms that change legal form while carrying on the same economically substantive business, which would be recorded as cessations in the LBF, Fabling (2011) constructed unique firm identifiers based on economic rather than legal continuity. He found that using identifiers based on economic continuity reduces the firm exit rate by only 1.5%.

[9] The BOS reference year depends on respondents' balance date. The reference year for an individual firm can be led or lagged up to 6 months relative to the 31 March year in the Fabling/Maré dataset. Most firms in New Zealand have a 31 March balance date.

[10] Fabling et al. (2016, 2019) used "Greater Christchurch", which includes the neighbouring Selwyn and Waimakariri TAs. Some parts of those TAs have concentrations of economic activity, but the urban areas in the region are almost entirely within the Christchurch TA. The sample contains very few firms with exposures in the other TAs, and their circumstances are likely to be quite dissimilar from those in Christchurch, especially given the large rural proportions of their TAs.

3.1.4 Control variables

The performance models variously include the following control variables. **Age** is defined using the LBF birth year. **Size** is measured in rolling mean employment (RME) sourced from the BOS. **Capital intensity** of production is defined as the natural log of the real cost of capital services less the natural log of FTE employment, both sourced from the Fabling/Maré dataset. **Foreign ownership** is defined dichotomously using the BOS item reporting percentage holding in the firm of any individual or business located overseas, with the firm coded as foreign-owned if the reported percentage exceeds 50%. **Industry** is defined using the BOS record, with the CI industry defined as the aggregate of ANZSIC 2006 Divisions D and E; MFG as Division C; and DR as the aggregate of Divisions F, G, H, I and L.

3.2 The sample

The maximum sample of firms for the performance modelling is the 5,379 firms that were alive at the time of the earthquake and sampled in the 2009 BOS (which is very close to the full 2009 BOS sample), which is the one both providing dynamic capabilities factor score estimates and closest to preceding the first earthquake in September 2010. That BOS year thus provides the best measurement of dynamic capabilities immediately before the shock. Of those firms, 1,173 firms, about a fifth of the sample, had a presence in the Christchurch TA in 2010. The corresponding proportions are similar in each of the three focus industries.

To reduce confounding risks (Steiner et al., 2010; Stuart, 2010) and sharpen the focus on the impacts of the earthquake shock, I match the characteristics of exposed and non-exposed firms on a number of dimensions, as follows. First, I reduce the sample to include only firms with 100% of their employment in one of Christchurch, Wellington, Lower Hutt, Hamilton or Auckland. This restricts the sample to firms with employment in a single major New Zealand urban area and nowhere else ("100% single-city-only" firms). This selection of 2,234 100% single-city-only firms excludes the roughly 3,000 firms with multi-city presence or any rural presence, which had either partial exposure (some, but not all, employment in Christchurch) or no exposure to Christchurch but exposure to multiple other cities. I exclude from the sample firms with only partial exposure on the basis that they might have been more readily able to shift their activities to locations outside Christchurch in response to the shock than firms with complete exposure. I exclude firms with rural presence on the basis that they might have been differently affected by the monetary policy response to the earthquakes, compared to urban-only firms.

I then further improve the match by excluding firms in the age and size tails of the pre-shock exposed and non-exposed industry-level groups such that their age and size distributions match more closely.[11] I first drop the exposed firms whose pre-shock age or size exceeds (falls short of) the maximum (minimum) pre-shock age and size of non-exposed firms. I then drop the non-exposed firms whose pre-shock age or size exceeds (falls short of) the maximum (minimum) pre-shock age and size of the exposed firms remaining after the first trim.

The distribution matching excludes just over 100 firms, the vast majority of which are non-exposed firms, to leave 2,124 groupwise-matched 100% single-city-only firms, of which 384 (around a sixth) are exposed firms. The proportions of exposed firms in each of the CI, MFG and DR industries are similar.

This matching procedure sharpens the contrast between exposed and non-exposed firms, and subsetting on single-city-only firms avoids having to assume a restrictive functional form for the relation of incomplete earthquake exposure to performance. However, it comes at the cost of considerably reducing the sample size. [12]

4 Modelling and results

4.1 General theoretical model

Let firm i's performance during and after the earthquake shock, conditional on exposure to the shock and the dynamic capabilities factors, be expressed formally as

$$y_{it} = f(E_{it}, \mathbf{DC_i}, \mathbf{z_{it}}) \tag{1}$$

where

y_{it} = outcome variable
E_{it} = exposure to the earthquake shock
$\mathbf{DC_i}$ = vector of dynamic capabilities immediately before the beginning of the earthquake shock
$\mathbf{z_{it}}$ = control variables

The function $f(.)$ allows for an interaction effect of general form between E_{it} and $\mathbf{DC_i}$,

[11] I match distributions of ln(age) as at 4 September 2010 and ln(size) as at March 2009 (from the BOS).

[12] As an alternative, I also estimate the models on the full sample of BOS 2009 firms that were live at the beginning of the shock, i.e. including firms with incomplete exposure, multi-city non-Christchurch firms, and rural firms in the sample. I assume a linear effect of exposure on the log hazard ratio in the survival models and on the intermediate outcomes, in the absence of any theoretical reason to choose some other functional form.

representing a moderating effect of dynamic capabilities on the earthquake's impact on performance. $f(.)$ can also include interactions between the $\mathbf{DC_i}$ and variables in $\mathbf{z_{it}}$. Depending on the outcome variable, control variables include some combination of ordinary capabilities, age, size, foreign ownership, industry and capital intensity.

The idea that dynamic capabilities improve a firm's response to disruption, whether or not the disruption represents a threat or an opportunity in net terms, predicts that

$$\frac{d(\frac{dy_i}{dE_{it}})}{dDC_{ki}} > 0 \tag{2}$$

where $DC_{ki}, k = 1, ..., 5$ is an element of $\mathbf{DC_i}$, for at least one $k, k = 1, ..., 5$, if an increase in y_{it} corresponds to better performance (if y_{it} is the hazard rate, as in a survival model, then the prediction is that the term on the left hand side < 0).

4.2 Firm survival

Of the 2,124 groupwise-matched 100%-single-city firms in the sample, 576 (about a quarter) failed in the 8.5 years between the day of the first earthquake, 4 Sep 2010, and 31 March 2019. Proportions of failures within the focus industries were similar (Table 4.1).[13]

Notably, the failure proportion of exposed CI firms is smaller than that of non-exposed firms (respectively 0.13 vs. 0.32), while the opposite is the case for DR firms (respectively 0.40 vs. 0.29). The modelling results, later, show how much of these differences can be attributed to the impact of the earthquake shock moderated by dynamic capabilities, controlling for the other explanatory variables. For now, it is worth noting that the number of failures is quite small for survival modelling, especially at the industry level.[14] Any effects of the explanatory variables on survival probability would thus have to be quite large to be detected accurately with these samples.

I use a continuous-time survival model setup, since a firm can fail at any time, and failure time data are available in the LBD at high (monthly) frequency. I model the firm's instantaneous

[13] The proportion of failures for the full sample of firms, with any level of exposure to the earthquake shock, was also similar.

[14] Harrell (2015, p.486) suggests that approximately 200 failures are needed for accurate estimation of an unconditional survival function with no censoring, and 500 for a hazard ratio for one dichotomous categorical covariate with the events distributed equally across the two categories.

Table 4.1
Failure rate between 4 September 2010 and 31 March 2019,
groupwise-matched 100% single-city firms

	All industries	Constr./Infra.	Manuf.	Distr./Ret.
All 100% single-city firms				
Firms	2,124	117	624	438
Failures	576	33	168	135
Proportion failed	0.27	0.28	0.27	0.31
Exposed				
Firms	384	24	120	60
Failures	105	3	27	24
Proportion failed	0.27	0.13	0.23	0.40
Non-exposed				
Firms	1,740	93	504	378
Failures	471	30	141	111
Proportion failed	0.27	0.32	0.28	0.29

Notes. "Constr./Infra." = Construction/Infrastructure; "Manuf." = Manufacturing; “”Distr./Ret." = Distribution/Retail. All firm counts are random rounded to base 3.

failure rate (its hazard rate) as a function of its age t, given the firm has survived until t:

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

where $S(t)$ is the probability of surviving beyond t and $f(t)$ is the PDF of $F(t) = 1 - S(t)$, the probability of not surviving beyond t. The term $h(t)$ is typically called the hazard function.

