Innovation, Science and Economic Development Canada
Innovation, Sciences et Développement économique Canada

From startup to employer

A duration analysis of the time until Canadian startups hire their first employee

2024

Innovation, Science and Economic Development Canada
Small Business Branch

Lyming Huang

Canada

From startup to employer: a duration analysis of the time until Canadian startups hire their first employee

Innovation, Science and Economic Development Canada

Small Business Branch

Lyming Huang

2024

Cat. No. Iu188-169/2024E-PDF

ISBN 978-0-660-73999-1

This publication is available online and in PDF format at ic.gc.ca/smeresearch. Cette publication est aussi disponible en français sous le titre *D'entreprise en démarrage à employeur : une analyse de la durée entre le démarrage d'entreprises canadiennes et l'embauche de leur premier employé*. To obtain a paper copy of this publication or an alternate format (Braille, large print, etc.), please fill out the Publication Request form or contact:

Web Services Centre

Innovation, Science and Economic Development Canada

C. D. Howe Building

235 Queen Street

Ottawa, ON K1A 0H5

Canada

Telephone (toll-free in Canada): 1-800-328-6189

Telephone (Ottawa): 613-954-5031

TTY (for hearing impaired): 1-866-694-8389

Business hours: 8:30 a.m. to 5:00 p.m. (Eastern Time)

Email: ised-isde@ISED-ISDE.gc.ca

Table of contents

Executive summary

For new firms, hiring their first employee is an important entrepreneurial milestone; entrepreneurs who hire and grow their businesses may have greater capacity to innovate, disrupt markets or create wealth. There is, however, little research into this topic, perhaps because until relatively recently, the data required for analysis of first hires were simply unavailable.

This research uses the recently developed Canadian Employer-Employee Dynamics Database (CEEDD), which contains the universe of firms that filed corporate income taxes in Canada, to study the time until new firms hire their first employee. First-hiring rates are at their highest in new firms' startup years, and decline sharply with time. Between 10% and 16% of incorporated firms hire their first employee in their first year of operation. In the four subsequent years, the first-hiring rate drops to between 7% and 8%, 3%, 2% and 1%, continuing to decline in the years that follow. These patterns hold across entry cohorts, provinces and industries.

The analysis reveals an intriguing trend of a decrease, over time, in first-hiring during firms' startup year: the rate of startup year first-hires drops from 16% for the 2003 entry cohort to 11% for the 2017 entry cohort, while the number of firms hiring their first employee in their startup year falls from just over 21,000 to under 16,500. In contrast, there is little change across entry cohorts in the first-hiring rates of subsequent years. Taken together, these trends imply a decrease in the propensity for new firms to transition from non-employer to employer over time. Using duration analysis to model the hazard rate of the time until first hiring, relationships between first-hiring hazard rates and a rich array of ownership and firm characteristics are quantified. The hazard model estimates imply that the likelihood of hiring employees decreases with successive entry cohorts even when controlling for ownership and firm characteristics that factor into first-hiring decisions.

1. Introduction

Small businesses play a key role in job creation. In Canada, for example, small businesses are an important source of job growth, responsible for 41% of net private sector job creation between 2021 and 2022.[1] At the same time, many businesses do not hire: for example, of the 2.7 million self-employed Canadians in 2023, 72% had no employees.[2]

Governments, policymakers and researchers are particularly interested in those firms that do hire since they contribute disproportionately to job creation. The first employee represents an important entrepreneurial milestone. A new firm's capacity to grow, innovate, disrupt markets and create wealth is ultimately constrained without employees. When a startup decides to hire their first employee, then, it is taking a step towards these activities.

This paper studies this critical hiring decision, which has to date received limited attention. In particular, it uses a confidential matched employer-employee dataset containing the universe of new firms that filed corporate income taxes in Canada to study the time until startups hire their first worker. The analysis builds off research by Fairlie and Miranda (2017), who present some of the first evidence on non-employer—employer transitions for U.S. firms.

