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Te Kōmihana Whai Hua o Aotearoa

Born in bad times: Economic conditions, selection and employment

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Abstract

Periods of recession can have long term impacts on the economy. Entry rates decline during recessions, depressing aggregate job creation in future. At the same time, conditions at entry may also affect long-run growth prospects at the firm level. This paper explores patterns of firm birth, growth, and death for cohorts of New Zealand firms born between 2002 and 2015, and examines the role of selection for explaining those patterns. Firms born in ``bad times'' – the years of and immediately following the Global Financial Crisis – are shown to start out, and remain, smaller than comparable firms born in more buoyant economic circumstances. Industry composition, firm type, and the characteristics of entrepreneurs are shown to vary across the economic cycle but cannot fully explain the size gap. While firm size gaps are small in absolute terms, as entering firms tend to be very small regardless of the economic conditions, when aggregated across firms these small employment gaps can lead to sizeable reductions in cohort employment.

JEL classification: D22; E32
Keywords: firm dynamics; entrepreneurship; employment; age-period-cohort (APC) model; start-ups; Global Financial Crisis (GFC)

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1 Motivation

Recessions can have long term impacts on the economy. Firm entry rates decline during recessions, depressing aggregate job creation in future (Sedláček 2020; Clementi and Palazzo 2016). Although start-ups have a limited impact on current employment they are an important source of employment growth (Haltiwanger et al. 2013) and have also been shown to provide opportunities for younger and less skilled workers (Ouimet and Zarutskie 2011), who tend to fare worse during economic downturns (Hoynes et al. 2012; Oreopoulos et al. 2012; Forsythe 2022).

Economic conditions at the time of a firm's birth have also been found to be associated with the growth prospects of the firms that do enter. In the short run, young (and small) firms are more affected by negative economic shocks (Fort et al. 2013; Criscuolo et al. 2014). In the longer run, the picture is somewhat mixed, with conflicting evidence on the link between conditions at entry and firms' growth prospects and performance. While researchers using US data have found that firms born in recessions tend to start out and remain smaller than firms born in good times, even long after economic conditions have improved (Sedláček and Sterk 2017; Moreira 2017), the opposite pattern has been observed for firms in Italy (Cavallari, Romano, and Naticchioni 2021).

The analysis of longer-term firm outcomes from poor conditions at entry has parallels in the study of wage scarring effects among recent graduates (eg, von Wachter 2020). However, individual graduates have already made significant investments in their own human capital and have limited ability to influence when they will arrive into the workforce.[1] In contrast, potential entrepreneurs have significant flexibility to delay or abandon their plans to start a new business.[2] This raises the possibility that long term differences in firm outcomes may be due not to "scarring" but rather to selection. That is, differences in the characteristics of individuals who choose to start a firm at different points in the economic cycle, and in the types of businesses they choose to start.

Economic conditions can affect the incentives for businesses to enter in multiple ways. In most cases, entrepreneurs must make an initial investment in order to establish their business – setting up their business location; hiring and training employees; investing in equipment, technology, and marketing. While some equipment can be on-sold if the business fails, much of this expenditure is irreversible. Potential entrepreneurs' willingness to make such investments therefore depends both on the probability that the firm will succeed and make a profit (relative to their potential alternative employment options) and on the costs of establishing the firm. Poor economic conditions (and low demand in particular) reduce the potential revenues of the firm, thus lowering the short-term expected profitability. At the same time, some business owners may have limited ability to accurately assess their own business prospects (Fabling et al. 2012), particularly when economic conditions are volatile. Recognising this, banks may be less willing to lend, fearing that firms will fail and default on their loans. Finance may

[1] That is not to say young people have no ability to time their labour market entry. See, for example, Dellas and Sakellaris (2003) and Smart (2009) for evidence of increased tertiary enrolment during downturns.

[2] Sedláček (2020) explores whether low entry rates for the US during the Global Financial Crisis (GFC) reflect a "lost generation" of potential entrants or simply a delay in entry. He finds no evidence of a corresponding over-shooting in entry activity after the recession, suggesting that potential business entry was indeed curtailed rather than simply postponed.

be particularly difficult to get if the recession itself is associated with financial sector shocks.

The goal of this paper is to establish some stylised facts for New Zealand and to examine the role of selection in explaining those facts. In particular, we explore how changes in the composition of entering firms, and the individuals who start those firms, influence employment outcomes over the first five years of a firm's life.

There are a number of reasons why firms born in recessions may be permanently different from those born in more affluent economic times. The reasons fall into two broad categories: the direct effects of recessions on firms, particularly on new and small firms, and the impact of recessions on the types of firms that enter.

Conditions at the time of birth may directly affect firms' future growth prospects if, for example, new firms have to make long-term investments (in both physical and intangible capital) at a time when banks and investors are more cautious. It can also happen if firms' future sales are dependent on building a customer base in the early years (eg, Foster et al. 2016). Reduced opportunities to invest and build scale during a firm's early years may lead to long-lasting differences in firm performance outcomes.

However, the direct impacts of starting life in a recession are not unambiguously negative. A lack of alternative employment opportunities makes it easier for young firms to attract highly skilled workers, while lower interest and rental rates can lower the costs of establishing a business. If firms can develop high quality products and practices from an early stage, and retaining good employees, businesses that enter in hard times may be well-positioned for growth when the economy improves.

Economic conditions can also affect the composition of entering firms. On the one hand, recessions can lead to negative selection on firm quality if there is a large increase in involuntary entrepreneurship. That is, if poor economic conditions lead to increased unemployment, some previously employed workers may look to start a business of their own, despite not being well-equipped to do so (Fairlie 2013). Involuntary, or "necessity" entrepreneurs tend to have lower levels of education than "opportunity" entrepreneurs, and the firms they start tend to have lower levels of business assets, are less likely to employ, and are less likely to be incorporated – an indicator of growth orientation of the business (Astebro and Tåg 2015; Fairlie and Fossen 2020; Levine and Rubinstein 2017; Levine and Rubinstein 2018).

In contrast, poor conditions raise the level of innate performance (productivity) required for firms to be profitable. If only the entrepreneurs with better ex ante prospects enter in hard times, and only the most successful survive, selection effects can lead recession-born firms to outperform others at a similar stage of life. Indeed, while US data shows that employment remains lower for recession-born firms, there is also evidence of positive selection on performance, with firms born in downturns having higher productivity and being in more skill and capital intensive industries (Moreira 2017).

Selection effects may also operate through changing the industry composition of entering firms. Certain industries experience more cyclical demand (eg consumer durables and restaurant meals) while others are largely insulated from cyclical shocks (eg, education, health care, and staple consumer goods) (Berman and Pfleeger 1997; Lien 2010). These differences can affect the composition of both the existing stock of firms (through exit and relative growth) and new cohorts of entering firms. Firms entering in recessions will tend to be skewed towards "recession-proof" industries and those with less cyclical volatility. As firm sizes differ dramatically across industries, changes in the industry composition of entrants may shift the observed average firm size across the economic cycle.

The complex and often conflicting effects on firm quality and future growth potential suggest that the medium-term employment impacts of economic downturns are likely to depend on the economic and institutional context. Looking at firm start ups in Italy, Cavallari et al. (2021) find that firms born in bad times tend to start, and remain, larger than cohorts from more affluent years, with positive self-selection outweighing the negative impact of conditions at birth. Indeed, even within the United States the evidence is not clear – where Moreira (2017) and Sedláček (2020) find "scarring" impacts of being born in bad times in the US, Lee and Mukoyama (2015) find that manufacturing plants established during a downturn are positively selected, with higher employment and productivity relative to incumbents than those established during an upswing in sectoral activity. There are a number of differences between the papers, including the use of levels vs changes in GDP as the main explanatory variable, plants vs enterprises as the unit of observation, and differences in the industries and time period covered, which may account for the differing conclusions.

Throughout the remainder of this paper, we examine how patterns of entry, exit, firm growth, and selection differ for cohorts of firms born before, during, and after the Global Financial Crisis (GFC) of 2008/09. While the New Zealand economy suffered less than many larger economies, New Zealand experienced 6 quarters of negative GDP growth between January 2008 and June 2009, with a further two quarters of decline between July and December 2010.[3] The employment rate suffered its first sustained decline since the late 1990s, and unemployment rose from 3.8 percent in the December 2007 quarter to 6.8 percent two years later, the highest rate in over ten years (StatsNZ 2012). Employment remained subdued for some time, with the employment rate among 15–64 year olds remaining below its 2007 peak of 75.8 percent until 2016.[4]

This paper focuses on the role of entering firms for employment, and the impacts of the recession for the birth and growth of new firms. Section 2 describes the data used to explore these questions, and sets out descriptive patterns of new firm entry, survival and growth since 2002. Section 3 outlines the method used to untangle, as best as possible, the related roles of current conditions, conditions at birth, firm age, and firm composition, and the findings of this analysis. Section 4 provides a summary and discussion.

[3]Statistics New Zealand Quarterly Real GDP (Production), Series reference SNE178AA
[4]Statistics New Zealand Household Labour Force Survey, Table reference HLF229AA.

2 Data

To explore patterns of employment and output growth across economic cycles, this research exploits detailed administrative data from Statistics New Zealand's Longitudinal Business Database (LBD) and Integrated Data Infrastructure (IDI). These data collections bring together a range of administrative and survey data sources at the firm- and individual-level respectively, linked together through individual and corporate income tax returns. See the Stats NZ website[5] for information on the IDI and Fabling and Sanderson (2016) for further detail on the structure and coverage of the LBD.

The core data covers the period from April 2000 to March 2021, a fairly short period over which to consider the medium term impacts of economic conditions.[6] In particular, although the period covers two major economic shocks – the GFC and the COVID-19 pandemic – the requirement to be able to track employment for a number of years after entry narrows attention to the GFC. In addition, in order that we observe young firms operating in a range of economic environments we are restricted to considering a relatively short period of time at the start of firms' lives. In the core analysis we focus on cohorts born between 2002 and 2015, observing each cohort for five years following entry.[7]

2.1 Definitions

Our key interest is in the role of early-life economic conditions on firms' future growth and performance. We define firm entry and exit based on observed labour input from the Fabling and Maré (2015) labour tables. A firm's year of entry is defined as the first year with observed labour input (employees or working proprietors) following at least two years of no labour input. Exit years are defined symmetrically as the final year before a period of at least two years with no observed labour input.[8]

Throughout the paper we use combined working proprietor and employee labour input as our measure of firm size. For conciseness we refer to this measure as "employment".[9] Cohort employment is the aggregation of firm employment for all (surviving) firms born in a particular year.

Labour input (employment) data is sourced from the Fabling and Maré (2015) labour tables. We make use of adjustments for identifiable deviations from full-time employment including: multiple job holdings or working-proprietor income from multiple firms; monthly earnings which are too low to be compatible with full-time employment at the statutory minimum wage; and adjustments to working-proprietor labour

[5] `https://www.stats.govt.nz/integrated-data/integrated-data-infrastructure/`

[6] Results are based on the 2021-10-20 archive of the IDI and the 2021-12 archive of the LBD.

[7] In robustness tests we considered a slightly longer period of seven years for each entry cohort, while restricting to cohorts born in 2013 or earlier. The results are qualitatively unchanged. These results, and other robustness checks mentioned throughout the paper, are available from the author on request.

[8] Alternative measures of entry are available. Stats NZ's Business Register records firms' birth date, based on a combination of tax registration and employment data. Indicators of activity based on observed labour input are preferred for this research as these are consistently measured across firms even in the event of long periods of inactivity and are consistent with the primary outcome measure.

[9] In specific cases we exclude working proprietors from the employment measure, as indicated in the text and table notes.

input which assume mid-year start and cease dates for the first and final year of firm activity (Fabling and Maré 2015). While this method cannot identify part-time employment of highly paid workers it gives a more accurate estimate of actual labour input than a straight headcount, especially for industries and firms with many short-hours employees. In the regression analysis we also consider value added, as captured by net GST sales, as an alternative measure of firm size and value added per worker as a proxy for labour productivity.[10]

We measure employment starting from the year after entry (age 1), rather than the year in which labour input is first observed (age 0). Measuring employment in the year of entry presents an inconsistent picture of firm size across firms born early in the year and those born in later months. In the regression analysis of section 3 we also exclude the year of exit, which will have a similar issue for firms which cease employing at different times of the year.