The effect of age on the likelihood of survival is given by the form of $h(t)$. The effect of other variables on the hazard rate can be captured in the general form

$$h_i(t) = g(h_0(t), \mathbf{x_i})$$

where $h_0(t)$ is the "baseline" hazard rate and $\mathbf{x_i}$ is a column vector of the explanatory variables E_{it}, $\mathbf{DC_i}$ and $\mathbf{z_{it}}$ as defined above, with the exception of age (since it is captured by the form of $h(t)$). The function $g(.)$ allows for interactions between the explanatory variables, including the key interaction of interest between E_{it} and $\mathbf{DC_i}$, measuring the moderation by dynamic capabilities of the earthquake impact on survival probability.

I specify the model for estimation as a proportional-hazard (PH) model. Interaction terms are specified as linear in the proportion of employment in Christchurch, in the level of each dynamic capability in 2009, and in any interaction terms between the $\mathbf{DC_i}$ and $\mathbf{z_{it}}$.

The model for estimation is

$$\begin{aligned}\ln\left(\frac{h_i(t)}{h_0(t)}\right) =&\psi_0 + \boldsymbol{\psi}_{\mathbf{DC}}'\mathbf{DC_i} + \boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{I}\,\prime}\mathbf{DC_i^{INT}} + \boldsymbol{\psi}_{\mathbf{z}}'\mathbf{z_i} \\ &+ \psi_0^E E_i + \boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{E}\,\prime} E_i \cdot \mathbf{DC_i} + \boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{IE}\,\prime} E_i \cdot \mathbf{DC_i^{INT}}.\end{aligned} \tag{3}$$

where $\mathbf{DC_i}$ is the vector of k dynamic capabilities factors, $\mathbf{DC_i^{INT}}$ is any interactions of those factors with the control variables $\mathbf{z_i}$[15], and E_i is exposure to the earthquake shock. E_i is in principle a continuous variable running from 0 to 1 since it is measured as the proportion of a firm's total employment located in Christchurch, although as set out above, the empirical model is estimated on a sample of 100% single-city-firms only, so in practice E_i is a dummy variable (Christchurch=1, 0 otherwise).

The second line in Equation 3 contains the terms capturing the effects on the hazard ratio of exposure to the earthquake shock, moderated by dynamic capabilities and dynamic capabilities interactions with control variables. The parameters of interest are the coefficient vectors $\boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{E}}$ and $\boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{IE}}$, which together determine the extent of moderation by dynamic capabilities, which depends linearly on the levels of the interaction terms.

This setup enables a test of the theoretical prediction in Equation 2 above, that dynamic capabilities improve performance after a shock. In the context of the empirical model Equation 3, we have

Hypothesis 1

$$\frac{d\left(\frac{d\ln\left(\frac{h_i(t)}{h_0(t)}\right)}{dE_i}\right)}{dDC_{ki}} = \psi_{DC,k}^E + \boldsymbol{\psi}_{\mathbf{DC,k}}^{\mathbf{IE}\,\prime}\mathbf{z_i} < 0,$$

for at least one $k, k = 1, ..., 5$, where $\psi_{DC,k}^E$ and $\boldsymbol{\psi}_{\mathbf{DC,k}}^{\mathbf{IE}}$ are the element and vector respectively corresponding to the kth dynamic capability within the coefficient vectors $\boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{E}}$ and $\boldsymbol{\psi}_{\mathbf{DC}}^{\mathbf{IE}}$.

Of contextual interest is the sign and magnitude of the effect of shock exposure on the log hazard ratio

[15] Interaction terms between the elements of $\mathbf{DC_i^{INT}}$ and $\mathbf{z_i}$ enter the estimated equation on the basis of the evidence of their relevance presented in Chapter 4 of Ng (2024)

$$\frac{d\ln\left(\frac{h_i(t)}{h_0(t)}\right)}{dE_i} \tag{4}$$

evaluated at the means of the explanatory variables, which measures whether the shock had positive or negative effects on the hazard rate for exposed firms on average. As discussed earlier, the expected sign of the effect of the shock on average is not clear *a priori*, since it involved both adverse and stimulatory effects on general business conditions. However, **Hypothesis 1** implies that exposed firms with higher dynamic capabilities should have performed better (faced a lower hazard rate) than exposed firms with lower dynamic capabilities, irrespective of whether the earthquake had a net favourable or net adverse impact on the hazard rate on average.

I estimate the models using Cox regression with industry dummies for the all-industry models as a base case, enabling tests of **Hypothesis 1** at the all-industry and for each of the three focus industries CI, MFG and DR. As robustness checks, I also estimate the all-industry models with stratification by industry, and using parametric survival model methods for all models.

I assume that firms become at risk and under observation on 4 September 2010[16] and remain so until 31 March 2019 (the "right-censoring" date), which is the end of the reference period for the 2019 vintage of the LBD used in this paper. I fix all explanatory variables at their 2010 levels, because doing so avoids conflating the shock's effects with those of endogenous changes in the explanatory variables that may have occurred in response to the shock.

4.2.1 Survival model results

The earthquake shock resulted in a significant and sizeable (nearly 50%) reduction of hazard ratios for exposed MFG firms, indicating that the shock improved business conditions for firms in that industry on average, relative to matched non-exposed firms (row 1, Table 4.2). The signs on the estimated impacts of the shock on the hazard ratios of exposed CI and DR firms are also on the favourable side, but these estimates are not significant.

However, I find little evidence that the dynamic capabilities factors, even at levels well above the mean, moderated the impact of the shock on the hazard ratios. Rows 2-6 in Table 4.2

[16]This treatment corresponds to the concept of "late entry" in the survival analysis literature. Firms' survival history from before the time of their sampling needs to be excluded from the estimates (which uses the "under observation" periods only), because their survival before then is certain, and therefore will bias the estimates of survival probability up to that point if included

show, for each capability at the all-industry and focus industry levels, the hazard ratio for an exposed firm with a 2 standard deviation higher than mean level of capability less that for an exposed firm with the mean level. None of the estimates are significantly different to zero. The signs are mixed negative and positive, rather than the theoretically predicted negative (**Hypothesis 1**).

Estimating the models on the full sample of firms (which features E_i ranging continuously from 0 to 1, rural firms and multi-city firms), using parametric models, and stratification on industry instead of using industry dummies made no difference to these results.

As noted earlier, there is only a small number of failures from which to estimate the hazard ratio effects, so interpretation of all estimates discussed in this section requires caution. The lack of evidence for a dynamic capabilities moderation effect could be due to lack of statistical power to detect any moderation effects if they are small, especially given that the survival models have many explanatory variables.[17]

[17] According to Harrell (2015), accurate estimation of an unconditional survival curve with no censoring requires a minimum of about 200 failures, and more if there is censoring (as there is here). In a model with a single dichotomous categorical covariate, accurately estimating the hazard ratio associated with it requires about 500 failures distributed evenly across the two categories. The number of failures in my sample at the all-industry level (576) is marginal in terms of these benchmarks, and well short at the industry level (Table 4.1), suggesting that statistical power is likely to be an issue for inference about survival probabilities in these samples.

Table 4.2
Dynamic capabilities moderation of earthquake shock hazard ratio impact, groupwise-matched 100% single-city firms

		All ind.	Constr./Infra.	Manuf.	Distr./Ret.
(1)	Earthquake shock impact (log haz. rat.)	-0.04	-1.27	-0.47*	-0.13
	(s.e.)	*(0.09)*	*(1.37)*	*(0.18)*	*(0.41)*
	Dynamic capabilities moderation of shock impact, per 2 standard deviations				
(2)	Cooperation	-0.09	0.04	-0.20	-0.45
	(s.e.)	*(0.20)*	*(1.30)*	*(0.18)*	*(0.53)*
(3)	Marketing/restructuring	0.02	-0.61	-0.21	1.28
	(s.e.)	*(0.17)*	*(1.36)*	*(0.19)*	*(1.88)*
(4)	Internal fitness	-0.05	0.80	-0.19	-0.62
	(s.e.)	*(0.16)*	*(3.84)*	*(0.18)*	*(0.37)*
(5)	Internationalisation	-0.09	0.76	0.46	-0.65
	(s.e.)	*(0.17)*	*(0.77)*	*(0.27)*	*(0.48)*
(6)	Awareness/responsiveness	0.01	0.40	0.03	0.13
	(s.e.)	*(0.17)*	*(1.15)*	*(0.19)*	*(0.61)*
	Interaction terms and controls				
	Dynamic capabilities interaction terms	ln(size)	-	-	OC-Ops.
	Industry dummies	yes	-	-	-
	50%+ foreign-owned dummy	yes	yes	yes	yes
	ln(size)	yes	yes	yes	yes
	no. firms	2,124	117	624	438
	no. failures	579	36	168	132

Notes. "All ind." = All industries; "Constr./Infra." = Construction/Infrastructure; "Manuf." = Manufacturing; ""Distr./Ret." = Distribution/Retail; "log haz. rat." = natural log hazard ratio. Estimates derived from model estimated using Cox regression. The moderation effect of dynamic capabilities on the earthquake shock impact is measured using the delta method. * $p < 0.05$; ** $p < 0.01$ against the null that the log hazard ratio (row 1) or the difference in log hazard ratio (rows 2-6) = 0. Figures in row 1 show the log hazard ratio for the average exposed firm relative to the non-exposed baseline. Rows 2 - 6 show the difference in the log hazard ratio associated with the shock on the log hazard ratio for an exposed firm with the respective dynamic capability at a level 2 standard deviations above the mean, less the hazard ratio for an exposed firm at the mean. All firm counts are random rounded to base 3.