Interesting patterns in first-hiring are documented. First, most first hires occur in firms' startup year: between 10% and 16% of startups hire in their first year of operation; thereafter, the first-hiring rates drop rapidly, from 7% and 8% in the second year of operation to 3% in the third, continuing to decline in subsequent years.

Note that the declining rate implies that well over half of new firms will not hire; over 65% of firms that entered in 2003, for example, had not hired by 2017. Of non-hiring firms, roughly one-third exit within five years without hiring, while nearly all that do not exit before hiring continue operating as non-employers. These patterns hold across the 2003 to 2017 startup cohorts, provinces and industries.

The second notable trend is of a declining propensity to hire by new firms. Specifically, the startup year first-hiring rate declines steadily over the fifteen-year period of study, from over 16% in 2003 to under 11% in 2017, while the first-hiring rates for subsequent years are essentially unchanged. A decline in startups' propensity to hire could have important macroeconomic implications for employment if, for example, hiring intensity remained unchanged.

To study whether this trend is related to observable owner or firm characteristics, duration models of the hazard of the time until first-hiring are estimated.

[1] Innovation, Science and Economic Development Canada, 2024.
[2] Statistics Canada, 2024.

The results indicate that, conditioning on observables significantly related to the hazard of the time until first-hiring, successive cohorts are between 44% and 48% less likely to hire their first worker, compared to the 2003 entry cohort.

This trend is more pronounced for a sub-population of startups that excludes firms likely to have incorporated for tax-planning purposes (rather than to engage in economic production).

Note that the hazard model estimates do not support causal interpretation and are best viewed as conditional correlations. The results nonetheless have implications for policymakers.

For example, a trend of decreasing propensity to hire, with no change in hiring intensity, would imply fewer jobs, and may, with no change in production, reflect increased productivity.

The remainder of the paper is structured as follows: Section 2 reviews related literature; Section 3 details our dataset and key definitions; Section 4 outlines interesting first-hiring trends observed for the population of new incorporated firms; Section 5 describes the duration modelling sample, approach and results; and, Section 6 offers conclusions.

2. Literature review

Interest in small businesses began with Birch (1979), who found that small firms create the majority of jobs in the U.S. This finding attracted widespread attention, generating a large body of research into the rapid growth of small firms (e.g., Neumark *et al.*, 2011; Decker *et al.*, 2016). Over time, researchers refined their conclusions: young firms, which tend to be small, drive job creation. It is, in fact, these young, small and high-growth firms that play such a crucial role in new net jobs. By contrast, mature small firms, which comprise the majority of small businesses, do not grow or grow slowly (Haltiwanger *et al.*, 2013).

A related strain of entrepreneurship research shows that, in addition to the important role they play in job creation, startups also factor importantly in productivity growth. In particular, firm entry and exit is linked to the reallocation of resources from low- to high-productivity businesses (e.g., Decker *et al.*, 2014; Clementi and Palazzo, 2016). These patterns are consistent with the predictions of canonical models of heterogeneous entrepreneurs, such as Lucas (1978) and Kihlstrom and Laffont (1979), and the more recent models of heterogeneous firms, such as Melitz (2003) and Klette and Kortum (2004), which link firm dynamics with broader economic outcomes. Before embarking on their growth paths, all new firms¸ high-growth or not, face an important decision: whether to hire employees. Entrepreneurs who do not hire face limited growth prospects; with no employees, firms lack the resources to innovate, disrupt markets or create wealth (and jobs) on a large scale.

The research into this critical decision is limited.[3] To the best of the author's knowledge, there are only four studies of first hires in economic literature using employer-employee matched data. This appears to be due primarily to the lack, until recently, of firm-level data linked to detailed employment information. There are more, though not many, studies which use household data to study transitions by own-account workers (i.e., self-employed with no employees) to self-employed with employees. These studies are reviewed below.