We adjust for breaks in longitudinal firm identifiers as per Fabling (2011). These breaks reflect changes in the legal status of a business, resulting in a new enterprise number being assigned by Stats NZ. We also correct for false entry and exit of large firms where these can be identified as mergers or restructuring rather than a true entry or exit. To do so, we identify entries (exits) of firms where the average monthly employment in the first (final) year of employment is 20 or more.[11] We then use individual-level data to identify employees who move from a large exiting firm to a large entering firm. If more than 20% of large-firm employees (firms with monthly FTE $\geq$ 50) or 50% of medium-firm employees (monthly FTE $\geq$ 20) move together from one firm to the next we treat both the entering and exiting firms as continuing firms.[12]

Table 1 documents the impacts of these adjustments on the number and initial size of entering firms. Of the 2,319 medium (20-49 FTE) and 1,014 large (50+ FTE) firms initially identified as entrants (column 1), 7% and 35% respectively have been reclassified as continuing firms (column 2). Columns 3 and 6 further show that 675 of the remaining 2,163 medium entrants (417 of the remaining 654 large entrants), accounting for 33% (76%) of employment in that size group (column 6), are subsidiaries of another company. We exclude subsidiary firms from our analysis of entry and growth dynamics as the objectives and constraints these firms face are expected to differ from those of independent businesses.[13]

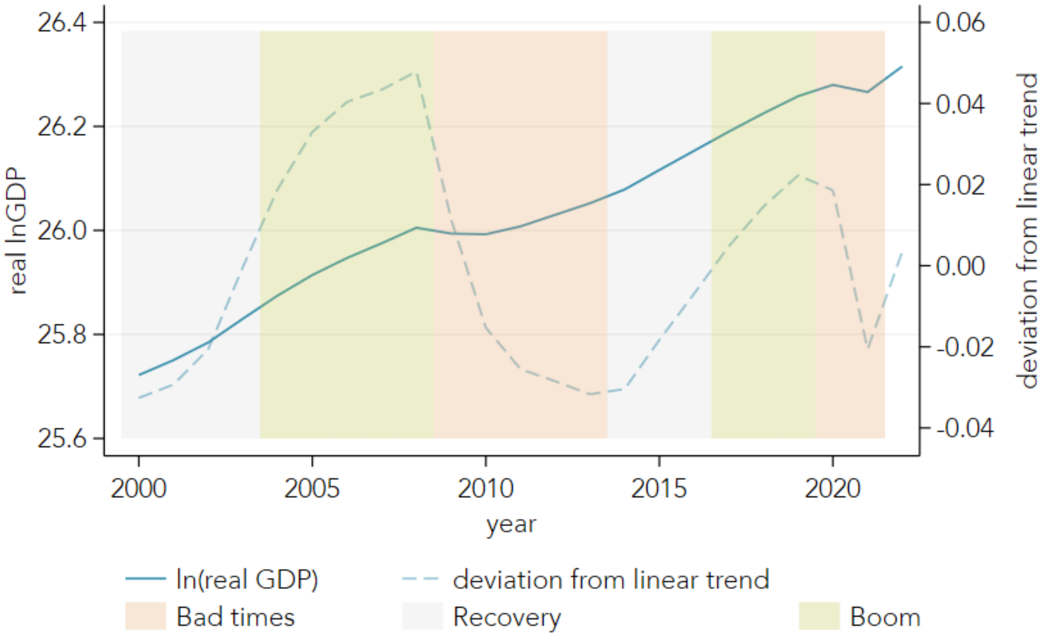
[10] GST of 15% is charged on almost all goods and services traded in New Zealand. Key exceptions are financial services, residential rental accommodation, and certain types of real estate transactions. Transactions of these products will not show up in the GST data. We therefore exclude the residential rental, real estate, and financial services industries from our analysis of firm value added. In addition, there are a number of transactions which are zero-rated for GST. These include exported products and sales of part or all of a business as a going concern. Despite being zero-rated, these transactions do appear in the GST data and are included in our firm-level value-added measures.

[11] Employment numbers are averaged only over those months with non-zero employment in order to treat firms which commenced (ceased) activity at the start of the year consistently with those that commenced (ceased) towards the end of the year. We exclude working proprietors from this calculation as we do not have monthly information on working proprietor activity.

[12] In robustness checks we forego this step and instead exclude entries with average monthly employment of 50 or more in their year of entry. The results are qualitatively unchanged.

[13] Subsidiaries account for only 2% of firm entries but make up 20% of monthly employment among entering firms. Repeating the core regressions including subsidiaries suggests a slightly stronger relationship between economic conditions at entry and firm size – firm size in subsidiaries is more procyclical than for independent firms – but the patterns are qualitatively very similar.

Figure 1: Aggregate economic conditions, 2000-2022



Source: Author's calculations based on Statistics New Zealand's Gross Domestic Product (production) series. Chain volume, Actual, Total. Year ending 31 March.

We also restrict attention to private-for-profit firms and exclude the Government Administration and Defence sector, as public sector and non-profit firms do not face the same market forces associated with economic downturns.[14]

Our core measure of economic conditions is based on deviations of annual log GDP from a linear trend.[15] Annual GDP is measured for the financial year ending in March – thus, the 2009 year refers to the period from 1 April 2008 to 31 March 2009. We allow for both the level and the growth rate of aggregate GDP to affect cohort outcomes. While recent papers have tended to focus on levels (Moreira 2017; Cavallari et al. 2021), Lee and Mukoyama (2015) argue that growth rates are the more appropriate indicator when examining cyclical patterns of entry and exit, and show that the use of aggregate levels is at odds with conventional distinctions between booms and busts. In the New Zealand case, using levels would result in 2009 (the year that saw the largest year-on-year decline in GDP since the current series began in 1978) being classified as a "good" year, while 2003 (with a real GDP growth rate of 4.7%) would be classified as "bad".[16]

We simplify the annual GDP measure into three categories based on the relative level and growth rate of the detrended GDP measure. A "bad year" is defined as one in which the detrended GDP measure fell relative to the previous year. We then distinguish two

[14] Estimates from robustness tests including not-for-profit firms are qualitatively the same.

[15] See Hamilton (2018), Phillips and Shi (2021) and Hall and Thomson (2021) for discussion of alternative detrending options. Real GDP is from Statistics NZ's GDP(P), Chain volume, Actual, Total (Annual-Mar) series (SNE053AA).

[16] Using purely levels-based measures of aggregate conditions in the regression analysis significantly affects outcomes. These results are not reported but are available from the author on request.

types of "good" years (those in which detrended GDP rose relative to the previous years) according to whether the *level* of GDP in that year was above or below trend. This definition thus distinguishes "boom" years in which GDP was both high and rising, from "recovery" years in which GDP was rising but remained low relative to trend.[17] Figure 1 plots actual log GDP and the detrended series for the years ending March 2000 to March 2022. Years defined as "bad" according to this definition are shaded in orange, while "boom" years are shaded in green. This distinction reflects that firms (and potential entrants in particular) are expected to consider both the current state of the economy and expectations about the future when making long-lived decisions such as whether to enter the market and how much to invest.

Annual GDP data relates to the year ending 31 March. Around 92% of private sector firms in New Zealand work to a March financial year. Firms can apply to report on an alternative balance date to align with the seasonality of their production.[18] For example, many cattle and dairy farms work to a 31 May balance date, while childcare businesses often report on a December financial year. As working proprietor information is available only annually, for the financial year of the firm, we align firms' financial year information with the March year with the greatest overlap. This creates some imprecision in the link between firm-level data and aggregate GDP information.[19]

To understand the mechanisms through which aggregate economic conditions affect firm-level outcomes we consider a range of firm and working-proprietor characteristics that may affect firm size and performance outcomes. For firms we control for industry, and also explore business type at birth (eg, sole proprietorship, limited liability company) as an indication of entrepreneurs' ex ante growth intentions (see, eg, Astebro and Tåg 2015; Levine and Rubinstein 2017). For working proprietors we consider age, sex, recent experience of business ownership, and a measure of skill based on relative log earnings in employment as used by Maré et al. (2017).

Summary statistics for the main regression populations are provided in Table 2. The regression population is restricted to entering firms and includes observations over the period from age 1 to age 5, excluding firm-years with zero labour input (consistent with the use of log employment as a dependent variable). Observations are defined as firm by working proprietor by year, weighted to give each firm a total weight of one in each year. That is, if a firm had three working proprietors in the year of entry each observation would be weighted by $1/3$, placing equal weight on the characteristics of each WP. Observations of firms that did not have a working proprietor at entry are given a weight of 1 in each year. For firm-level analysis this gives identical results to using equally weighted firm-year observations.

A number of features of the population are worth noting. In particular, entering firms tend to be very small, with mean observed employment of 2.25 (FTE-adjusted) workers over their first five years across the regression population as a whole (column 1).[20]

[17] In principle, one could also distinguish among bad years according to whether the low GDP growth was observed alongside high or low GDP levels. In the New Zealand data only 2009 had both low growth and a high level of GDP. We therefore combine all years in which detrended GDP fell into the category of "bad" years.

[18] `https://www.ird.govt.nz/income-tax/income-tax-for-businesses-and-organisations/balance-dates`.

[19] In robustness tests we restrict attention to firms reporting on a March balance year, with minimal impact on the estimated coefficients.

[20] This small average size partly reflects the population restrictions we make to exclude subsidiaries of other firms and apparent mergers and restructures. The average firm size for the regression

Around 30% of entrants are sole proprietorships – that is, entities for which the firm is not legally separable from the owner. Although sole proprietors can employ staff, this firm type is generally associated with self-employment, implying that most of these firms can be expected to remain small. However, as nearly 80% of firm-year observations have at least one identifiable working proprietor in the year of entry, and sole proprietorships and partnerships together make up only 43 percent of observations, we also see that there are many limited liability companies with identifiable working proprietors at the time of entry.

Column 2 focuses on the firms with at least one working proprietor at birth, with column 3 further restricting to firms for which we have relative earnings measures for the working proprietors (86% of firm-year observations with working proprietors). Firms with working proprietors tend to be smaller than other firms on average, consistent with the high share of sole proprietorships in this group. In contrast, industry composition is quite consistent with that of the full population. Individual working proprietors have a measure of relative earnings only if they have been observed earning wage or salary income in a firm with sufficient employee turnover to separately estimate the contribution of firm and worker effects to individual earnings (see Maré et al. 2017). Restricting to firms where we have relative earnings information reduces the available sample by 14% but does not substantially affect the sample characteristics.

2.2 Entry, exit, and growth over the economic cycle

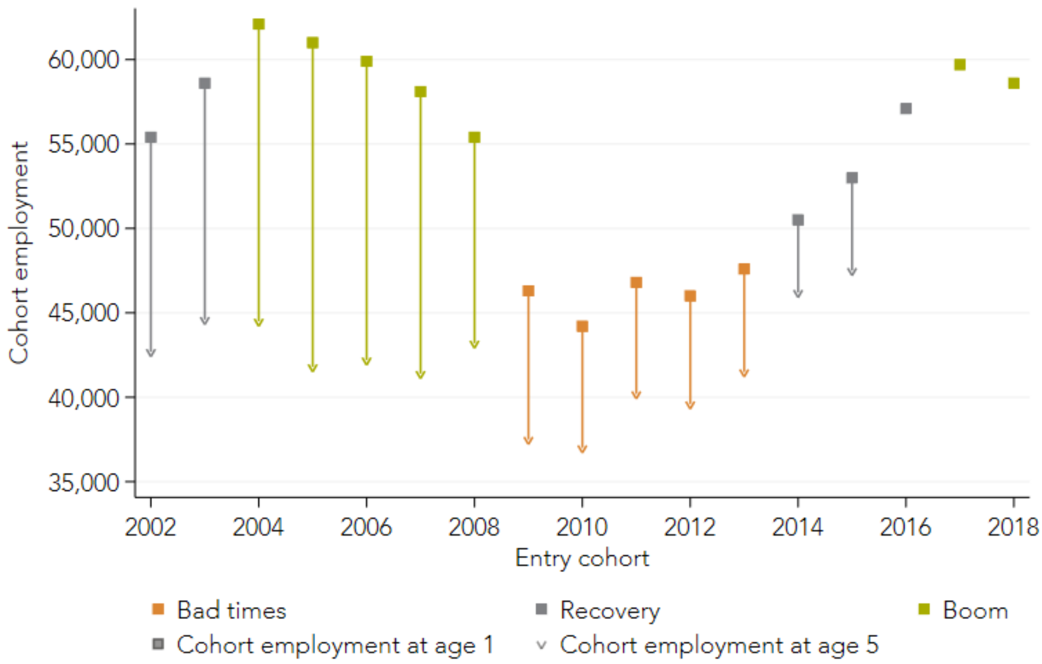
The remainder of this section describes patterns of entry, exit, survival and growth over period from 2002 to 2021, with a focus on employment.