4.3 Other performance outcomes

I model the impact of the earthquake shock on the other performance outcomes and test for the moderating influence of dynamic capabilities using linear regression models. I use cumulative **sales** and **employment**, rather than their annual levels or growth rates, to take account of the dynamics of the impact over the five years following the first earthquake. The cumulation allows for different trajectories of these outcome variables over the five-year period, and thus provides a summary measure of the overall medium-term impacts of the shock.

Figures 4.1 and 4.2 provide a sense of the average size of the shock to activity for exposed CI and DR firms. Those sectors would be expected to have experienced the most disruption during the shock, as discussed earlier. As noted, the direction of the impact on demand and activity is not clear *a priori*, either on average across firms or for individual firms.

Inspecting the figures suggests that, on average, the shock added to demand in those two industries, especially CI. Median annual sales and employment growth for exposed CI firms for the year to March 2012, roughly one year after the second (Christchurch CBD) earthquake, are visibly higher compared to those for non-exposed firms in that industry (solid red squares and solid blue circles respectively; Figures 4.1a and 4.2a). (The charts also show little noticeable difference between the performance of non-exposed firms before and after the shock. Thus, they do not indicate that it would be unreasonable to take the difference between performance of exposed and non-exposed firms as a measure of the impact of the shock, as is essentially done in the "differences in differences" (DiD) specification below.)[18]

These sharp increases in sales and employment growth for exposed CI firms are consistent with the surge in construction demand in the early period after the second earthquake, as

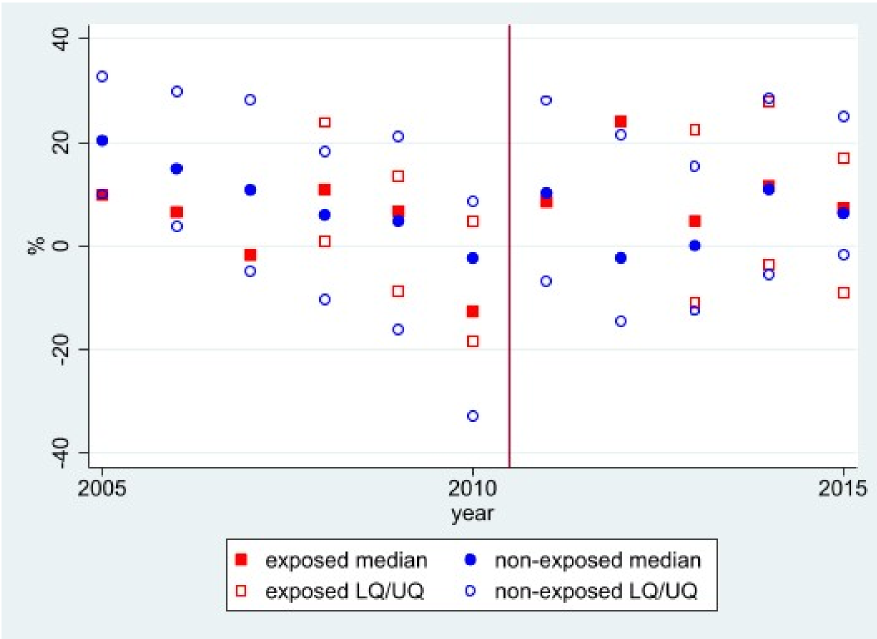
[18] One requirement for the validity of DiD estimates is that there is no omitted variable causing a time-trended difference between exposed and non-exposed firm performance over the period. This requirement is often assessed by checking for "parallel trends" prior to the shock (Roth, 2022). Inspection of the paths of the firm-median outcomes for exposed (solid red squares) and non-exposed (solid blue circles) firms from 2005-2010 in Figures 4.1a to 4.3b does not suggest that the parallel trends requirement is violated for any of the three intermediate outcomes and two industries shown; the pictures for the other intermediate outcomes and remaining industry are similar. Running a simple formal test for parallel trends, I find no significant time-trended difference in exposed and non-exposed firm performance before the shock, consistent with the visual impression. In this test, I regress performance on exposure E_i and exposure interacted with a linear time trend, $E_i \cdot t$, and test for the significance of the coefficient on the interaction term. As Roth (2022) notes, such tests may suffer from low power to detect violations of parallel trends that may be quantitatively important in the context of the study. In the present case, the difference between exposed and non-exposed firm groups is purely geographical (location in Christchurch TA or not), and the most obvious reasons for potentially trended differences in performance – age, size and industry – are controlled for in the matching process, the specification, or both.

previously documented (Parker and Steenkamp, 2012; Potter et al., 2015). Figures 4.1a and 4.2a suggest that median annual sales growth for exposed CI firms was almost 30 percentage points higher, and median employment growth around 15 percentage points higher, in 2012 compared to non-exposed firms from that industry.

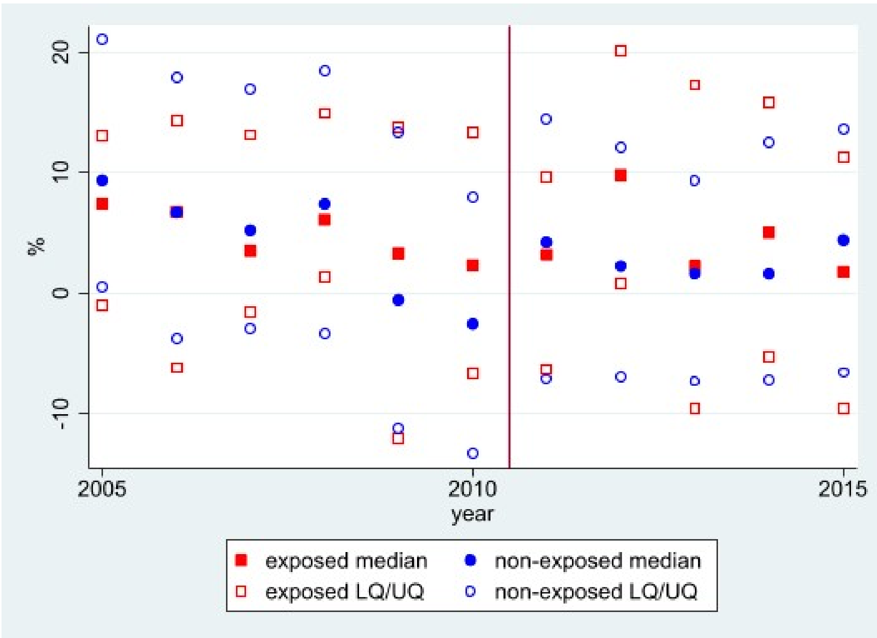
To the eye, the impact of the earthquake on activity for exposed DR firms appears smaller. Median sales for exposed firms look higher than those for non-exposed firms in that industry in 2012 (Figure 4.1b). However, there is little difference in employment growth for DR firms in that year evident to the eye (Figure 4.2b). Despite the severe disruption to foot traffic and staffing for many retailers (Parker and Steenkamp, 2012; Potter et al., 2015), it is possible that other less affected retailers picked up sales and employees, to leave overall activity in the industry only a little higher overall.