Using the European Community Household Panel for the EU-15, Millán *et al*. (2013) study two types of transitions: from own-account worker to employer, and from employer to own-account worker. Results from estimates of their binary choice models indicate that the stricter the employment protections, the less likely there are to be both types of transitions. Congregado *et al*. (2010) use the same dataset to estimate multinomial logit models for transitions of self-employed with no employees (whom they label own-account workers) to self-employment with employees, to paid employment, to unemployment or to inactivity. Their results show no effect of gender on transitions to self-employment with employees. Human capital, including that acquired through higher education, through self-employed relatives, or through previous experience, positively impacts transitions to hiring employees. Transitions to hiring by self-employed vary significantly by sector, with self-employed in construction most likely to transition.

Burke *et al*. (2000, 2001) present evidence based on National Child Development Study data from the U.K. that non-pecuniary motivation, higher education, and inheritance impact hiring by self-employed. The latter study also suggests that the determinants of entrepreneurial performance (including job creation) by male and female self-employed differ significantly.

Cowling *et al*. (2004) finds similar results using British Household Panel Survey (BHPS) data, as well as a substantial role for informal human capital: formal education is no more important than business experience in deciding whether to hire. Henley (2005) uses data from the BHPS to estimate the probability of hiring employees, with the number of employees hired modelled as a decision of ordered choice. His estimates indicate that a number of owner characteristics, such as housing wealth, self-employed parents, higher education, local labour market slackness and age increase the likelihood of hiring one or more employees.

Caliendo *et al*. (2019) use German Socioeconomic Panel data to analyze the role of individual personality characteristics in the transitions between employer, non-employer, paid employee and non-employed. The authors find evidence that personality traits factor into transitions into non-employer entrepreneurship and into employer entrepreneurship.

While these studies, which are based on household-level data, make interesting links between hiring and demographic characteristics, there are key advantages to using firm-level data.

[3] A related and broader field of literature, as noted in Fairlie and Miranda (2017), studies links between employment and owner characteristics: for example, owner education, age, experience, gender, wealth and parental self-employment have been shown to positively impact firm employment. Parker (2009) offers a comprehensive review of this research. These findings, however, are based on all firms rather than only startups, and do not necessarily extend to first hires.

First, household-level data do not include, as do firm-level data, information needed to control for firm performance, such as sales or assets. Second, data on self-employed tends to represent a different population than data on firms: the former tend to include fewer businesses with employees, while the latter tend to include larger firms that contribute more to employment and production, such as those that have incorporated or registered for sales tax numbers.

However, as noted above, firm-level datasets with sufficiently rich information to study first hires have only recently become available. Indeed, to the best of the author's knowledge, there are only four other firm-level studies of first-hiring, Coad *et al*. (2017), Fabling (2018), Cockx and Desiere (2023) and Fairlie and Miranda (2017), that use matched employer-employee data comparable to the data used in this research. Each of these papers was published within the past eight years.

Coad *et al*. (2017) use Danish matched employer-employee data to estimate logit models of owner characteristics associated with first-hiring. Their results show that the probability of hiring a first employee increases significantly with owner age, education and wealth. Interestingly, startups founded by the unemployed or those outside the labour force are less likely to hire, which, according to the authors, suggests owners' motivation for starting their own business plays an important role. Coad *et al*. additionally study firm performance for non-employers that have transitioned to employers, finding that hiring sales outcomes and profit dispersion increase subsequent to transitions. They also find, however, that sales growth increases in the year preceding first-hiring, interpreting this result to suggest only entrepreneurs with sufficient sales growth to justify expansion should hire.

Fabling (2018) studies transitions into entrepreneurship, including both entrepreneurs that hire and do not hire, using a linkage of the New Zealand Longitudinal Business Database linked to administrative data on employees, and to the country's 2013 Population Census. This analysis finds a negative correlation between owner skill and hiring employees, suggesting that high-skilled employees simply prefer self-employment over working for others, rather than being interested in entrepreneurship with the goal of growing a company.

Cockx and Desiere (2023) analyze the impact of a change in labour costs on a new firm's decision to hire a first employee in Belgium. In 2016, Belgium introduced an exemption on Social Security Contributions for a firm's first employee, reducing the labour cost of that employee by up to 16%. Using a regression discontinuity framework, the authors find that the number of new employers increased by 31% in response to the reform. This result corresponds to an elasticity of the decision to hire a first employee with respect to labour cost of -2.39, implying that for a 1% increase in labour cost, the likelihood of hiring a first employee decreases by 2.39%.