Figure 2 plots cohort employment at age 1 and age 5 for firms born between 2002 and 2015 (and cohort employment at age 1 for firms born from 2016 to 2018). In every cohort total employment at age 5 is lower than at age 1. That is, employment growth in surviving firms is outweighed by employment decline and exit. Looking across cohorts shows that total employment is lower for cohorts of firms born in poor economic conditions at both age 1 (orange squares) and age 5 (orange arrows). In contrast, cohorts of firms born prior to the GFC started out larger, in terms of total employment, but experienced a much larger employment decline. This is particularly true for the cohorts born in the pre-GFC boom period (green) but is also evident for cohorts born in the early 2000s (grey, 2002-2003) even though these firms had reached age 5 prior to the onset of the GFC. During the recovery period of the mid-2010s (grey, 2014-2016) we see a steady increase in birth cohort size, but employment loss over the first five years remains low.

Figure 3 digs into the post-entry dynamics of survival, growth and decline that underpin the net employment change in cohorts' first five years. Each bar represents a cohort of entrants, from those entering in the year to March 2002 to those entering in the year to March 2015. The black diamonds represent cohort employment at age 5 (March years 2007 to 2020). This total is decomposed into four parts: initial employment as measured at age 1 (blue bars); the increase in employment between ages 1 and 5 due to growing firms (green bars); and the declines in employment due to exiting (orange) and shrinking (grey) firms.

population shown in Table 2 is slightly higher than that for young firms as a whole (shown in Figure 7) due to the exclusion of exit years in the regression population.

Figure 2: Cohort employment at age 1 vs age 5



Source: Author's calculations based on data from the LBD and IDI.

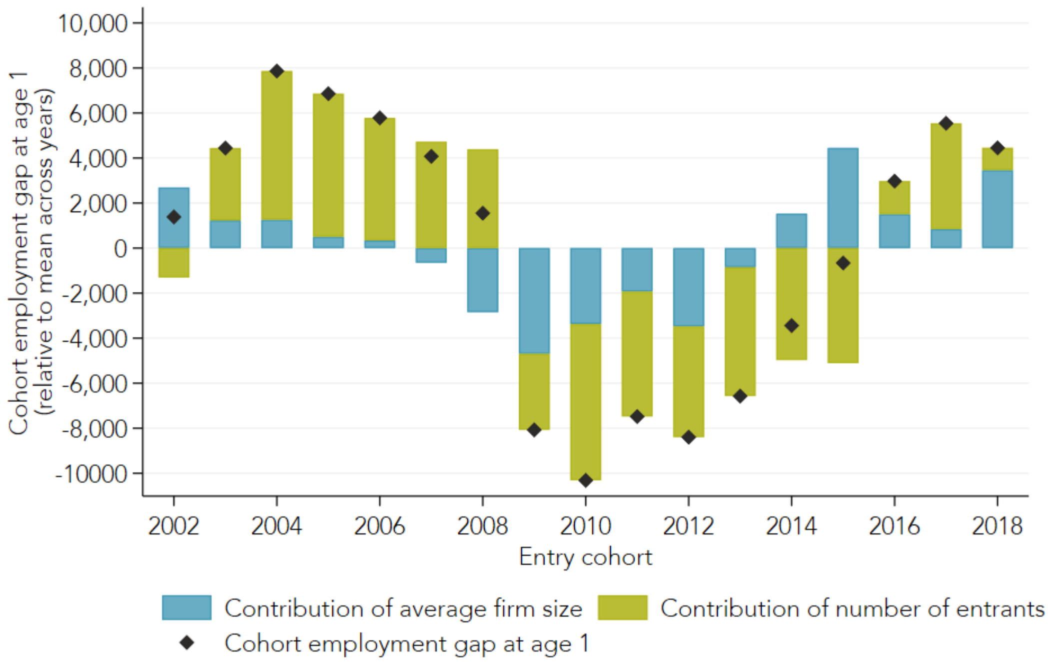
Figure 3: Cohort contributions to employment at age 5

Source: Author's calculations based on data from the LBD and IDI.

At age 5, cohorts born during the GFC were notably smaller than cohorts born in better economic conditions. Cohort employment for firms born in 2009 and 2010 was 14% lower than the cohorts born in 2004 and 2005, and 20% lower than the cohorts born in 2014 and 2015. As indicated also by Figure 2, the dominant source of this difference is the difference in initial employment levels – cohorts born in bad times exhibit similar levels of employment growth and decline among surviving firms to those born in good times, but start from a much lower base. The gap in initial employment levels is partially offset by a reduction in employment loss due to firm exit (orange bars), leading to the convergence in cohort size at age 5 compared to age 1 shown in Figure 2.

Cohort employment at age 1 is itself a mix of two distinct elements: the number of firms and the average size of those firms. Figure 4 indicates how each of these measures contributes to cohort employment at age 1. Black diamonds indicate the gap between cohort-level employment for a particular cohort and the mean across cohorts. This gap is decomposed into the contribution of differences in the number of entrants (excluding transitory firms that exit at age 0) (green bars) and the contribution of the average size of those entrants at age 1 (blue bars). Underlying counts and mean firm sizes by entry cohort are also provided in Table 3.

Figure 4: Decomposition of cohort employment gaps at age 1



Source: Author's calculations based on data from the LBD and IDI. *Notes:* Each bar represents the cohort of firms entering in a given year. Bar height reflects the gap between total employment in each entry cohort at age 1 and mean employment at age 1 across cohorts. The decomposition is $\Delta L_t = (\Delta S_t * \overline{N}) + (\overline{S} * \Delta N_t)$ where L represents the total labour input at age 1 in each cohort, S is the average firm size at age 1, and N is the number of entrants surviving to age 1, $\overline{X}$ indicates the mean of a value across all 17 cohorts, and Δ indicates the difference between each cohort and the mean ($\Delta X_t = X_t - \overline{X}$).

During the pre-GFC boom, the positive initial employment gap was due almost entirely to variation in the number of firms entering and surviving to age 1. The GFC saw a dramatic drop in both the number of entrants and the average size of those entrants, with both measures contributing to the overall negative employment gap.[21] Firms born in 2009 and 2010 had, on average, just 0.15 fewer workers at age 1 than firms born in 2004 and 2005 (a gap of 10%). With over 58,000 surviving entrants over those two years (30,141 in 2009 and 28,023 in 2010), that implies a drop in employment of nearly 9000 workers across the two years due to the reduction in firm size, compared to the cohorts born in 2004 and 2005. There were also 13,800 fewer surviving entrants (a 20% drop), contributing to an overall employment gap of 32,600 workers between the cohorts born in 2009 and 2010 and those born in 2004 and 2005.

As the economy recovered following the GFC, average firm sizes increased more rapidly than entry rates, initially off-setting the negative contribution of low entry in the 2014 and 2015 cohorts. While there were only 200 more entrants that survived to age 1 across the 2014 and 2015 cohorts than in the 2008 and 2009 cohorts, average firm size was 14% higher than the GFC cohorts, and 4% higher than the 2004 and 2005 cohorts. Above average cohort employment at age 1 can be seen from 2016 onwards as entry rates also recovered.

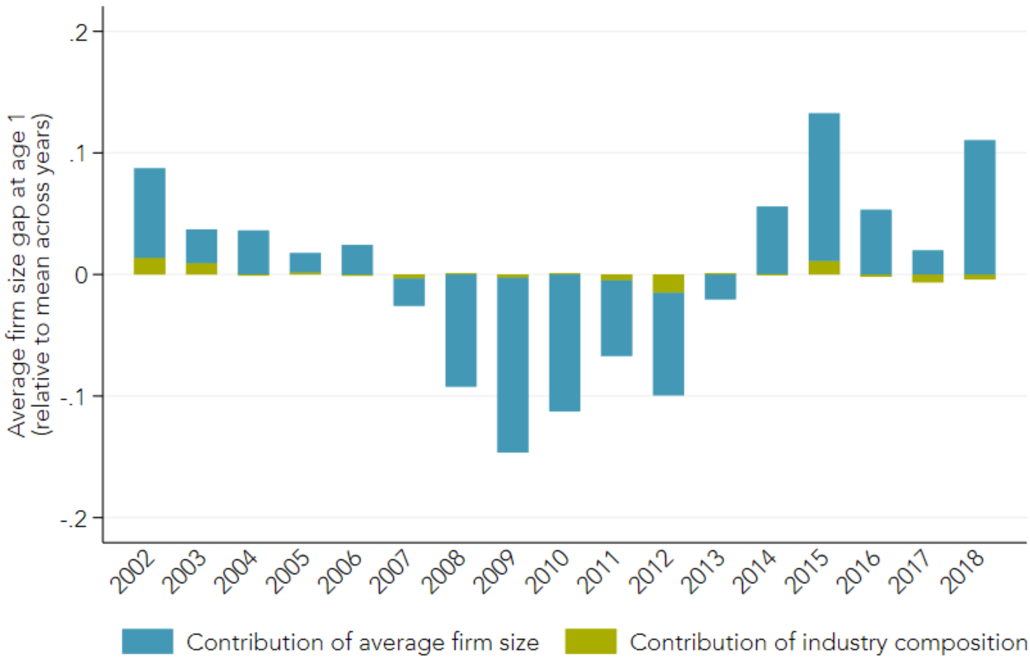
Differences in the average size of entering firms across the cycle may reflect more than just the effect of economic conditions on employment in individual firms. Some industries are more pro-cyclical than others (Berman and Pfleeger 1997; Lien 2010), and industry is a strong predictor of firm size. Figure 5 examines whether the drop in average firm sizes that we see during the GFC period can be explained by a shift in the industry composition of entering firms, decomposing the gap in the average firm size relative to the mean into contribution of changes in average firm size within industries (green bars) and changes in the industry composition of entry cohorts (blue bars). This decomposition indicates the overall drop in firm size during the GFC was driven almost entirely by individual entrants being smaller than usual for their industry, rather than a higher share of entrants in industries which traditionally have smaller firms.

Figure 3 shows that by the time surviving firms reach age 5, firm exit reduces aggregate employment by around 35 percent compared to the initial level. The negative effect of exit is stronger for firms born prior to the GFC.[22] As noted above, periods of economic expansion are expected to draw in firms with relatively lower innate performance, as the barriers to entry are lower and the returns higher. These firms are less likely to survive when times get tough, as they did during the GFC.

[21] The 2008 cohort represents the turning point, with entries in the year to March 2008 remaining strong but average firm size falling sharply. This reflects measurement of firm size (conditional on survival) at age 1, rather than the year of entry. For the 2008 cohort we are measuring firm size in the first year of the GFC, for a cohort of firms that entered just prior to the negative economic shocks.

[22] Employment loss due to exit accounts for 35% of initial (age 1) employment on average for firms born between 2002 and 2008 compared to 32% for the 2009-2014 cohorts.