Figure 4.1
Annual sales growth, groupwise-matched 100% single-city firms

(a) Construction/Infrastructure



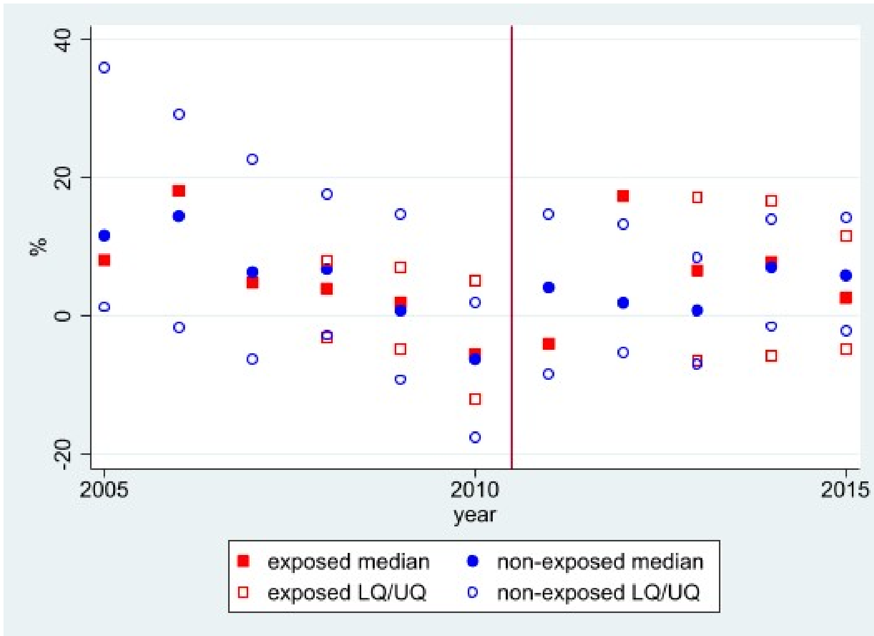
(b) Distribution/Retail



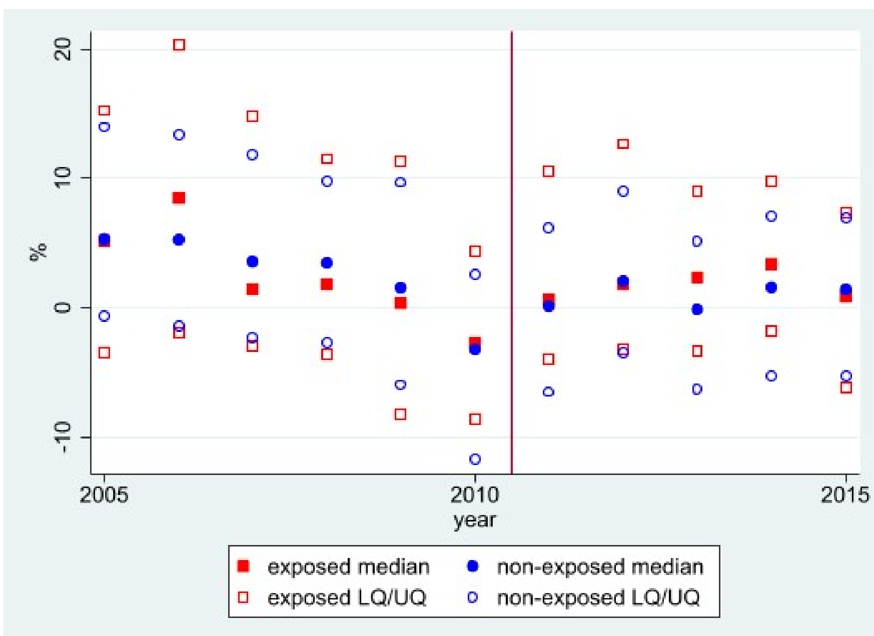
Notes. Years to 31 March. Vertical line shows the beginning of the shock. UQ = upper quartile. LQ = lower quartile. UQ and LQ suppressed due to low underlying counts if required under Stats NZ confidentialisation rules.

Figure 4.2
Annual FTE employment growth, groupwise-matched 100% single-city firms

(a) Construction/Infrastructure



(b) Distribution/Retail

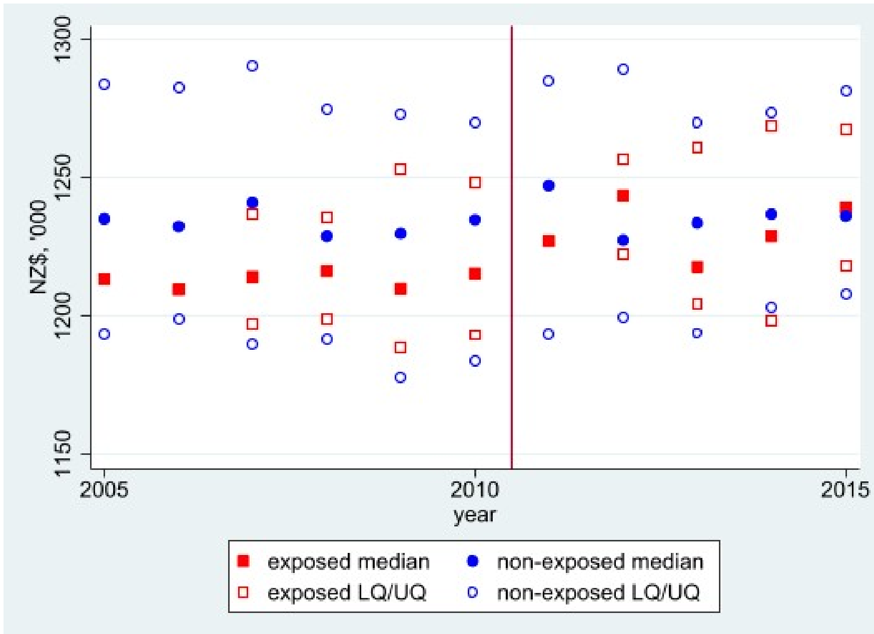


Notes. Years to 31 March. Vertical line shows the beginning of the shock. UQ = upper quartile. LQ = lower quartile. UQ and LQ suppressed due to low underlying counts if required under Stats NZ confidentialisation rules.

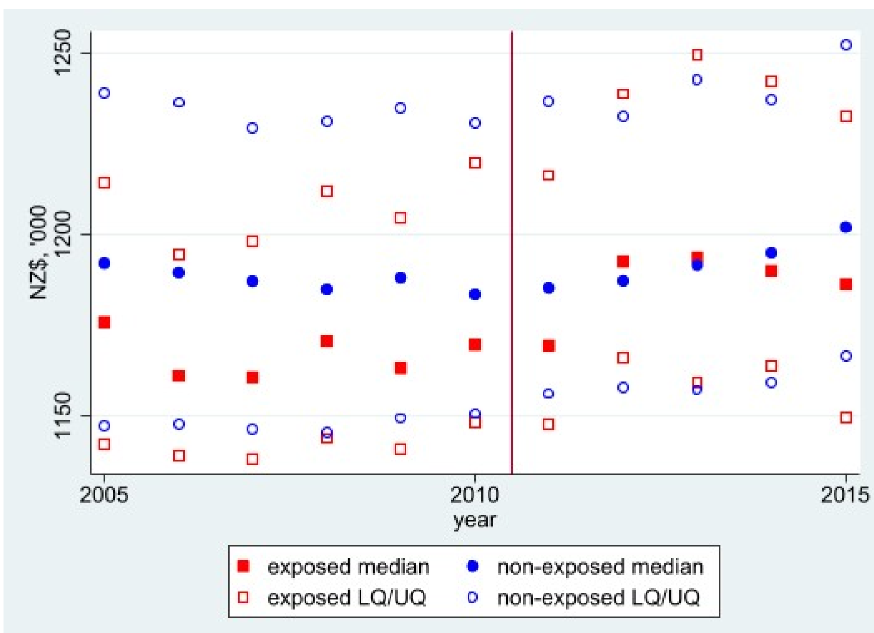
The large increases in 2012 in both sales growth and employment growth in the CI industry appear to have had a relatively muted net effect on sales per employee for exposed firms, with only a small increase evident in 2012 relative to non-exposed firms (Figure 4.3a). A jump in sales per employee is much more obvious in DR, and it persists for a year or two, which is consistent with the lift in sales growth in the industry in 2012 (that does not appear to have been quickly unwound subsequently in terms of the level of sales) while employment growth stayed broadly similar (Figure 4.3b).

Figure 4.3
Annual sales per employee growth, groupwise-matched 100% single-city firms

(a) Construction/Infrastructure



(b) Distribution/Retail



Notes. Years to 31 March. Vertical line shows the beginning of the shock. UQ = upper quartile. LQ = lower quartile. UQ and LQ suppressed due to low underlying counts if required under Stats NZ confidentialisation rules.