Fairlie and Miranda (2017; hereafter, FM) provide some of the first evidence in the literature on non-employer—employer transitions by startups in the U.S. Using administrative data from the U.S. Census Bureau's Integrated Longitudinal Business Database (iLBD), which contains the universe of non-employer and employer firms, linked to the Kauffman Firm Survey (KFS), and to data collected for an experimental entrepreneurship training program, FM study first-hiring patterns among non-employer startups, and estimate determinants of non-employer—employer transitions. To a large extent, this research builds off FM so their work is described in some detail.

FM present two key findings on non-employer—employer transition patterns in the iLBD. First, transition rates for non-employer startups are, overall, quite low. The first-year transition rate is 2%, and with the rate falling dramatically in subsequent years, only 2.5% of non-employers have hired an employee after seven years of operation. Transition rates are substantially higher for growth-oriented businesses, such as corporations or businesses with Employee Identification Numbers (EINs).

For example, the first-year transition rates for incorporated and EIN non-employers are, respectively, 16.2% and 11%, while the transition rates after seven years of operation are, respectively, 21.2% and 14.3%. The other notable pattern is that non-employers, if they do hire, are most likely to do so in their first year of operation. Transition rates in the second year of operation decrease to a fraction of their first-year value, and by the third year of operation even transition rates of growth-oriented firms fall to 1% or lower.

One shortcoming of the iLBD is that it lacks important information on firm and owner characteristics likely to impact transitions. To study transition determinants, then, FM use the rich set of covariates contained in the KFS, identifying non-employers therein through a linkage with the iLBD. Firms included in the KFS are known to be particularly growth-oriented; the first-year transition rate for this subset, for example, is 37%—considerably higher than the rates for incorporated or EIN non-employers. For a wide range of specifications and subsets, FM estimate binary choice regressions of the probability of non-employers hiring by one, two and seven years after startup, and of non-employers hiring in the following year. They find that Asian-owned and Hispanic-owned non-employer startups are more likely to hire, while their female-owned counterparts are less likely to do so. Notably, owner education does not significantly impact transitions.

Firm characteristics are also important: business assets and intellectual property are significantly associated with first hires by non-employers, while transitions vary significantly with the industry within which firms operate. Finally, a linkage of data from the Growing America through Entrepreneurship (GATE) experiment, the largest-ever random experiment providing entrepreneurship training in the U.S., with the iLBD allows FM to study the impact of entrepreneurship training on non-employer first hires. They find no evidence that this training impacted transitions.

Building off the analysis presented in FM, this analysis studies the time, for new incorporated firms in Canada, until firms' first hires, as well as the associated ownership and firm characteristics. The dataset used in this analysis, the Canadian Employer-Employee Dynamics Database (CEEDD), is a confidential employer-employee matched dataset that includes the universe of new firms that filed corporate income taxes in Canada. This research offers three contributions to the literature.

First, to the author's knowledge, the finding of declining rates of hiring a first employee has not been shown elsewhere. Declining rates of hiring a first employee could have macroeconomic impacts on firm dynamics, employment and productivity. This research is also the first study of non-employer—employer transitions in Canada. More broadly, in using a dataset comprising the universe of new firms that filed corporate income taxes in Canada that is both rich and comprehensive, the analysis is able to both show that the finding of declining first hiring rates is robust to controls for a wide array of owner and firm characteristics that factor into first-hiring decisions, and to present a comprehensive analysis of how those owner and firm characteristics relate to first-hiring for a sub-population of startups of policy interest.

Second, the duration analysis framework, which models the hazard of the time until first-hiring, provides an alternative perspective to, for example, the binary choice analysis of FM, which models the probability of non-employer—employer transitions.