Figure 5: Decomposition of average firm size at age 1, within and between industry effects



Source: Author's calculations based on data from the LBD and IDI.
Notes: Each bar represents the cohort of firms entering in a given year. The overall gap in average firm size between each cohort and the average of all cohorts is decomposed into the contribution of differences in the average firm size within industries (blue bars) and the contribution of differences in industry composition (green bars). The decomposition is $\Delta S_t = S_t - \overline{S} = \sum_j (\Delta s_{jt} * \overline{\lambda}_j) + \sum_j (\Delta \lambda_{jt} * \overline{s}_j)$ where S is the average entering firm size across all industries, s_{jt} is the average entering firm size in industry j in entry cohort t, and λ_{jt} is the share of industry j firms in all firms in entry cohort t. $\overline{X}$ indicates the mean of a value across all 17 cohorts, and Δ indicates the difference between each cohort's value and that mean $(X_t - \overline{X})$.

Figure 6 plots exit rates for the full population of firms, by firm age group.[23] Exit is a substantial factor in the dynamics of young firms, with almost 15% of firms less than five years old exiting each year. Exit propensity falls with age, with 10% of firms aged 5 to 9 years, and 7% of older firms exiting each year on average. Somewhat surprisingly, the GFC period did not see a rise in exit rates for any age group. Rather, the decrease in aggregate employment over this time was driven by the drop-off in firm entry and growth (Figure 3 and 4) and by falling employment in established and older firms (Figure 7). The employment share of older firms (10+ years) grew over this period while those of young and established firms fell.

The overall impact of firm exit is slightly stronger than Figure 3 suggests. In order to capture employment growth, Figure 3 focuses on the difference between employment at age 1 and age 5, excluding part-year employment in the year of birth. The top line in Figure 6 shows that around 15% of entering firms do not survive beyond their entry year. That is, they do not make it into the age 1 employment counts for Figure 3. The share of transient firms – firms that exit immediately after entry – was trending up prior to the GFC, consistent with the entry of many small firms over this period. Entry rates slowed after the onset of the GFC. The share of transitory firms peaked in 2009 then stabilised and began to fall again from 2013 as economic conditions improved. Examination of patterns of entry and exit at the industry level indicate that the effects of the GFC are clearly observable across almost all industries, with a rapid and prolonged drop in entries starting from 2009. Most industries also exhibit a peak in transient entry in 2008 or 2009, consistent with many new entrepreneurs being caught off guard by the rapid change in the economic environment.[24]

Finally, we compare the age profile of employment for firms born at different points in the economic cycle. Figure 8 provides an initial graphical comparison of age-employment profiles for (surviving) firms born before (blue), during (black) and after (green) the GFC. Firms born during the GFC start out smaller, on average, than firms born either earlier or later. Firms born prior to the recession start out somewhat larger, but grow more slowly than either recession-born or post-recession firms, even prior to the onset of the GFC.

The effects of the GFC on these firms can be seen in the changing growth trajectories of different cohorts. For example, the growth trajectory of the combined 2002 and 2003 cohorts flattens from age 6, while that of the 2004 and 2005 cohort flattens from age 4. In contrast, firms born after the GFC tend to both start out larger and to grow more rapidly. This growth pick-up can also be observed among recession-born firms, which show a steeper age profile after age 6.

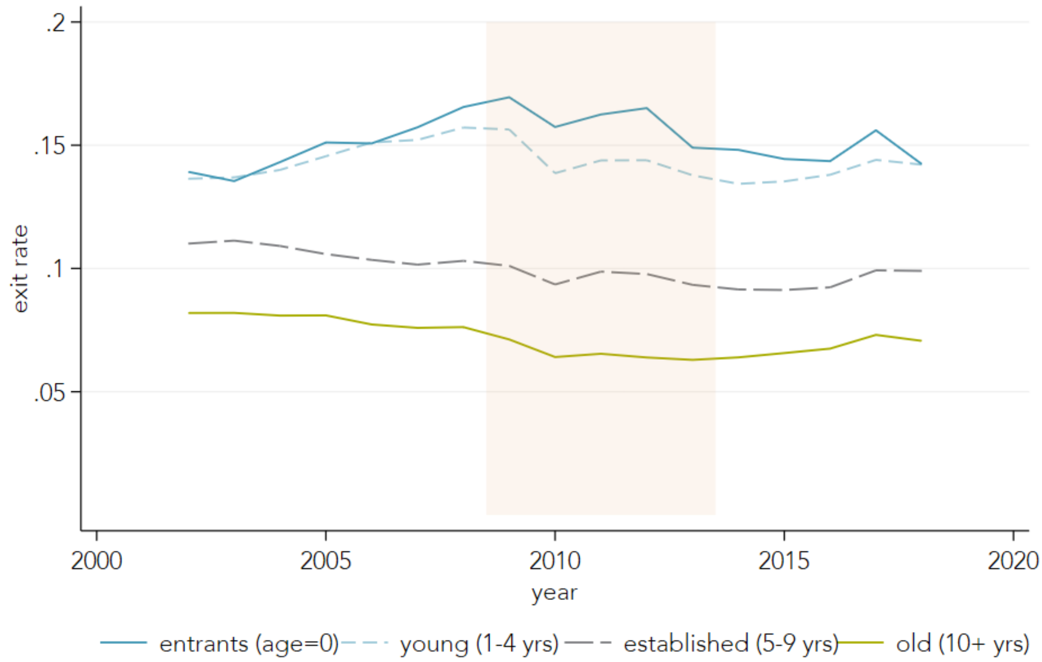
Firms are included in the age profile calculation in Figure 8 only if they are employing in a particular year – that is, the average size at age 5 is calculated only across those firms that survive to age 5. Selective exit of smaller firms results in a steeper age profile than would be observed if we restricted to firms that survive for the full 10-year observation window.

Across all age groups, exiting firms are substantially smaller than survivors. Among young firms, the average exiting firm is around 30% smaller than the average surviving firm (Table 4, column 2). Among older firms (column 4), exiting firms are less than

[23] That is, including firms which entered prior to 2002. For these firms, age is defined as years since birth year based on recorded birth date in the Business Register.

[24] Results available from the author on request.

Figure 6: Exit rate by firm age



Notes: Share of firms with labour input in year t which have no observed labour input in $t+1$ and $t+2$. Population includes firms born prior to 2002. For these firms, the birth date recorded in Stats NZ's business register is used to calculate firm age. Exit is defined as a period of at least two years with no observed labour input.

Figure 7: Average firm size by firm age

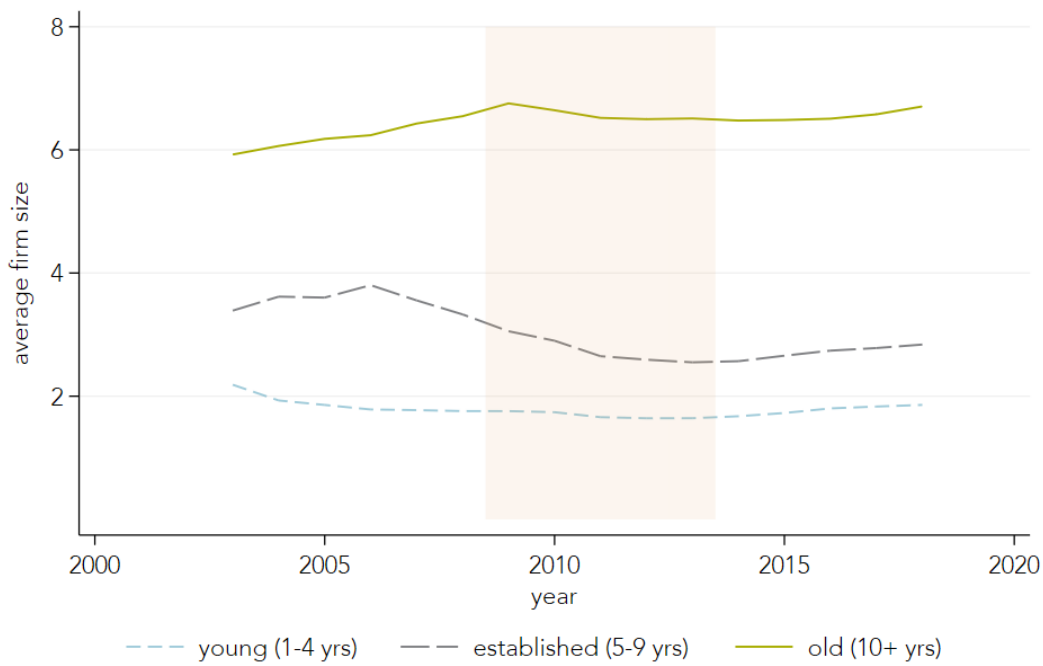
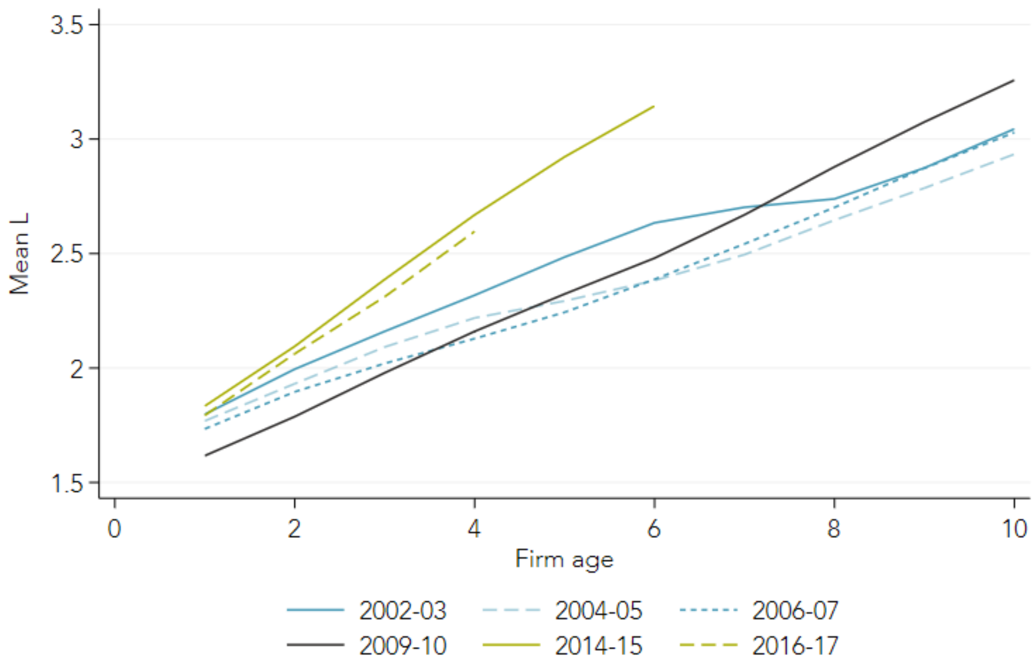


Figure 8: Average age-size profile, by entry cohort



half the size of surviving incumbents. When we examine the role of selective entry in determining differences in firm size across cohorts, it is also important to take account of potential differences in the selectivity of exit.

These simple descriptive comparisons point to the difficulties of determining whether, and how, firms born in recessions differ from those born in more affluent times. Firms born under different economic conditions may be inherently different due to selective entry, but also face different economic environments over their life leading to differences in both their growth rate and exit propensity. Untangling the impacts of birth conditions and selection from the impact of current conditions requires a more formal analysis.

3 Age-period-cohort model

To examine the relationship between aggregate economic conditions and the selection, entry, and growth of new firms, we make use of an age-period-cohort (APC) model. APC models are used to distinguish differences between different birth cohorts (in our case, between those born in more or less favourable economic conditions) from the roles of both aging and the impact of current conditions.

The basic model can be represented by expressing the outcome of interest (Y) of firm i as a linear summation of age ($\mathbf{a}$), period ($\mathbf{p}$) and cohort ($\mathbf{c}$) functions:

$$\ln(Y_i) = \alpha(\mathbf{a}) + \beta(\mathbf{p}) + \gamma(\mathbf{c}) \tag{1}$$

As there is an exact linear relationship between the three variables (current year = entry year + current age), this simple model is not identified. Several methods have been proposed to enable the identification of the different components, including functional form (spline) restrictions (Carstensen 2007; Rutherford et al. 2012), case-specific normalisations (Deaton 1997), focusing on second derivatives (McKenzie 2006), and treating one or more of the effects as being a proxy for an underlying variable which is not itself linearly related to the others (Heckman and Robb 1985). We follow this latter approach, using indicators of aggregate economic conditions at the time of entry in place of cohort dummies. The use of the APC model with aggregate conditions in place of cohort effects also serves to make our results more comparable with existing papers in the literature, including Moreira (2017) and Cavallari et al. (2021).