The other performance outcomes (**margins**, **average wages** and **MFP**) do not show obvious differences between exposed and non-exposed CI and DR firms (not shown). Excepting survival, across no performance outcome is there any obvious change after 2010 for exposed MFG firms, on average, relative to non-exposed MFG firms. As noted earlier, industry-average shock effects being close to zero does not mean that individual exposed firms did not experience pressures from the shock in either direction. Uneven incidence of supply chain disruption combined with reshuffling of demand could have meant quite heterogeneous experiences at the firm level regardless of the industry average effect.[19]

To test formally whether exposed firms with high dynamic capabilities performed better on any of the performance outcomes other than survival (irrespective of the direction and magnitude of industry-average effects, I estimate the "difference-in-differences" linear regression model

$$\begin{aligned} y_{it} = & \alpha + \boldsymbol{\gamma}'_{\mathbf{DC}}\mathbf{DC_{it}} + \boldsymbol{\gamma}^{\mathbf{INT}'}_{\mathbf{DC}}\mathbf{DC^{INT}_{it}} + \boldsymbol{\gamma}'_{\mathbf{z}}\mathbf{z_{it}} \\ & + \gamma^q_0 E_{it} + \sum_{h=2011}^{2015} \gamma^q_h D_h \cdot E_{it} + \sum_{h=2011}^{2015} D_h \cdot E_{it} \cdot \boldsymbol{\gamma}^{\mathbf{q}}_{\mathbf{hDC}}{}'\mathbf{DC_{it}} \\ & + \eta_{it} \end{aligned} \tag{5}$$

where, as in the survival model, $\mathbf{DC_{it}}$ contains the five dynamic capabilities factors, $\mathbf{DC^{INT}_{it}} = \mathbf{DC_{it}} \otimes \mathbf{z_{it}}$ (where $\otimes$ denotes the Kronecker product) contains the terms for interactions between the factors and the control variables in $\mathbf{z_{it}}$, which are the same set as for the survival model above but with the addition of age, and in the models for sales per employee and average wages, capital intensity. E_{it} is again earthquake exposure. The D_h , spans the pre- and post-earthquake period and captures a time-invariant "Christchurch effect" on exposed firms ($E_{it} = 1$) compared to non-exposed firms ($E_{it} = 0$). I include a set of five dummies are five year dummies, one for each year $h = 2011, ..., 2015$ where $D_h = 1$ in year h and 0 otherwise. Each $D_h \cdot E_{it}$ term captures the earthquake shock effect on exposed firms for year h after the beginning of the shock, with moderation by the dynamic capabilities factors allowed for by further terms $D_h \cdot E_i \cdot DC_{ki}, k = 1, ..., 5$.

I estimate the linear regression models for the CI, DR and MFG industries on a sample running from 2005 to 2015, i.e. 6 years before the first earthquake to 5 years after. The

[19] While the figures in Section **??** show visible differences in the medians for employment and sales growth, the interquartile ranges look similar in the five years after the earthquake event compared to the six years before, suggesting little marked shift in the heterogeneity of performance across firms on average before and after the beginning of the shock.

models in effect use the average performance outcomes over the six years before as the baseline against which performance outcomes afterwards are measured.

As in the survival model, the second line in Equation 5 contains the terms to capturing the effects of exposure to the earthquake shock, moderated by dynamic capabilities. Again, the $\mathbf{DC_{it}}$, $\mathbf{DC_{it}^{INT}}$ and $\mathbf{z_{it}}$ are fixed at their immediately pre-shock levels, except for age (which is out of control of the firm), to avoid conflating any (possibly moderated) shock effects on the intermediate outcomes with effects due to responses of the control variables to the shock.

The parameters of interest are the $\boldsymbol{\gamma^{q}_{hDC}}$ for all $h = 2011, ..., 2015$. In the case of the linear regression models, the relevant hypothesis is

Hypothesis 2

$$\gamma^{q}_{hDCk} > 0$$

where $\gamma^{q}_{hDCk}, k = 1, ..., 5$ is an element of $\boldsymbol{\gamma^{q}_{hDC}}, h = 2011, ..., 2015$ for at least one h and one k.

Again, the effects of the earthquake shock itself on the performance of exposed firms on average in each year $h = 2011, ..., 2015$ after the beginning of the shock,

$$\frac{dy_{it}}{dD_h}$$

evaluated at $E_{it} = 1$ (i.e. for exposed firms) and at the mean levels of dynamic capabilities, are of contextual interest as an indicator of whether the shock's impact was positive or negative for the average exposed firm. Its sign for the average firm is not clear *a priori*, and it might not be the same for all h.

I estimate the models using the random effects (RE) estimator with standard errors clustered by firm as a base case, since it uses both the within-firm and between-firm variance. To reduce the effect of extreme observations, I discard the highest and lowest 1% of dependent variable observations. I retain any firms that ceased before 2015 in the sample, even though this makes the data an unbalanced panel. Selection bias is unlikely to affect the linear regression model estimates, since the failure data (Table 4.1) and survival model results (Section 4.2.1) suggest little impact on the relative failure rates of exposed firms compared to non-exposed firms (which accords with the Stats NZ data to February 2012 cited in Kachali et al., 2015).

4.3.1 Other outcome model results

Construction/Infrastructure. Looking first at the results for the sample of groupwise-matched 100% single-city-only firms, the surge in CI **sales** for exposed firms caused by the shock is clearly evident in the econometric estimates (Table 4.3), confirming what is suggested to the eye in Figure 4.1a. On average in the exposed group of such firms, cumulative growth in sales to 2015 compared to the 2010 base (i.e. the growth in the level of sales between those years) was 0.51 log points (approximately 51 percentage points; pp) higher than for the non-exposed group (row 7). The peak annual sales growth difference between the two groups is 0.32 log points (approx. 32 pp; row 1), in 2012.

I find significant, sizeable and persistent moderation effects of high *marketing strategy adjustment* (labelled "Marketing/restructuring" in the tables for brevity) and *Internal improvement* ("Internal fitness") capabilities on the impact on sales for exposed firms, consistent with **Hypothesis 2**. Exposed firms with 1 standard deviation higher levels of those capabilities had respectively 0.28 and 0.57 log points (approx. 28 and 57 pp) higher cumulative sales growth from 2010 to 2015 (rows 9 and 10). The peak moderation effect of these two capabilities on the impact on annual sales growth for exposed firms occurs in 2012, coinciding with the peak impact on sales for exposed firms on average (rows 3 and 4).

This pattern of results suggests that these dynamic capabilities factors positioned exposed firms to proactively make the most of the surge in demand conditions caused by the shock, as predicted by the theory. Interestingly, higher *external cooperation* ("Cooperation") capability also appears to have had a positive moderation effect on the impact on annual sales growth in 2012 and 2014 (row 2), and higher *internationalisation* likewise in 2011 (row 5), for firms in the exposed group, but these effects do not appear to persist (rows 8 and 11).[20]

[20]Estimates from the larger sample of CI firms, including those with partial exposure to the shock and those purely rural or multi-city with no exposure, suggest that these results for sales are robust to inclusion in the sample of (3,000-odd) firms excluded by the matching procedure. The same patterns of significance and magnitude are evident with the larger sample, albeit generally less significant and with slightly smaller magnitudes (not shown).

Table 4.3

Sales impact of earthquake shock with dynamic capabilities moderation, *Construction/Infrastructure*, groupwise-matched 100% single-city-only firms

		Year				
		2011	2012	2013	2014	2015
	Impact on annual sales growth (log pts)					
(1)	Earthquake shock	0.10	0.32**	0.04	0.01	0.04
	(s.e.)	*(0.06)*	*(0.09)*	*(0.13)*	*(0.09)*	*(0.08)*
	Dynamic capability moderation effect, per 1 s.d.					
(2)	Cooperation	-0.04	0.08**	0.04	0.07*	0.00
	(s.e.)	*(0.03)*	*(0.03)*	*(0.05)*	*(0.03)*	*(0.04)*
(3)	Marketing/restructuring	0.06	0.11*	0.10	-0.01	0.02
	(s.e.)	*(0.03)*	*(0.05)*	*(0.08)*	*(0.05)*	*(0.04)*
(4)	Internal fitness ideation	0.17*	0.35**	0.11	-0.14	0.07
	(s.e.)	*(0.08)*	*(0.12)*	*(0.16)*	*(0.12)*	*(0.09)*
(5)	Internationalisation	0.10*	0.01	0.10	-0.09	0.03
	(s.e.)	*(0.05)*	*(0.06)*	*(0.11)*	*(0.07)*	*(0.07)*
(6)	Awareness/responsiveness	-0.03	-0.08	0.12	-0.20	0.02
	(s.e.)	*(0.05)*	*(0.11)*	*(0.07)*	*(0.12)*	*(0.07)*
	Impact on sales, cumulative since 2010 (log pts)					
(7)	Earthquake shock	0.10	0.42**	0.46**	0.47**	0.51*
	(s.e)	*(0.06)*	*(0.12)*	*(0.11)*	*(0.16)*	*(0.22)*
	Dynamic capability moderation effect, per 1 s.d.					
(8)	Cooperation	-0.04	0.04	0.08	0.15	0.15
	(s.e.)	*(0.03)*	*(0.04)*	*(0.08)*	*(0.10)*	*(0.14)*
(9)	Marketing/restructuring	0.06	0.17*	0.27**	0.27*	0.28*
	(s.e.)	*(0.03)*	*(0.06)*	*(0.09)*	*(0.11)*	*(0.14)*
(10)	Internal fitness ideation	0.17*	0.53**	0.64**	0.50**	0.57**
	(s.e.)	*(0.08)*	*(0.17)*	*(0.11)*	*(0.15)*	*(0.19)*
(11)	Internationalisation	0.10*	0.11	0.22	0.13	0.16
	(s.e.)	*(0.05)*	*(0.09)*	*(0.13)*	*(0.16)*	*(0.22)*
(12)	Awareness/responsiveness	-0.03	-0.11	0.02	-0.18	-0.15
	(s.e.)	*(0.05)*	*(0.14)*	*(0.12)*	*(0.15)*	*(0.19)*
	Control variables					
	ordinary capabilities factors					
	ln(size)					
	ln(age)					
	50%+ foreign-owned					
	N 877					
	R^2 0.13					

Notes. Impact estimates calculated using delta method based on random effects model estimates. * $p < 0.05$; ** $p < 0.01$ against the null that the effect = 0. Cumulative impacts to year $h, h = 2011, ..., 2015$ calculated by summing the impacts on annual growth from 2011 to h.