In particular, the question of interest is reframed from "How likely is a firm to hire?" to "How long until a firm hires?" One methodological advantage in adopting this approach is that duration analysis, in contrast to logit and probit models, it uses information on the timing of first hires, which increases the precision of the estimates (Allison, 2010).

Finally, the research question in this analysis is broader in scope than that of FM.

Specifically, the first hires of all incorporated firms in Canada are included in the analysis, not only transitions by non-employers; this research additionally studies firms that hire in their first year of operation. Although this limits comparability between the results here and those presented in FM, the importance of including in the analysis firms that hire in their first year of operation is underlined by the fact that most firms that hire do so in their first year.

Studying only non-employer—employer transitions, then, would exclude the majority of first hires. This is particularly important in light of the trend of declining startup year first hires, the pattern of which is only observed when including first hires taking place in firms' first year of operation.

3. Canadian Employer-Employee Dynamics Database

This analysis uses the Canadian Employer-Employee Dynamics Database (CEEDD). CEEDD is a confidential matched worker-firm dataset developed by the Economic Analysis Division at Statistics Canada by linking administrative records. All records are anonymized, removing Business Numbers, company names and address (except for province/territory). The subset of CEEDD used in this paper includes the universe of new incorporated firms during the years 2001 to 2017.

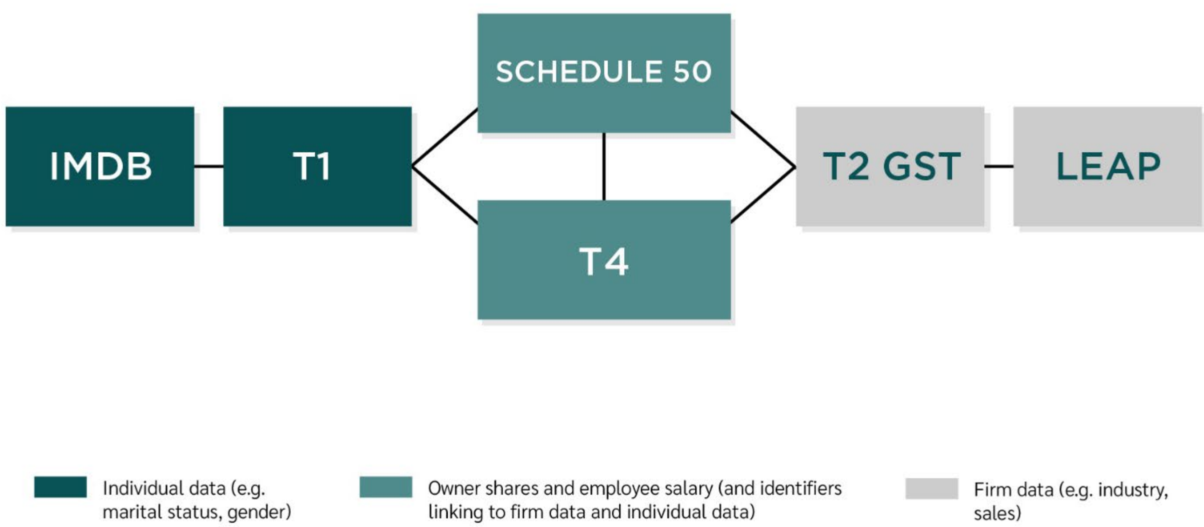
Private corporations are a population of policy interest, especially in the context of entrepreneurial milestones, since incorporation is likely a much better proxy for entrepreneurship than is, for example, self-employment. In particular, the primary benefits of incorporation, limited liability and the creation of a separate legal entity, are more valuable for firms undertaking risky ventures and engaged in other "entrepreneurial" activities (Levine and Rubenstein, 2017).[4]

[4] One concern, when using incorporation to proxy for entrepreneurship, is that incorporated businesses include entities incorporated primarily for tax-planning reasons rather than engaged in economic production. Strategies to deal with this issue are described in detail below.

Furthermore, with the majority of new incorporated firms having incorporated from startup, and nearly all unincorporated firms having chosen to start up without incorporating,[5] the choice of whether to incorporate could reflect ex ante entrepreneurial nature rather than ex post performance (Levine and Rubenstein, 2017).