Age dummies are used to capture common patterns of firm growth over the lifecycle, and year dummies are used to capture the role of current economic conditions which affect all firms. By including these as dummy variables we implicitly assume that the impacts of age may be non-linear (that is, the effect of going from age 2 to age 3 may differ from that of going from age 3 to age 4). At the same time, this approach restricts the effect of both aging and the economic environment to be the same across the population.[25] By using overlapping cohorts of firms, including firms active before, during, and after the GFC, and by separating young firms out from more established firms, we maximise our ability to disentangle the effect of conditions at birth from those of other contemporaneous shocks.

In addition to the basic APC measures, we also control for firm and, in section 3.1, working proprietor characteristics. These controls are introduced sequentially in order to gain an understanding of how the overall size differences between firms born in good and bad economic conditions are related to selection in the firms that enter.

[25] To explore this assumption we present our core results separately for 1-digit ANZSIC06 industry groups in Table 7.

The core estimating equation is:

$$\ln L_{it} = \gamma + \beta_1 \textit{bad times} + \sum_{a=1}^{5} \alpha_{it} + \sum_{t=2002}^{2020} \phi_t + \lambda Z_i + \epsilon_{it} \tag{2}$$

where L_{it} is firm-level labour input, *bad times* is a dummy variable equal to 1 for firms born between 2009 and 2013 (cohort), α_{it} is a set of dummy variables for firm age, ϕ_t is a set of year dummies (period), and Z_i is a set of industry dummies.

The alternative specification, which allows for firm size to be related to both the level and the direction of change in economic conditions, is:

$$\ln L_{it} = \gamma + \beta_1 \textit{recovery} + \beta_2 \textit{boom} + \sum_{a=1}^{5} \alpha_{it} + \sum_{t=2002}^{2020} \phi_t + \lambda Z_i + \epsilon_{it} \tag{3}$$

where *recovery* indicates firms born in years in which detrended GDP was below trend but increasing, and *boom* indicates firms born in years in which detrended GDP was above trend and increasing.

Results for these base models are presented in Table 5. Columns 1-3 use the simple “bad times” dummy (equation 2), comparing employment for cohorts born between 2009 and 2013 to all other entry cohorts, while columns 2-6 set the “bad” years as the base case and estimate the relative employment levels for cohorts born in periods of “boom” (high/rising GDP) and “recovery” (low/rising GDP) (equation 3). Column 1 shows that, on average over the first five years after entry, absent any other controls, firms born in bad years are roughly 3.4 percent smaller than those born in good years. There is also a distinction within “good” years (column 4). Firms born in the “boom” period are around 2.3% larger on average than those born in bad years, while those born in the recovery period are 4.9% larger. These percentage differences translate to negligible changes in firm size at the individual level – given the average firm size is only 2.25, a 5% difference is only 0.01 FTE per firm-year on average. However, as shown in Figure 4, even small differences in average firm size can translate to substantial differences in total employment between entry cohorts.

Of course, the effects of poor economic conditions continue to affect firms beyond their first year of life. Columns 2 and 5 account for this, including the age and year dummies which are core to the APC model. Controlling for age and current conditions substantially reduces the apparent effect of being born into a slowing economy – the coefficient on being born in bad times roughly halves, dropping (in absolute value terms) from -0.034 to -0.016. Firms that lived through the GFC recession all experienced a period of poor economic conditions, weighing on their growth regardless of whether they entered before or during the recession.

Columns 3 and 6 add controls for industry to allow for differences in industry composition across cohorts. This further reduces the apparent effect of having been born during a downturn by roughly one quarter, but does not negate it. Industry composition plays a stronger role in explaining firm size over the first five years of a firm’s life than suggested by the initial employment decomposition of Figure 5, which did not control for current conditions, but is not sufficient to explain the remaining employment gap.[26]

Coefficients on age dummies show the expected positive age-size trajectory, with the age coefficients increasing monotonically in all specifications. This partly reflects selective attrition – in any given year, young (1-4 year old) firms that are about to exit are, on average, around 30% smaller than surviving firms (Table 4). In order to eliminate the effects of selective exit Table 6 repeats the analysis of Table 5, restricting the population to firms that survive through till at least age 5. The shallower age-size trajectory for the balanced panel of surviving firms is consistent with selective attrition – part of the increase in average size with each additional year of age shown in Table 5 is due to higher exit rates among smaller firms.

Conversely, despite dropping over 15% of the sample, and increasing the average observed firm size by roughly 5%, restricting to a balanced panel of firms makes little difference to the estimated cohort coefficients. That is, the selectiveness of exit among firms born in good and bad times does not seem to differ enough for the shift to a balanced panel to have an appreciable impact on the relationship between birth cohort and firm size when averaged across the first five years of a firm's life.

As indicated by Figure 8, gaps in the average firm size between cohorts need not be stable over a firm's life. If the effects of poor economic conditions on firm performance are temporary, we might expect to see convergence in the age profile of different cohorts of firms over time as the direct effects of low initial demand dissipate. Conversely, if early conditions permanently affect firm structure or the composition of different cohorts, the firm size gap may remain steady or even increase as firms age.

To further explore the roles of selection, growth and attrition in explaining the average firm size gap between cohorts, Figure 9 plots estimated age profiles for log firm size from a model interacting firm age and economic conditions at entry:

$$\ln L_{it} = \gamma + \sum_{a=1}^{5} \alpha_{it} + \sum_{a=1}^{5} \beta_a(\textit{bad times} \times \alpha_{it}) + \sum_{t=2002}^{2015} \phi_t + \lambda Z_i + \epsilon_{it} \tag{4}$$

.

Annual dummies are included to capture the contemporaneous effects of aggregate economic conditions, while cohorts of firms are allowed to differ in both their initial size and their growth dynamics over time. Figure 9 depicts the estimated age profiles over time, with and without industry and year controls. The top two panels report estimates for the unbalanced panel while the bottom panels restrict to a balanced panel of firms that survive to at least age 5.

The estimated age-profiles differ dramatically according to whether industry and year dummies are included. With no controls (left panels), firms born in difficult economic conditions tend to start out smaller but converge to a similar size by age 5 to those firms born during better years. This pattern is consistent with economic conditions having a direct and contemporaneous effect on average firm size – firms born in bad times will tend to experience an improvement in the economic environment over time,

[26] Columns 3 and 6 are also the first to have a semi-respectable R^2, indicating that by themselves age and cohort have very little explanatory power for firm size.

while those that were born during more affluent periods are more likely to experience declining conditions.

However, after controlling for current economic conditions (and industry composition), the opposite pattern appears – firms born in bad times start out at a similar size but grow more slowly over time (right hand panel). Comparing the full population (top panels) with their respective balanced panel equivalents (lower panels) confirms the weaker age-size gradient seen when comparing tables 5 and 6, while also strengthening the conclusion that this divergence in firm size is not driven by differences in selective attrition between cohorts.

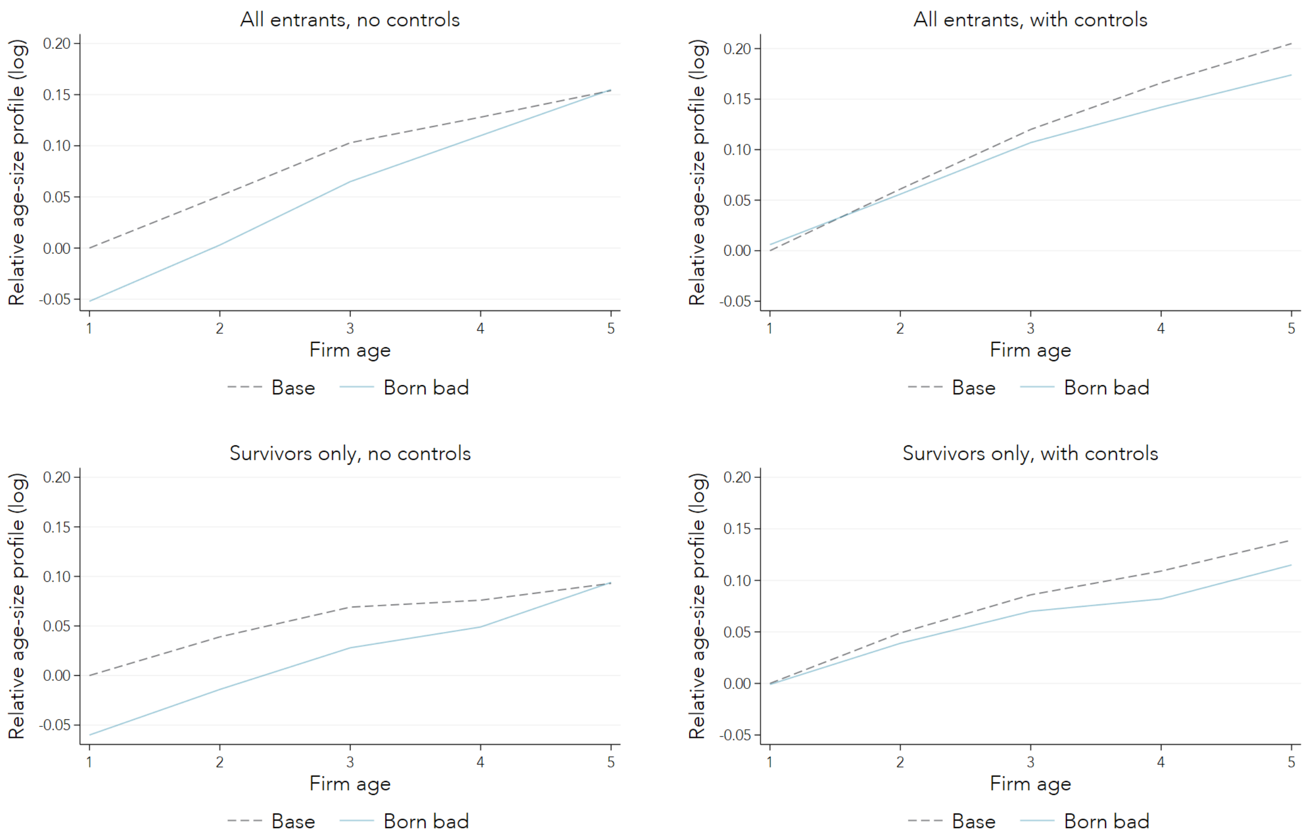
These age profiles – in which poor economic conditions clearly affect contemporaneous firm size, but controlling for current conditions shows a widening gap between cohorts of firms with different economic conditions at their time of birth – imply that early economic conditions have a long-term effect on firm size. This may occur either through "scarring" effects, for example if firms are unable to access capital or to build up a customer base in their early years, or through selection in the types or qualities of firms that enter.

We return to the question of selection in section 3.1, in which we explore the characteristics and possible motivations of individuals who start firms at different points in the economic cycle. In the remainder of this section we address two additional questions – whether the finding of smaller average firm sizes among recession-born firms is consistent across industries, and whether the differences apparent in employment figures are also seen for other firm outcomes.

As noted above, the APC estimation implicitly assumes that the impacts of entry conditions, the expected age profile, and the relationship between employment growth and other firm characteristics are all consistent across industry groups. To examine the validity of this assumption, Table 7 reports results of the core APC regressions, estimated separately by 1-digit industry. The results indicate the finding that firms born in recessions tend to be smaller (after controlling for current conditions and observable firm characteristics) is reasonably consistent, but is only statistically significant in a selection of industries.