Estimates from the **employment** model for the sample of 100% single-city-only firms show the positive difference in annual employment growth in 2012 for exposed firms on average, compared to non-exposed firms, apparent in Figure 4.1a (row 1, Table 4.4). However, the estimates also suggest that the difference did not persist on average (the cumulative difference in firm-average employment growth to 2015 for the two groups is not significantly different to zero; row 7).

Despite the higher employment in exposed firms on average being only temporary, those exposed firms with higher *external cooperation* capability retained higher levels of employment until the end of the period. Exposed firms with a 1 standard deviation higher level of that capability showed a 0.32 log point (approx. 32 pp) difference in cumulative employment growth from 2010 to 2015 (row 8, Table 4.4). Higher *external cooperation* capability led to significantly higher annual employment growth in 2012, 2014 and 2015, suggesting that the capability underpinned relatively steady growth in terms of employment, in contrast to the more front-loaded effect of higher *marketing strategy adjustment* and *internal improvement* capabilities in terms of sales growth noted above.[21]

Finally, estimates from the model for **sales per employee** for CI 100% single-city-only firms suggests that while the shock caused a positive difference in sales per employee to emerge on average between exposed and non-exposed firms in the industry (row 1, Table 4.5), there is little consistent evidence that any of the dynamic capabilities factors had a moderating effect on this increase for exposed firms. There is a mildly significant positive moderation effect from higher *external cooperation* capability in 2011 (row 2), but significantly negative moderation effects from *situational awareness and responsiveness* ("Awareness/responsiveness") in 2012 and 2013. The model for **average wages** also did not show a consistent pattern of positive moderation from dynamic capabilities (not shown).

[21] Employment growth model estimates from the larger sample of CI firms do not show the same significant and persistent moderation by the *external cooperation* capability of the shock impact, suggesting either that the effect is markedly stronger for 100% single-city-firms, or that the simple functional form I use to capture the effect of partial exposure is not accurate.

Table 4.4
Employment impact of earthquake shock with dynamic capabilities moderation, *Construction/Infrastructure*, groupwise-matched 100% single-city-only firms

		Year				
		2011	2012	2013	2014	2015
	Impact on annual employment growth (log pts)					
(1)	Earthquake shock	-0.03	0.17**	0.13	0.02	-0.02
	(s.e.)	*(0.07)*	*(0.05)*	*(0.08)*	*(0.06)*	*(0.05)*
	Dynamic capability moderation effect, per 1 s.d.					
(2)	Cooperation	0.02	0.11*	0.05	0.06*	0.08**
	(s.e.)	*(0.02)*	*(0.05)*	*(0.03)*	*(0.02)*	*(0.02)*
(3)	Marketing/restructuring	-0.02	0.07	0.10	0.06	-0.02
	(s.e.)	*(0.02)*	*(0.07)*	*(0.05)*	*(0.03)*	*(0.03)*
(4)	Internal fitness ideation	0.03	0.16	0.13	-0.03	0.05
	(s.e.)	*(0.09)*	*(0.09)*	*(0.10)*	*(0.07)*	*(0.06)*
(5)	Internationalisation	0.01	0.06	0.06	0.05	-0.04
	(s.e.)	*(0.04)*	*(0.09)*	*(0.07)*	*(0.05)*	*(0.05)*
(6)	Awareness/responsiveness	-0.05	-0.17*	-0.12	-0.06	0.10
	(s.e.)	*(0.06)*	*(0.07)*	*(0.09)*	*(0.06)*	*(0.06)*
	Impact on employment, cumulative since 2010 (log pts)					
(7)	Earthquake shock	-0.03	0.14	0.27	0.30	0.27
	(s.e.)	*(0.07)*	*(0.11)*	*(0.18)*	*(0.24)*	*(0.27)*
	Dynamic capability moderation effect, per 1 s.d.					
(8)	Cooperation	0.02	0.12*	0.17*	0.24*	0.32*
	(s.e.)	*(0.02)*	*(0.06)*	*(0.08)*	*(0.10)*	*(0.11)*
(9)	Marketing/restructuring	-0.02	0.04	0.14	0.20	0.18
	(s.e.)	*(0.02)*	*(0.09)*	*(0.12)*	*(0.14)*	*(0.16)*
(10)	Internal fitness ideation	0.03	0.19	0.32	0.30	0.34
	(s.e.)	*(0.09)*	*(0.15)*	*(0.22)*	*(0.29)*	*(0.30)*
(11)	Internationalisation	0.01	0.08	0.13	0.18	0.14
	(s.e.)	*(0.04)*	*(0.12)*	*(0.18)*	*(0.21)*	*(0.24)*
(12)	Awareness/responsiveness	-0.05	-0.22	-0.35	-0.41	-0.31
	(s.e.)	*(0.06)*	*(0.13)*	*(0.21)*	*(0.26)*	*(0.29)*
	Controls					
	ordinary capabilities factors					
	ln(size)					
	ln(age)					
	50%+ foreign-owned					
	N 867					
	R^2 0.16					

Notes. Impact estimates calculated using delta method based on random effects model estimates. * $p < 0.05$; ** $p < 0.01$ against the null that the effect = 0. Cumulative impacts to year $h, h = 2011, ..., 2015$ calculated by summing the impacts on annual growth from 2011 to h.

Table 4.5
Sales per employee impact of earthquake shock with dynamic capabilities moderation, *Construction/Infrastructure*, groupwise-matched 100% single-city-only firms

		Year				
		2011	2012	2013	2014	2015
(1)	Earthquake shock	0.12*	0.33**	0.23**	0.23**	0.31**
	(s.e.)	*(0.06)*	*(0.10)*	*(0.06)*	*(0.07)*	*(0.06)*
	Dynamic capability moderation effect, per 1 s.d.					
(2)	Cooperation	0.24*	-0.06	-0.04	-0.03	0.00
	(s.e.)	*(0.10)*	*(0.06)*	*(0.07)*	*(0.07)*	*(0.08)*
(3)	Marketing/restructuring	-0.10	-0.02	-0.02	-0.02	-0.09
	(s.e.)	*(0.09)*	*(0.08)*	*(0.10)*	*(0.08)*	*(0.11)*
(4)	Internal fitness ideation	-0.05	-0.08	0.11	0.08	0.00
	(s.e.)	*(0.09)*	*(0.12)*	*(0.12)*	*(0.09)*	*(0.09)*
(5)	Internationalisation	-0.02	-0.14	-0.23	-0.19	-0.32
	(s.e.)	*(0.08)*	*(0.11)*	*(0.15)*	*(0.14)*	*(0.17)*
(6)	Awareness/responsiveness	-0.28	-0.18**	-0.27*	0.00	-0.12
	(s.e.)	*(0.17)*	*(0.05)*	*(0.13)*	*(0.06)*	*(0.09)*
	Controls					
	ordinary capabilities factors					
	ln(size)					
	ln(age)					
	50%+ foreign-owned					
	Capital intensity					
	N 956					
	R^2 0.25					

Notes. Impact estimates calculated using delta method based on random effects model estimates. * $p < 0.05$; ** $p < 0.01$ against the null that the effect = 0.

Estimates from the models for **MFP** and **margins** in the CI industry showed significantly negative impacts from the shock on exposed firms in 2014 and 2015, with some positive and some negative moderation effects across the dynamic capabilities for the shock's impact on margins, and mostly negative moderation effects for TFP (not shown). Results for these two intermediate outcomes are therefore somewhat difficult to interpret.