The CEEDD linkage, shown in Figure 1, includes the following records: personal income tax (T1), corporate income tax (T2), remuneration paid by corporations to their employees (T4), corporate shareholder information (Schedule 50), General Sales Tax (GST), enterprise information from the Longitudinal Employment Analysis Program (LEAP) and immigrant information from the Longitudinal Immigration Database (IMDB).[6] Some key definitions are described below.

Figure 1: CEEDD linkage of administrative databases



---

[5] Between 2002 and 2013, between 35% and 40% of newly incorporated businesses had transitioned from unincorporated self-employment, while under 10% of unincorporated self-employed had transitioned from business ownership (Grekou and Lui, 2018).
[6] CEEDD and the data linkages used to form it are described in greater detail in Green *et al*. (2016).

Firms

Businesses are defined at the Business Number (BN) level. This is effectively equivalent to defining businesses at the firm level, since less than 0.1% of new businesses have more than one BN attached to them. To allow for cleaner attribution of primary owner and ownership characteristics in the dataset, these multi-BN firms are removed.

New firms

The analysis starts from the year 2003. A firm is considered to be new, or a startup, in a given year when its BN and enterprise-level identifier do not appear from 2001 until that year. The shortcoming of this definition is that it does not account for firms operating under new BNs due to activities such as mergers and acquisitions or restructuring; this information is not available in the dataset. But the proportion of such firms is low enough, particularly for smaller firms such as startups, that any impact on the results should be negligible.[7]

First hires

Analysis of first hires is limited to formal[8] employer-employee relationships, using the strictest definition of hiring available in the data, based on whether a firm pays Employment Insurance premiums.[9] Specifically, a firm's year of first-hiring is identified in the data as the first year in which the firm pays employer EI premiums for at least one employee.[10]

An alternative definition considered defines a firm's year of first-hiring as the first year in which the firm pays to non-owners renumeration recorded in T4 slips. For this research, the EI definition is preferred over the T4 definition because it gives a cleaner definition of hiring. EI premiums are paid for employed family members only when the family members are employed under conditions (e.g. renumeration or nature of the work performed) substantially similar to those of non-family member employees. The payment of EI premiums therefore indicates that the employees hired are not, for example, the owner's spouse or child, except in cases where the spouse or child is treated similarly to other employees.

Excluding first hires of family members is preferable in light of research by Wolfson et al. (2016) indicating that a substantial number of Canadian Controlled Private Corporations (CCPCs) may be formed by high-income individuals primarily for tax-planning purposes. For example, by channelling income through a corporation a high-income individual could pay her spouse and children wages from that corporation. To the extent that her family members are in a lower income-tax bracket, the family's effective tax rate would be reduced. Defining first hires based on EI premiums aligns with the view of first hires as an entrepreneurial milestone, rather than a mechanism for income-splitting or other tax-planning ends.

[7] According to rough estimates from the National Accounts Longitudinal Microdata File at Statistics Canada, an administrative dataset containing the universe of firms in Canada, the percentage of firms that are not entrants but with new BNs is below 0.4% and comprised primarily of larger firms.
[8] Informal hires, such as contractors who are considered by Canada Revenue Agency as self-employed, are excluded. While contractors may be an important source of labour for certain start-ups, they are not identifiable in our data.
[9] Canada's Employment Insurance program provides temporary income support to unemployed workers, and special benefits to workers who take time off work due to life events such as illness, pregnancy, or caring for a newborn. Benefits are based on premiums, which are paid by both employers and employees.
[10] That is, a firm is considered to have hired when EI premiums are greater than $0. The use of different thresholds, e.g. $100 or $1000, has no qualitative impact on the results.

More generally, using the EI definition allows for cleaner comparisons: first hires of family members are included only when they are employed similarly to non-family members. EI first hires, then, are more policy-relevant.