A significant negative coefficient on "bad times" (or a significant and positive coefficient on recovery, boom, or both) is observed for Agriculture, forestry and fishing (A); Construction (E); Retail trade (G); Professional, scientific and technical services (M); Education (P); and Other services (S). After controlling for age and current economic conditions, firms born in bad economic conditions are between 1.4 and 6.4 percent smaller than other firms (panel A). Panel B indicates that, consistent with the full economy results above, the gap is primarily between firms born in bad times and those born during periods of recovery. The only exception to this pattern is seen in a negative coefficient on boom periods for the Finance and insurance services industry (K), which may reflect the opportunities available for independent financial advisers and brokers when market conditions are buoyant, leading previously-employed individuals to establish their own businesses. Restricting to surviving firms only (panels C & D) gives qualitatively similar patterns, but suggests a stronger relationship between economic conditions at birth and firm size for several industries. These industries – including Construction (E), Rental, hiring and real estate (L) and Professional, scientific and technical services (M) – have strongly cyclical entry rates, consistent with low entry costs and a tendency

Figure 9: Employment-age profiles by economic conditions at birth



Notes: Age profiles of log employment by economic conditions at entry. Base category is employment at age 1 for firms born in non-recession years. Controls are industry and year dummies. Without controls, size gaps are significant at 1% or better prior to age 5. With controls, size gaps are significant at 1% or better from age 3 onwards.

for opportunistic entry during booms. The observed negative link between firm size and economic conditions at birth is strengthened by excluding the many small, short-lived firms that entered in the years leading up to the GFC.

Finally, while this paper has been focused on the employment impacts of economic conditions at entry, this is not the only outcome variable of interest. In particular, one explanation for lower employment levels could be that firms born in recessions are more efficient producers, remaining lean by focusing on productivity rather than expanding employment. Table 8 explores this hypothesis, replacing employment outcomes with value-added as an alternative measure of firm size (columns 1&2) and value-added per worker as a measure of labour productivity (columns 3&4).

As well as being smaller in employment terms (Table 5, columns 3 and 6), firms born in bad times have lower value added (Table 8, columns 1 and 2), with the value-added effect being roughly twice as strong in percentage terms as the employment effect. That is, while firms born in bad times tend to have around 1.1 percent smaller workforces, they have 2 percent lower value-added. The distinction is due to differences between firms born in the downturn and those born as economic conditions begin to improve, rather than those born nearer the peak of the economic cycle (column 2).

In contrast, the negative effect of poor entry conditions on value-added per worker are weaker than those observed for employment. The main gap between firms born in good and bad economic conditions is in their size – output and employment – rather than their labour productivity. This suggests that a lack of demand in the formative years of a firm's life may be an important contributor to the firm size gap, beyond the potential effects of negative selection on entrepreneurial ability or an inability to finance investment.

3.1 Potential sources of selection – growth intentions and characteristics of firm owners

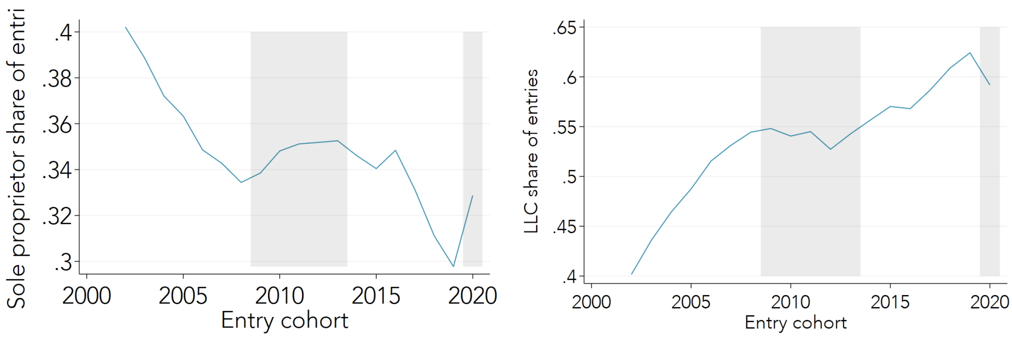
This section returns to the question of the innate differences between firms born in good and bad economic conditions, with a focus on the motivations and characteristics of firms' founding owners. While individual motivations are unobservable, we can gain some indication of business owners' growth intentions through looking at the business's legal status (firm type) at the time when the business was established.

The three main firm types in New Zealand are sole proprietors, partnerships, and limited liability companies (LLCs).[27] Business type provides some indication of the owners' ambition and intent to grow the business, as different structures involve different levels of protection from legal and financial risk, ability to seek external financing, and requirements for tax and administrative processes. Sole proprietorships (and partnerships) tend to be administratively simpler, but as these businesses are not legally separable from their owners, they come with greater risk in case of financial or legal difficulties and prevent the owner from selling shares in the business in order to raise capital.[28] Thus, selection into a structure such as a limited liability company tends to

[27] Over 99% of private sector, independent entries fell into one of these categories between 2002 and 2020. Examples of other possible firm types include co-operative companies, joint ventures and trusts. These are grouped into a single "other" category in the analysis.

[28] Sole proprietors are not precluded from employing staff – the term "sole" relates to the ownership of the business, not the number of people working there.

Figure 10: Business type composition of entering firms



Notes: Share of new entrants in each year, by firm type.

indicate a stronger growth motivation at the outset.

Moreover, if a business owner does not explicitly choose a business structure when they start the business, they are assumed to be acting as a sole proprietor. If business owners are less inclined to specify a business type for activities they expect to remain small, or if failure to specify is an indication of a less experienced or capable business owner, this will further contribute to an expected size gap between sole proprietorships and other business types.

Figure 10 plots the share of new entrants in each year for the two most common firm types – sole proprietorships and limited liability companies. Over the period since 2002 there has been a strong downward trend in the number of sole-proprietor entries, mirrored by an upward trend in the share of LLCs. Two periods stand out as going against this trend. After the onset of the GFC the share of sole proprietorships temporarily rose and remained steady through till 2013. The steady increase in the LLC share observed since the early 2000s flattened out over the same period. The COVID-19 pandemic in turn saw a sharp uptick in the number of sole proprietorships with a corresponding downturn in the share of LLCs.[29]

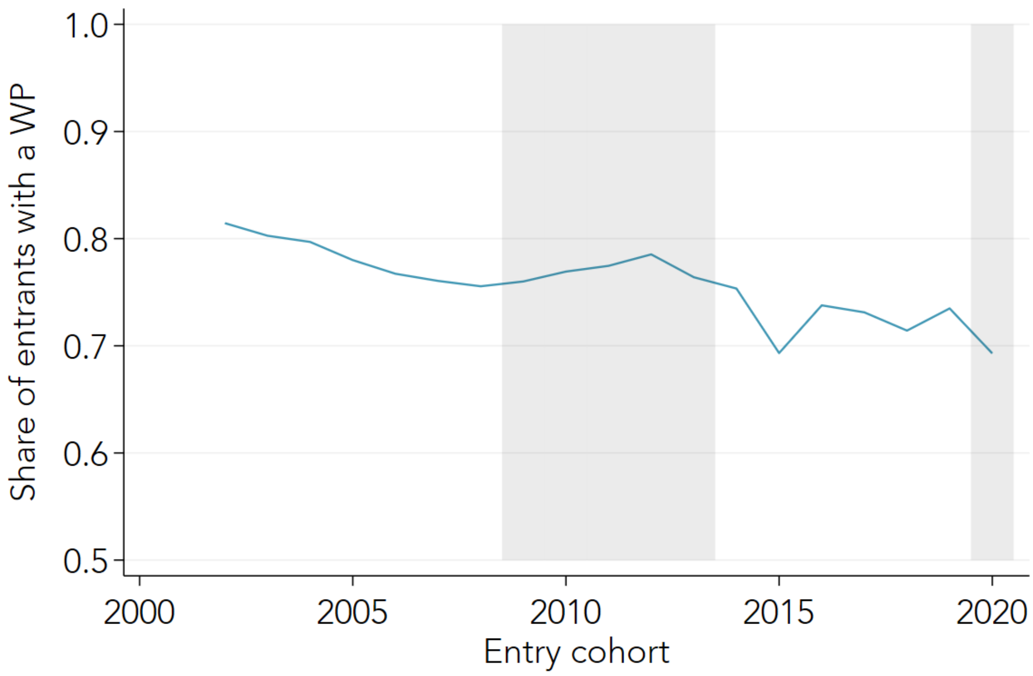
Table 9 extends the analysis in tables 5 and 6 by adding firm type as an additional control variable. While there is indeed a strong relationship between firm type and firm size – Partnerships and Limited Liability Companies (LLCs) are around 70% larger on average than Sole Proprietorships[30] – controlling for firm type has limited impact on the relationship between economic conditions at birth and firm size when compared to the results in tables 5 and 6. Although poor economic conditions seem to encourage entry of sole proprietorships relatively more than other, usually larger, firm types, the difference does not explain the overall size gap between cohorts.

Finally, we consider the role of observable differences in the types of people who start a firm under different economic conditions. Fabling (2018) finds that working proprietor characteristics are significant predictors of who will start a new firm, whether those new firms will survive, and for those that do, whether they will hire employees. Individuals with formal qualifications and those at the top end of the earnings distribution

[29] Due to variation in reporting dates across firms and industries, the 2020 financial year captures both the initial effects of the March 2020 lockdown for firms working to a March 30 year-end but also the longer term impacts for firms with balance dates up to out to August 31.

[30] The estimated size premium for LLCs is $e^{0.504} = 1.66$ in the full sample or $e^{0.544} = 1.72$ when restricted to surviving firms.

Figure 11: Share of entrants with a working proprietor



Notes: Share of all entrants with one or more working proprietors at the time of entry

when employed are more likely to move into self-employment, but less likely to employ others, consistent with highly-skilled individuals choosing to supply labour to the market as independent contractors, rather than employees. Conversely, recent negative employment shocks also appear to increase the probability that an individual will transition to self-employment, suggesting that involuntary entrepreneurship is a relevant factor in business entry for at least some people. Meanwhile, Shaw and Sørensen (2019) find that firms belonging to "serial entrepreneurs" – individuals who open more than one business over time – have higher sales and greater productivity than those of first-time business owners. If the characteristics of individuals that choose to start a firm differ according to the economic conditions, these differences in ex ante motivations and capabilities may help to explain the remaining gap between firms born at different points in the economic cycle.

Table 10 repeats the regressions in Table 5 above, introducing working proprietor characteristics as additional explanatory variables. Columns 1 and 7 a simple repeat of the analysis of columns 3 and 6 in Table 5, with the addition of a dummy variable set to one if the firm had at least one working proprietor drawing an income from the firm in the year of entry.[31] The inclusion of this dummy reduces the apparent effect of having been born during the downturn. Firms with one or more working proprietor tend to have lower observed labour input in their early years of life. The slight increase in the share of such firms during the GFC (Figure 11) partly explains the negative relationship between entry conditions and observed labour input.

[31] Recall that entry is defined as the first year that a firm has observed labour input (following a gap of at least two years). Thus a firm without working proprietors must have at least one paid employee to be counted as an entrant.

Columns 2-5 (and 8-11) restrict attention to firms that have at least one working proprietor in their first year, and sequentially introduce controls for the characteristics of those working proprietors: age and sex; whether they had earned income as a working proprietor of another firm two years prior to this entry; and a measure of relative earnings in employment across all time, which we use as a proxy for skill. While a number of these characteristics are associated with firm size – firms with female, older, more highly skilled working proprietors, and those who have recent experience as a working proprietor of another firm tend to be larger – none of the additional control variables has an appreciable effect on the estimated coefficients on economic conditions at birth.

Table 11 indicates why this is the case. Each column of Table 11 reports results of an OLS regression of a particular characteristics – sex, age, relative earnings, and prior experience – on entry conditions, industry, and a time trend. After controlling for firm characteristics which are already included in the model, firms started during the GFC period had working proprietors that were around 8 months older on average and marginally more likely to be male (columns 1 and 2) – characteristics expected to have opposite relationships with firm size. Working proprietor entrants in bad times tended to be more highly skilled, based on their relative earnings in employment (column 3), but the practical impact of this relationship is very small. With the skill measure defined on a log scale, a 1% increase in relative earnings is associated with a 0.03-0.04% increase in firm size (Table 10, column 5), but the average firm in born in the GFC period has a working proprietor with a skill level only 0.005% higher than those born in better times, a difference which is not large enough to influence the overall firm size distribution.