Distribution/Retail. Turning to the DR industry, estimates from the model for **sales** growth for 100% single-city-only firms in that industry show that the impact on sales growth for exposed compared to non-exposed firms in 2012 (row 1, Table 4.6), that is apparent to the eye in Figure 4.1b, did not persist (row 7), for the average exposed DR firm. However, there is evidence that exposed DR firms with higher *marketing strategy adjustment* capability benefited from higher sales persistently, compared to their exposed peers. Exposed DR firms with a 1 standard deviation higher level of that capability had higher cumulative sales growth by 0.27 log points (approx. 27 pp) over the five years to 2015 (row 9). This result suggests that the *marketing strategy adjustment* capability positioned the firms well to capture market share from competitors, as one might expect for retailing firms in particular.

The beneficial effects for exposed DR firms of dynamic capabilities appears to be mostly limited to sales. There is little evidence of a positive moderation effect on exposed-firm employment outcomes apart from a short-lived positive effect from *internal improvement* (rows 4 and 10, Table 4.7) – although the point estimate for this effect does continue to increase through to 2015.

Estimates from the DR model for **sales per employee** show a similar pattern to the model for CI. Despite the shock having had a positive impact on the level of sales per employee, there is no evidence for a moderation effect from dynamic capabilities on the impact. The models for **average wages**, **MFP** and **margins** show no evidence of a shock impact on exposed DR firms, and no evidence for a consistent positive moderation effect from any of the dynamic capabilities.

Manufacturing. Estimates for the MFG industry suggest that the shock had little net impact on any of the non-survival performance outcomes for exposed MFG firms on average, consistent with other studies of disaster impacts on manufacturing. I also find no evidence of a moderation impact from dynamic capabilities for any of the non-survival performance outcomes for MFG firms.

Table 4.6
Sales impact of earthquake shock with dynamic capabilities moderation, *Distribution/Retail*, groupwise-matched 100% single-city-only firms

		Year				
		2011	2012	2013	2014	2015
	Impact on annual sales growth (log pts)					
(1)	Earthquake shock	-0.01	0.09*	0.03	0.01	-0.05
	(s.e.)	*(0.03)*	*(0.04)*	*(0.04)*	*(0.04)*	*(0.03)*
	Dynamic capability moderation effect, per 1 s.d.					
(2)	Cooperation	0.02	0.05*	0.07*	-0.12**	0.00
	(s.e.)	*(0.03)*	*(0.02)*	*(0.03)*	*(0.04)*	*(0.05)*
(3)	Marketing/restructuring	0.09	0.05	0.00	0.05	0.08*
	(s.e.)	*(0.05)*	*(0.04)*	*(0.05)*	*(0.04)*	*(0.03)*
(4)	Internal fitness ideation	-0.01	0.03	0.08	-0.02	0.03
	(s.e.)	*(0.03)*	*(0.03)*	*(0.05)*	*(0.03)*	*(0.02)*
(5)	Internationalisation	-0.03	0.10**	0.06	-0.07	-0.01
	(s.e.)	*(0.02)*	*(0.03)*	*(0.03)*	*(0.04)*	*(0.04)*
(6)	Awareness/responsiveness	-0.03*	0.05	0.05*	0.00	0.01
	(s.e.)	*(0.02)*	*(0.04)*	*(0.02)*	*(0.03)*	*(0.02)*
	Impact on sales, cumulative since 2010 (log pts)					
(7)	Earthquake shock	-0.01	0.08	0.11	0.11	0.06
	(s.e.)	*(0.03)*	*(0.06)*	*(0.08)*	*(0.10)*	*(0.13)*
	Dynamic capability moderation effect, per 1 s.d.					
(8)	Cooperation	0.02	0.08	0.15**	0.03	0.03
	(s.e.)	*(0.03)*	*(0.04)*	*(0.04)*	*(0.06)*	*(0.08)*
(9)	Marketing/restructuring	0.09	0.14*	0.14*	0.19*	0.27*
	(s.e.)	*(0.05)*	*(0.06)*	*(0.06)*	*(0.09)*	*(0.10)*
(10)	Internal fitness ideation	-0.01	0.02	0.10*	0.08	0.11
	(s.e.)	*(0.03)*	*(0.04)*	*(0.05)*	*(0.06)*	*(0.08)*
(11)	Internationalisation	-0.03	0.07	0.13*	0.06	0.05
	(s.e.)	*(0.02)*	*(0.04)*	*(0.05)*	*(0.09)*	*(0.10)*
(12)	Awareness/responsiveness	-0.03	0.02	0.07	0.07	0.08
	(s.e.)	*(0.02)*	*(0.05)*	*(0.06)*	*(0.08)*	*(0.09)*
	Controls					
	ordinary capabilities factors					
	ln(size)					
	ln(age)					
	50%+ foreign-owned					
	N 3002					
	R^2 0.06					

Notes. Impact estimates calculated using delta method based on random effects model estimates. * $p < 0.05$; ** $p < 0.01$ against the null that the effect = 0. Cumulative impacts to year $h, h = 2011, ..., 2015$ calculated by summing the impacts on annual growth from 2011 to h.

Table 4.7
Employment impact of earthquake shock with dynamic capabilities moderation, *Distribution/Retail*, groupwise-matched 100% single-city-only firms

		Year				
		2011	2012	2013	2014	2015
	Impact on annual employment growth (log pts)					
(1)	Earthquake shock	-0.03	-0.03	0.00	0.00	-0.05
	(s.e.)	*(0.03)*	*(0.03)*	*(0.03)*	*(0.04)*	*(0.04)*
	Dynamic capability moderation effect, per 1 s.d.					
(2)	Cooperation	-0.02	0.03	-0.02	-0.03	0.03
	(s.e.)	*(0.01)*	*(0.02)*	*(0.02)*	*(0.02)*	*(0.05)*
(3)	Marketing/restructuring	0.04	-0.06	0.01	0.00	0.05
	(s.e.)	*(0.03)*	*(0.04)*	*(0.03)*	*(0.05)*	*(0.04)*
(4)	Internal fitness ideation	0.03	0.08*	0.01	0.02	0.06*
	(s.e.)	*(0.02)*	*(0.03)*	*(0.02)*	*(0.04)*	*(0.03)*
(5)	Internationalisation	0.00	-0.02	0.03	-0.02	0.03
	(s.e.)	*(0.02)*	*(0.04)*	*(0.03)*	*(0.04)*	*(0.05)*
(6)	Awareness/responsiveness	0.02	-0.05	0.06*	-0.03	-0.01
	(s.e.)	*(0.03)*	*(0.04)*	*(0.02)*	*(0.04)*	*(0.03)*
	Impact on employment, cumulative since 2010 (log pts)					
(7)	Earthquake shock	-0.03	-0.06	-0.06	-0.06	-0.11
	(s.e.) *(0.03)*	*(0.05)*	*(0.08)*	*(0.11)*	*(0.14)*	
	Dynamic capability moderation effect, per 1 s.d.					
(8)	Cooperation	-0.02	0.01	-0.01	-0.04	0.00
	(s.e.)	*(0.01)*	*(0.03)*	*(0.04)*	*(0.05)*	*(0.08)*
(9)	Marketing/restructuring	0.04	-0.02	-0.01	0.00	0.04
	(s.e.)	*(0.03)*	*(0.07)*	*(0.09)*	*(0.13)*	*(0.15)*
(10)	Internal fitness ideation	0.03	0.11*	0.12*	0.14	0.20
	(s.e.)	*(0.02)*	*(0.05)*	*(0.05)*	*(0.09)*	*(0.11)*
(11)	Internationalisation	0.00	-0.02	0.01	-0.01	0.02
	(s.e.)	*(0.02)*	*(0.06)*	*(0.08)*	*(0.12)*	*(0.16)*
(12)	Awareness/responsiveness	0.02	-0.03	0.03	0.00	0.00
	(s.e.)	*(0.03)*	*(0.05)*	*(0.06)*	*(0.10)*	*(0.13)*
	Controls					
	ordinary capabilities factors					
	ln(size)					
	ln(age)					
	50%+ foreign-owned					
	N 3013					
	R^2 0.09					

Notes. Impact estimates calculated using delta method based on random effects model estimates. * $p < 0.05$; ** $p < 0.01$ against the null that the effect = 0. Cumulative impacts to year $h, h = 2011, ..., 2015$ calculated by summing the impacts on annual growth from 2011 to h.

5 Discussion and conclusions

The key results from this paper are that, in the CI and DR sectors in particular, firms with high dynamic capabilities exposed to the earthquake shock performed better for some years after the shock, compared to exposed firms with lower dynamic capabilities. This finding is consistent with claim in the dynamic capabilities literature that dynamic capabilities position firms to cope well with, and exploit, environments of rapid change.

The most straightforward and strong results are for the CI industry, for which the *marketing strategy adjustment* and *internal improvement* capabilities showed sizeable beneficial moderating effects on the impact of the shock on cumulative sales and employment for exposed firms. This result makes sense given that of the three focus industries, the CI industry is the one that appears to have experienced the largest shock, which was in a favourable direction (creating an environment of excess demand).

I also find that *marketing strategy adjustment* capability helped exposed DR firms outperform their peers in terms of sales growth in a persistent manner, even though the impact of the shock on sales growth on exposed DR firms on average was small and temporary. The evidence is consistent with exposed DR firms with strong *marketing strategy adjustment* capability (which one would expect to be a key "competence" of retailers) being able to exploit opportunities to gain market share even when the general environment is one of disruption.

Unsurprisingly, given the heterogeneous impacts of a disaster such as a major earthquake, the most useful capabilities were not the same across all dimensions of firm performance, nor did all industries benefit from higher capabilities to the same degree or in the same way in the face of the disruption. While the two dynamic capabilities that stood out as strengthening performance of exposed firms during the shock were *marketing strategy adjustment* and *internal improvement*, *external cooperation* also played a role in some cases.

These results are generally robust to changes of the estimation sample to include firms with partial exposure to the earthquake shock, rural firms and non-exposed multi-city firms, and different estimation techniques.

Relative to the bulk of the dynamic capabilities and disaster empirical literatures, the approach in this paper offers some methodological advantages. First, the work combines dynamic capabilities and medium-term (multi-year) outcomes, using an official, large and statistically representative survey and longitudinal administrative data. Second, the estimated moderation effects of dynamic capabilities on performance can be given a causal interpretation, under the reasonable assumption that exposure to the earthquake is uncorrelated with any time-varying influences on performance not included in the model.[22]

5.1 Limitations and further work

Three limitations of the results presented in this paper are evident.

A first limitation is that the specifications for both the survival models and the linear regression models for the other outcomes only capture the dynamics of the relevant impacts in a very simple manner. In the linear regression models, the use of year dummies to capture the time profiles of the impacts of the shock and dynamic capabilities moderation leave the dynamics completely unrestricted, which also limits their relevance to the specific years studied. Parametric approaches to characterising these dynamics could shed light on the relevant dynamics more generally and enable extrapolation to broader settings and longer horizons.

Second, the identification of the effects of the earthquake shock in the DiD approach used here depends on the validity of the parallel-trends assumption prior to the shock, on the assumption that the shock did not affect the non-exposed group of firms, and on the quality of the match between the exposed and non-exposed groups (that they are the same in expectation for unobserved relevant variables). Results of formal testing for parallel trends and informal (graphical) evidence do not suggest on their face that these key assumptions are invalid, but they could nevertheless be tested further and the estimates possibly sharpened by recently developed approaches to matching, such as synthetic differences-in-differences (Arkhangelsky et al., 2021).

Finally, the lack of evidence for any role for dynamic capabilities in enhancing survival probability of exposed firms in the earthquake shock studied here either reflects that the effect is small, or possibly more likely given the results of the modelling of other outcomes, that there were insufficient failures in either the exposed or the non-exposed groups to reveal any such effect. The evidence from the linear regression models that the earthquake shock on net created a beneficial environment for firms on average in two key industries – CI and DR – implies that the shock is perhaps not so suitable for investigating effects on survival, since such circumstances would tend to *reduce* the number of observed failures (and therefore the amount of variance to work with in survival modelling). In either case, a longer observation period, larger samples of exposed and non-exposed firms, and different kinds of shocks would help to resolve moderation effects in the context of survival probability as a measure of

[22]Bun and Harrison (2019) and Nizalova and Murtazashvili (2016) show that coefficient estimates for interaction terms are consistent if one of the terms in the interaction is exogenous.

long-term performance.

Appendices

Appendix A Data sources, derivations and dataset construction

I source all data from Longitudinal Business Database tables, as follows.

Business Operations Survey

Business Operations Survey data are from the tables
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2005_mod_a`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2005_mod_b`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2005_mod_c`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2009_mod_a`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2009_mod_b`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2009_mod_c`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2013_mod_a`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2013_mod_b`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2013_mod_c`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2017_mod_a`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2017_mod_b`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2017_mod_c1`
`ibuldd_clean_archive_dec_2019.dbo.fact_bos_enterprise_2017_mod_c2`

Item codes are generally organised in the BOS tables for each module such that digit 2 identifies the module, digits 3-4 the question number, digits 5-6 subquestions and digits 8-9 subquestion-level response options. For example, the LBD variable `LA2200` from the 2017 BOS is question 22 from module A. In the main text, the item codes are digits 2-5 from the corresponding LBD variable. Note - the 2005 BOS tables do not have L as the first digit, and digit 7 is # instead of _ as in the other three BOS years used in this study.

I use the following BOS stratification variables to construct the sample of for-profit firms at the ANZSIC 2006 1-digit industry level:
`strata_code`
`substrata_code`

I source ANZSIC code descriptions for the identification of 1-digit industry and for member-

ship of the high-tech and medium-high-tech manufacturing, and knowledge-intensive services industries at higher levels of disaggregation from
`anzsic06_code` in the BOS tables, with descriptions in the lookup table
`ibuldd_clean_archive_dec_2019.dbo.ref_anzsic06`

ANZSIC code descriptions: `anzsic06_text`

I map the ANZSIC 1996 industry codes used in the 2005 BOS to ANZSIC 2006 (`anzsic06_code`) equivalents using the concordance table provided by Stats NZ:
`http://aria.stats.govt.nz/aria/?_ga=2.126732045.1606885408.1660881886-1676645843.1656569216#ConcordanceView:uri=http://stats.govt.nz/cms/ConcordanceVersion/CARS2357`

I aggregate the ANZSIC Divisions (1-digit level industries) recorded in the BOS into six broad industry aggregates as follows:
Primary: Divisions A, B
Manufacturing: C
Construction/Infrastructure: D, E
Distribution/Retail: F, G, H, I, L
Technical Services: J, K, M
Other: N, O, P, Q, R, S

I source employment and foreign-ownership control variables from the BOS as follows:
employment: `rme`
foreign ownership: `LA1201_01` (in the 2017 BOS, or equivalent questions in the other BOS years used) where I code a response of 50% or more as 1 and 0 otherwise.

Survival dataset

I source birth and failure dates for the derivation of firm age and for the construction of the survival dataset from the Longitudinal Business Frame table
`ibuldd_clean_archive_dec_2019.dbo.fact_lbf_enterprise_year`
Firm birth date: `birth_date`
Firm failure date: `cease_date`

Fabling/Maré productivity dataset

I source or derive data for the intermediate outcome models (where not available from the other sources) from the Fabling and Maré (2015b) and Fabling and Maré (2019) productivity

and labour tables
`[ibuldd_research_datalab].[STATSNZ\dl_RFabling].[pent_year_L_IDI_20201020]`
`[ibuldd_research_datalab].[STATSNZ\dl_RFabling].[pent_prod_IDI_20201020]`
`[ibuldd_research_datalab].[STATSNZ\dl_RFabling].[pent_prod_IDI_20200120]`
margins: `go_nom`/(`total_gross_earn` + `M_nom` + `K_nom`)
sales: `go_nom`
FTE employment: `fte`
sales per employee: `go_nom`*exp(`lnL`)
average wages: `total_gross_earn`*exp(`lnL`)
total factor productivity (TFP): `mfp_go_tl`
capital intensity: `lnK_real - lnL`

Data in the Fabling/Maré dataset are identified by their longitudinal unique enterprise identifier `pent`, which I link to the unique identifier for the rest of the LBD variables `enterprise_nbr` via the link table
`[ibuldd_research_datalab].[STATSNZ\dl_RFabling].[pent_IDI_20201020]`

Spatial data

I source data on firm employees by location from the LBF table
`ibuldd_clean_archive_dec_2019.dbo.load_lbf_fact_business`

I calculate employment by Territorial Authority in 2010 as the average over all available monthly entries for that year in the table, ignoring missing months (i.e. treating missing months as having the same employment as the average of the non-missing months), dated by `dim_start_month_key` and where `geo_live_ind` coded as `y` indicates a live GEO. employment by geographic unit (GEO): `geo_employee_count_nbr` GEO Territorial Authority (TA): `geo_ta_code`

I identify the Territorial Authority name `ta_name_text` using the lookup table
`ibuldd_clean_archive_dec_2019.dbo.ref_territorial_authority`

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