4 Conclusion

Overall, this paper has shown that firms born during and immediately after the 2008/9 recession tend to be smaller than their counterparts born in more affluent times. The cohort of firms born in 2009 employed roughly 9,000 fewer FTE workers at age one than the average across the 2002 to 2018 cohorts, while total employment in firms born in 2004 was 8,000 above the average. The main source of variation in cohort-level employment across time was differences in entry rates – firm entry falls during recessions and rises during booms. However, differences in average firm size also made a substantial contribution to the decline in cohort employment during the GFC, accounting for over half the employment gap in in the 2009 cohort and one third of the gap for the 2010 cohort.

The difference in size – which shows through both in terms of employment and value-added – is not simply a reflection of the immediate impacts of the recession on current employment and profitability. Rather, after controlling for contemporaneous conditions, employment gaps between firms born during the recession, recovery and boom periods widen as firms age. In contrast, lower exit rates among firms born during and after the GFC tend to mitigate the effect of lower entry rates on cohort-level employment.

Selection in entry and exit and the consequent differences in composition of entering cohorts have a role to play, but observable differences in firm composition do not fully explain the size gap between cohorts. Similarly, the gaps are not significantly affected by differences in the observable characteristics of the entrepreneurs who start firms at different points of the economic cycle. Further work is required to better understand the driving forces behind these persistent size gaps, distinguishing between the role of early-life finance constraints, demand shocks affecting market share, and other possible causes. Such work could also focus on differences across the broader firm-size distribution, to identify whether lower average firm sizes for cohorts born in bad times are due to an increase in the share of very small firms or a decline in the size or number of larger firms.

While this paper has focused on firm entry and growth dynamics around the GFC, future work can also provide valuable insights by comparing and contrasting the financially-led recession and drawn out recovery of the late 2000s-early 2010s with the sharp shocks of the COVID pandemic, which had potentially long-term impacts on patterns of demand as well as labour supply. While the firm-level data is not yet available to extend this study to cover the COVID period, Stats NZ's Business Demography statistics indicate a solid recovery in firm entry in the year to March 2022 (StatsNZ 2023). Early work using US data suggests that the COVID shock has had significant consequences for firm entry, with many new firms starting but a shift in composition towards non-employing firms (Dinlersoz et al. 2021).

Finally, it is important to note that high numbers of transient and short-lived firms during both the pre-GFC economic boom and during the recession that followed are not necessarily a bad thing. Increases in short-lived firms during hard economic times, in particular, point to a flexibility to seek alternative sources of income through self-employment. A key area for future research is to follow up those new entrepreneurs who started businesses over this time and look at whether they transitioned back into similar employment when the business ceased, consistent with a brief period of involuntary entrepreneurship.

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Tables

Table 1: Adjustments for large-firm entries and removal of subsidiaries

	Firm counts			Monthly FTE counts		
	Original	Adjusted	Subsidiaries	Original	Adjusted	Subsidiaries
Firm size	(1)	(2)	(3)	(4)	(5)	(6)
WP only	478,488	478,488 (0)	1,050 (0)			
(0,5)	254,895	254,895 (0)	8,514 (0.03)	339,500	339,500 (0)	15,600 (0.05)
[5,10)	16,707	16,707 (0)	1,782 (0.11)	114,700	114,700 (0)	12,700 (0.11)
[10,20)	5,958	5,958 (0)	1,122 (0.19)	80,700	80,700 (0)	15,700 (0.19)
[20,50)	2,319	2,163 (0.07)	675 (0.31)	68,400	63,000 (0.08)	20,900 (0.33)
$[50, \infty)$	1,014	654 (0.36)	417 (0.64)	193,400	100,600 (0.48)	76,500 (0.76)

Notes: For this table, firm size defined as monthly averages of observed FTE employment in employing months, excluding working proprietors. Indicators of working proprietor labour input are not available at the monthly level. Columns 1 and 4 refer to the count of firm entries, and average monthly employment in those firms, between 2002 and 2020. Columns 2 and 5 exclude those entries which appear to be mergers or restructures, based on the transfer of employees between exits and entrants. Columns 3 and 6 report the number of entries which are further excluded from the main analysis as they were a subsidiary of another firm at the time of entry. Numbers in parentheses refer to the share of the base which is excluded due to each restriction.

Throughout this paper, random rounding (base 3) and graduated random rounding have been applied to firm and employment counts in accordance with Stats NZ confidentiality protocols.

Table 2: Regression population summary statistics

	Main regression population (1)	Firms with WP at entry (2)	WPs have relative earnings measure (3)
Firm Characteristics			
L (= WP+FTE-adjusted employees)	2.25	1.77	1.77
	(5.17)	(2.67)	(2.68)
ln(L)	0.37	0.29	0.29
	(0.82)	(0.65)	(0.65)
firm age	2.75	2.76	2.75
	(1.41)	(1.41)	(1.41)
ln(value added)*	11.13		
	(1.39)		
LP = ln(value added/L)*	10.67		
	(1.15)		
Firm type composition			
Sole proprietor	0.30	0.37	0.39
Partnership	0.13	0.16	0.15
LLC	0.57	0.47	0.45
Industry composition			
Agriculture, Forestry & Fishing	0.12	0.13	0.13
Mining	0.00	0.00	0.00
Manufacturing	0.05	0.04	0.04
Electricity, Gas, Water & Waste Services	0.00	0.00	0.00
Construction	0.16	0.17	0.17
Wholesale Trade	0.03	0.03	0.03
Retail Trade	0.07	0.06	0.06
Accommodation & Food Services	0.06	0.04	0.04
Transport, Postal & Warehousing	0.05	0.05	0.05
Information Media & Telecommunications	0.01	0.01	0.01
Financial & Insurance Services	0.02	0.02	0.01
Rental, Hiring & Real Estate Services	0.08	0.08	0.07
Professional, Scientific & Technical Services	0.17	0.18	0.19
Administrative & Support Services	0.05	0.05	0.05
Education & Training	0.01	0.01	0.01
Health Care & Social Assistance	0.05	0.05	0.05
Arts & Recreation Services	0.02	0.02	0.02
Other Services	0.05	0.05	0.05
WP characteristics			
firm had WP at birth	0.79	1.00	1.00
female		0.34	0.36
age (at firm entry)		42.35	41.13
		(11.52)	(10.98)
has recent WP experience			0.20
has relative earnings measure		0.86	1.00
relative earnings in employment			0.04
			(0.00)
Observation count	1,737,717	1,440,057	1,226,169
Firm-year count	1,402,653	1,105,725	953,097

Notes: Standard deviations in brackets. Observations are firmXyearXworking proprietor counts, weighted to give a weight of one to each firmXyear observation.
*Mean and standard deviation for value-added measures refer to the population of firms used in the value-added regressions (table 8), which exclude firms with missing or negative value-added as well as industries for which GST returns do not provide a good proxy for output (primarily finance and real estate).

Table 3: Entry and employment by entry cohort, 2002–2018

	Age 0	Age 1			Age 5		
	N_0	N_1	Cohort L	Mean L	N_5	Cohort L	Mean L.
Entry cohort	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2002	36,444	31,371	55,400	1.766	17,190	42,700	2.484
2003	39,399	34,062	58,600	1.720	18,555	44,600	2.404
2004	42,099	36,075	62,100	1.721	19,338	44,500	2.301
2005	42,324	35,928	61,000	1.698	19,035	41,800	2.196
2006	41,670	35,388	59,900	1.693	19,164	42,200	2.202
2007	41,487	34,959	58,100	1.662	18,783	41,400	2.204
2008	41,655	34,761	55,400	1.594	18,954	43,200	2.279
2009	36,291	30,141	46,300	1.536	16,980	37,500	2.208
2010	33,258	28,023	44,200	1.577	15,687	37,000	2.359
2011	34,452	28,851	46,800	1.622	16,224	40,200	2.478
2012	35,004	29,226	46,000	1.574	16,578	39,600	2.389
2013	33,783	28,749	47,600	1.656	16,296	41,500	2.547
2014	34,269	29,193	50,500	1.730	16,497	46,200	2.801
2015	34,026	29,112	53,000	1.821	18,429	47,500	2.577
2016	38,559	33,024	57,100	1.729			
2017	41,406	34,944	59,700	1.708			
2018	38,172	32,739	58,600	1.790			

Notes: Number of entering firms (N_0) in the year of entry. Number of employing firms at age 1 (N_1)and age 5 (N_5). Cohort employment (Cohort L), and mean firm size (Mean L) at age 1 and age 5.

Table 4: Characteristics of exiting firms, by age group

	entrants (age=0) (1)	young (1-4 yrs) (2)	established (5-9 years) (4)	old (10+ years) (4)
Exit rate	0.152	0.144	0.100	0.071
Exit share of empl.		0.104	0.063	0.031
Average size: all		1.789	3.039	6.441
Size ratio: exits vs survivors		0.719	0.642	0.434
Age group share of total employment		0.154	0.169	0.652
N. firms	37,900	98,944	73,444	134,337

Notes: Average annual figures, 2002-2018. Employment measured with a one-year lag as employment in the final year before exit will be biased downwards by partial years of employment. Employment figures are therefore unavailable for entrants as they did not exist in the prior year.

Table 5: Age-period-cohort model of firm size

	(1)	(2)	(3)	(4)	(5)	(6)
Bad times	-0.034***	-0.016***	-0.012***			
	(0.003)	(0.004)	(0.003)			
Recovery				0.049***	0.025***	0.019***
				(0.004)	(0.004)	(0.004)
Boom				0.023***	0.008**	0.007*
				(0.003)	(0.004)	(0.004)
Age = 2		0.056***	0.057***		0.056***	0.057***
		(0.001)	(0.001)		(0.001)	(0.001)
Age = 3		0.112***	0.113***		0.112***	0.113***
		(0.001)	(0.001)		(0.001)	(0.001)
Age = 4		0.154***	0.155***		0.153***	0.155***
		(0.002)	(0.002)		(0.002)	(0.002)
Age = 5		0.189***	0.191***		0.189***	0.191***
		(0.002)	(0.002)		(0.002)	(0.002)
Constant	0.381***	0.340***	0.316***	0.347***	0.315***	0.296***
	(0.002)	(0.005)	(0.013)	(0.002)	(0.006)	(0.013)
R-squared	0.000	0.007	0.073	0.001	0.007	0.073
N. firm years	1,402,265	1,402,265	1,402,265	1,402,265	1,402,265	1,402,265
Test: Recovery=Boom				0.000	0.000	0.001
Controls for:						
Age dummies		X	X		X	X
Year (period) dummies		X	X		X	X
Industry dummies			X			X

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Entry and exit years are excluded as employment measures in these years are not consistent between firms that start (cease) activity at the start of the year and those that start (cease) towards the end of the year.

Table 6: Age-period-cohort model of firm size, survivors only

	(1)	(2)	(3)	(4)	(5)	(6)
Bad times	-0.037***	-0.019***	-0.015***			
	(0.003)	(0.004)	(0.004)			
Recovery				0.053***	0.027***	0.021***
				(0.004)	(0.005)	(0.005)
Boom				0.025***	0.012***	0.011**
				(0.004)	(0.004)	(0.004)
Age = 2		0.045***	0.046***		0.045***	0.045***
		(0.001)	(0.001)		(0.001)	(0.001)
Age = 3		0.079***	0.080***		0.079***	0.080***
		(0.002)	(0.001)		(0.001)	(0.001)
Age = 4		0.098***	0.099***		0.097***	0.099***
		(0.002)	(0.002)		(0.002)	(0.002)
Age = 5		0.128***	0.130***		0.128***	0.131***
		(0.002)	(0.002)		(0.002)	(0.002)
Constant	0.420***	0.396***	0.374***	0.383***	0.369***	0.354***
	(0.002)	(0.006)	(0.014)	(0.003)	(0.007)	(0.015)
R-squared	0.000	0.004	0.073	0.001	0.004	0.073
N. firm years	1,177,759	1,177,759	1,177,759	1,177,759	1,177,759	1,177,759
Test: Recovery=Boom				0.000	0.001	0.022
Controls for:						
Age dummies		X	X		X	X
Year (period) dummies		X	X		X	X
Industry			X			X

Notes: See notes to Table 5. Restricted to firms which survive at least to age 5.

Table 7: Age-period-cohort model – Industry specific

All firms	AgFF	Manu	Const	WST	RTT	Hosp	Trans	InfoMed	FinIns	RHRE	ProfTech	Admin	Educ	HealSoc	ArtRec	OtherS
Panel A	A	C	E	F	G	H	I	J	K	L	M	N	P	Q	R	S
Bad times	-0.022**	-0.026	-0.014*	-0.022	-0.047***	0.010	-0.004	0.041	0.044	-0.011	-0.012*	0.007	-0.064*	0.015	-0.002	-0.033**
	(0.010)	(0.019)	(0.008)	(0.022)	(0.015)	(0.017)	(0.014)	(0.030)	(0.027)	(0.011)	(0.007)	(0.016)	(0.037)	(0.016)	(0.023)	(0.015)
R-squared	0.048	0.039	0.022	0.017	0.031	0.007	0.006	0.023	0.013	0.022	0.008	0.008	0.013	0.005	0.004	0.012
N. firm years	175,173	67,587	219,630	47,415	98,733	88,800	65,751	16,788	23,586	106,782	235,308	72,048	18,459	67,905	26,625	67,458
Panel B	A	C	E	F	G	H	I	J	K	L	M	N	P	Q	R	S
Recovery	0.037***	0.030	0.023**	0.037	0.053***	-0.017	0.007	-0.032	-0.035	0.002	0.026***	-0.010	0.129***	-0.012	-0.007	0.038**
	(0.011)	(0.023)	(0.010)	(0.026)	(0.018)	(0.019)	(0.017)	(0.036)	(0.031)	(0.012)	(0.008)	(0.019)	(0.043)	(0.019)	(0.028)	(0.017)
Boom	0.011	0.022	0.005	0.010	0.041**	-0.003	0.002	-0.048	-0.052*	0.019	0.001	-0.003	0.002	-0.018	0.009	0.028*
	(0.011)	(0.021)	(0.009)	(0.024)	(0.017)	(0.019)	(0.016)	(0.034)	(0.030)	(0.012)	(0.008)	(0.018)	(0.043)	(0.018)	(0.026)	(0.017)
R-squared	0.048	0.039	0.022	0.017	0.031	0.007	0.006	0.023	0.013	0.022	0.008	0.008	0.014	0.005	0.004	0.012
N. firm years	175,173	67,587	219,630	47,415	98,733	88,800	65,751	16,788	23,586	106,782	235,308	72,048	18,459	67,905	26,625	67,458
Surviving firms only																
Panel C	A	C	E	F	G	H	I	J	K	L	M	N	P	Q	R	S
Bad times	-0.019*	-0.015	-0.024***	-0.009	-0.047***	0.015	-0.012	0.041	0.056*	-0.018	-0.018**	-0.015	-0.082**	0.012	-0.009	-0.028*
	(0.011)	(0.021)	(0.009)	(0.025)	(0.017)	(0.019)	(0.016)	(0.033)	(0.030)	(0.012)	(0.008)	(0.018)	(0.041)	(0.017)	(0.026)	(0.016)
R-squared	0.048	0.035	0.020	0.008	0.025	0.003	0.003	0.021	0.008	0.026	0.004	0.004	0.008	0.002	0.002	0.009
N. firm years	152,919	57,876	185,859	39,843	81,216	70,962	53,979	14,028	19,425	84,486	197,583	59,022	15,822	59,730	22,548	58,419
Panel D	A	C	E	F	G	H	I	J	K	L	M	N	P	Q	R	S
Recovery	0.032**	0.008	0.033***	0.023	0.050**	-0.023	0.018	-0.035	-0.046	0.003	0.031***	0.015	0.146***	-0.009	-0.009	0.030
	(0.012)	(0.025)	(0.011)	(0.029)	(0.020)	(0.022)	(0.019)	(0.040)	(0.035)	(0.014)	(0.010)	(0.022)	(0.048)	(0.021)	(0.030)	(0.019)
Boom	0.010	0.021	0.016	-0.002	0.043**	-0.009	0.007	-0.047	-0.065*	0.030**	0.007	0.014	0.021	-0.015	0.025	0.027
	(0.012)	(0.023)	(0.010)	(0.027)	(0.019)	(0.022)	(0.018)	(0.038)	(0.034)	(0.014)	(0.009)	(0.020)	(0.047)	(0.019)	(0.029)	(0.018)
R-squared	0.048	0.035	0.020	0.008	0.025	0.003	0.003	0.021	0.008	0.026	0.004	0.004	0.009	0.002	0.002	0.009
N. firm years	152,919	57,876	185,859	39,843	81,216	70,962	53,979	14,028	19,425	84,486	197,583	59,022	15,822	59,730	22,548	58,419

Notes: See notes to Table 5. Estimated separately by 1-digit ANZSIC06 sector, with 2-digit industry dummies included.

Table 8: Age-period-cohort model of value added and value added per worker

	lnVA		lnVApp	
	(1)	(2)	(3)	(4)
Bad times	-0.023***		-0.008*	
	(0.006)		(0.005)	
Recovery		0.037***		0.011**
		(0.007)		(0.006)
Boom		0.011		0.005
		(0.007)		(0.005)
Age = 2	0.106***	0.105***	0.044***	0.043***
	(0.003)	(0.003)	(0.002)	(0.002)
Age = 3	0.178***	0.177***	0.060***	0.060***
	(0.003)	(0.003)	(0.003)	(0.003)
Age = 4	0.225***	0.224***	0.065***	0.065***
	(0.004)	(0.004)	(0.003)	(0.003)
Age = 5	0.269***	0.269***	0.071***	0.071***
	(0.004)	(0.004)	(0.004)	(0.004)
Constant	10.354***	10.317***	9.926***	9.914***
	(0.028)	(0.029)	(0.024)	(0.025)
Observations	1,276,989	1,276,989	1,276,989	1,276,989
R-squared	0.065	0.065	0.088	0.088
N. firm years	1,039,922	1,039,922	1,039,922	1,039,922
Test: Recovery=Boom		0.000		0.247

Notes: See notes to Table 5. Regressions include controls for age, period, and industry (comparable with columns 4 and 8 of table 5). Value added calculated as GST sales less GST purchases. Excludes the Financial and insurance services and Rental, hiring and real estate services industries as the main products for these industries are GST exempt.

Table 9: Age-period-cohort model of employment, including controls for firm type

	All		Survivors only	
	(1)	(2)	(3)	(4)
Bad times	-0.011***		-0.012***	
	(0.003)		(0.004)	
Recovery		0.022***		0.022***
		(0.004)		(0.004)
Boom		0.001		0.004
		(0.004)		(0.004)
Type = Part.	0.517***	0.517***	0.530***	0.530***
	(0.003)	(0.003)	(0.004)	(0.004)
Type = LLC	0.504***	0.504***	0.544***	0.544***
	(0.002)	(0.002)	(0.003)	(0.003)
Type = Other	0.907***	0.907***	0.989***	0.989***
	(0.043)	(0.043)	(0.050)	(0.050)
Age = 2	0.054***	0.054***	0.049***	0.049***
	(0.001)	(0.001)	(0.001)	(0.001)
Age = 3	0.108***	0.107***	0.087***	0.086***
	(0.001)	(0.001)	(0.001)	(0.001)
Age = 4	0.147***	0.147***	0.108***	0.108***
	(0.002)	(0.002)	(0.002)	(0.002)
Age = 5	0.181***	0.181***	0.137***	0.137***
	(0.002)	(0.002)	(0.002)	(0.002)
Observations	1,737,717	1,737,717	1,473,642	1,473,642
R-squared	0.148	0.148	0.156	0.156
N. firm years	1,402,265	1,402,265	1,177,759	1,177,759
Test: Recovery=Boom		0.000		0.000

Notes: See notes to Table 5. Regressions include controls for age, period, industry, and firm type. Omitted category for firm type is Sole Proprietorship.

Table 10: Age-period-cohort model with working proprietor characteristics

All firms	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)	(10)	(11)
Bad times	-0.006*	-0.012***	-0.011***	-0.011***	-0.011***					
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)					
Recovery						0.012***	0.015***	0.015***	0.014***	0.014***
						(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Boom						0.000	0.010***	0.008**	0.008**	0.009**
						(0.004)	(0.003)	(0.003)	(0.003)	(0.004)
had WP at entry	-0.299***					-0.299***				
	(0.005)					(0.005)				
female			0.090***	0.092***	0.092***			0.090***	0.092***	0.092***
			(0.002)	(0.002)	(0.002)			(0.002)	(0.002)	(0.002)
WP age at entry			0.004***	0.003***	0.006***			0.004***	0.003***	0.006***
			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
WP age at entry2			-0.000***	-0.000***	-0.000***			-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
recent WP experience				0.031***	0.027***				0.031***	0.027***
				(0.003)	(0.003)				(0.003)	(0.003)
relative earnings					0.030***					0.030***
					(0.003)					(0.003)
Observations	1,737,717	1,442,517	1,440,057	1,440,057	1,226,169	1,737,717	1,442,517	1,440,057	1,440,057	1,226,169
R-squared	0.093	0.083	0.091	0.091	0.096	0.093	0.083	0.091	0.091	0.096
N. firm years	1,402,653	1,107,456	1,105,725	1,105,725	953,097	1,402,653	1,107,456	1,105,725	1,105,725	953,097

Survivors only	(1)	(2)	(3)	(4)	(5)	(7)	(8)	(9)	(10)	(11)
Bad times	-0.007*	-0.012***	-0.011***	-0.011***	-0.011***					
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)					
Recovery						0.010**	0.012***	0.011***	0.011***	0.011***
						(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Boom						0.003	0.013***	0.011***	0.011***	0.011***
						(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
had WP at entry	-0.355***					-0.355***				
	(0.005)					(0.005)				
female			0.089***	0.092***	0.093***			0.089***	0.092***	0.093***
			(0.002)	(0.002)	(0.003)			(0.002)	(0.002)	(0.003)
WP age at entry			0.004***	0.003***	0.007***			0.004***	0.003***	0.007***
			(0.001)	(0.001)	(0.001)			(0.001)	(0.001)	(0.001)
WP age at entry2			-0.000***	-0.000***	-0.000***			-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)			(0.000)	(0.000)	(0.000)
recent WP experience				0.043***	0.037***				0.043***	0.037***
				(0.003)	(0.004)				(0.003)	(0.004)
relative earnings					0.041***					0.041***
					(0.003)					(0.003)
Observations	1,473,642	1,235,532	1,233,411	1,233,411	1,044,990	1,473,642	1,235,532	1,233,411	1,233,411	1,044,990
R-squared	0.101	0.082	0.090	0.091	0.097	0.101	0.082	0.090	0.091	0.097
N. firm years	1,177,599	9,394,89	9,380,40	9,380,40	804,408	1,177,599	9,394,89	9,380,40	9,380,40	804,408

Notes: Regressions include controls for firm age, period, and industry, comparable with columns 3 and 6 of table 5.

Table 11: Working proprietor characteristics

	female (1)	WP age (2)	relative earnings (3)	prior WP exp (4)
Bad times	-0.009***	0.626***	0.005***	-0.002
	(0.001)	(0.033)	(0.001)	(0.001)
year	-0.001***	0.270***	0.001***	-0.005***
	(0.000)	(0.003)	(0.000)	(0.000)
Observations	674,300	674,000	580,800	675,300
R-squared	0.069	0.099	0.129	0.028
Mean dep. var.	0.361	43.597	0.045	0.227

	female	WP age	relative earnings	prior WP exp
Recovery	0.005***	-0.580***	-0.005***	-0.003**
	(0.002)	(0.041)	(0.001)	(0.001)
Boom	0.011***	-0.651***	-0.005***	0.004***
	(0.001)	(0.036)	(0.001)	(0.001)
year	-0.001***	0.270***	0.001***	-0.005***
	(0.000)	(0.003)	(0.000)	(0.000)
Observations	674,300	674,000	580,800	675,300
R-squared	0.069	0.099	0.129	0.028
Mean dep. var.	0.361	43.597	0.045	0.227

Notes: Each column reports core results of a regression of the relevant working proprietor characteristic (sex, age, earnings, recent WP experience) on dummies for economic conditions at the time of entry, industry dummies, and a linear time trend. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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