Many of the results described below—the first-hiring trends, the non-parametric estimates of the hazard, and most of the regression results—do not change qualitatively when the T4 definition is used. However, one result which changes depending on the definition used is particularly noteworthy: the coefficient for the variable indicating married or common-law status changes from having, under the T4 definition, a substantial positive impact on the hazard of first-hiring, to being statistically insignificant under the EI definition. This suggests that the EI definition does indeed exclude spousal first hires that may be substantively different from the first hires of interest.

4. First-hiring trends

First-hiring trends[11] for the universe of private sector new incorporated firms that began operating between 2003 and 2017 are presented here.[12] These first-hiring patterns are documented both within and across startup cohorts.

Within startup cohorts, a number of patterns stand out. First, most firms do not hire. Between 70% and 75% of new firms do not hire within their first five years of operation,[13] while first-hiring rates after 5 years of operation are consistently below one percent and decline further with time. Many startups simply continue to operate as non-employers, with over 50% of all startups neither hiring nor exiting within their first five years of operation.[14]

Second, many of the firms that remain non-employers exit, with between 17% and 24% of startups exiting within their first five years of operation. Within cohorts, non-employer exit rates peak within firms' first four years of operation, and decline gradually over time.[15]

[11] Counts of businesses are rounded to the nearest 5 in accordance with Statistics Canada confidentiality restrictions.
[12] While there are privately owned firms in public sector industries (North American Industry Classification System [NAICS] 22, 61, 62 and 91), these are conventionally excluded from analysis of firms (e.g. Decker et al., 2014 or Baldwin et al., 2000). This is because economic activity in public sector industries, particularly in Canada, is dominated by government-owned entities, which are less likely to engage in profit-maximizing or cost-minimizing behaviour. No additional sample restrictions are imposed for this part of the analysis, though qualitatively similar patterns and trends are observed for the restricted sample used in Section 5.
[13] These figures refer to the 2003 up to the 2013 startup cohorts since the dataset ends in 2017 and five-year hiring rates are not observed for the 2014, 2015, 2016 and 2017 startup cohorts.
[14] Similar to the hiring rates presented for startups' first five years of operation, these figures refer to the 2003 up to the 2013 startup cohorts.
[15] Across cohorts, exit rates trend down slightly in the years leading up to 2012, then begin to increase in subsequent years.

Finally, for firms that do hire, first-hiring rates decrease rapidly with time, particularly over the first three years of operation. When employees are hired, they are most often hired during a firm's startup year, with between 10% and 17% of new firms hiring employees in their first year of operation.

The first-hiring rate drops steeply in the years after startup, with 8%, 3%, 2% and 1% of startups, on average, hiring their first employee in their second, third, fourth and fifth years of operation. These rates continue to decline in subsequent years of operation.

These trends are presented in Table 1, taking the 2003 startup cohort as an example. Most firms—roughly two-thirds—from the 2003 cohort had not hired by 2017. Of the firms that did not hire, 64% had exited by 2017, while the remaining 36% of firms continued to operate non-employers over this 15-year period.

Table 1: Annual first-hiring rates and counts, 2003 startup cohort

Year of operation	Hired		Exited		Did not hire or exit by 2017		Total
	%	# of businesses	%	# of businesses	%	# of businesses	# of businesses
Start-up year (2003)	16.2	21,135	-	-	-	-	-
Second year (2004)	8.1	10,595	3.5	4,505	-	-	-
Third year (2005)	3.0	3,935	5.2	6,755	-	-	-
Fourth year (2006)	1.8	2,385	4.6	6,010	-	-	-
Fifth year (2007)	1.3	1,670	4.4	5,780	-	-	-
Sixth year (2008)	0.9	1,190	3.7	4,795	-	-	-
Seventh year (2009)	0.7	920	3.7	4,805	-	-	-
Eighth year (2010)	0.5	700	2.7	3,505	-	-	-
Ninth year (2011)	0.5	630	2.4	3,085	-	-	-
Average over tenth to fifteenth years (2012–2017)	0.3	348	1.9	2,440	-	-	-
Total	34.8	45,255	41.7	54,270	23.5	30,640	130,165

Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

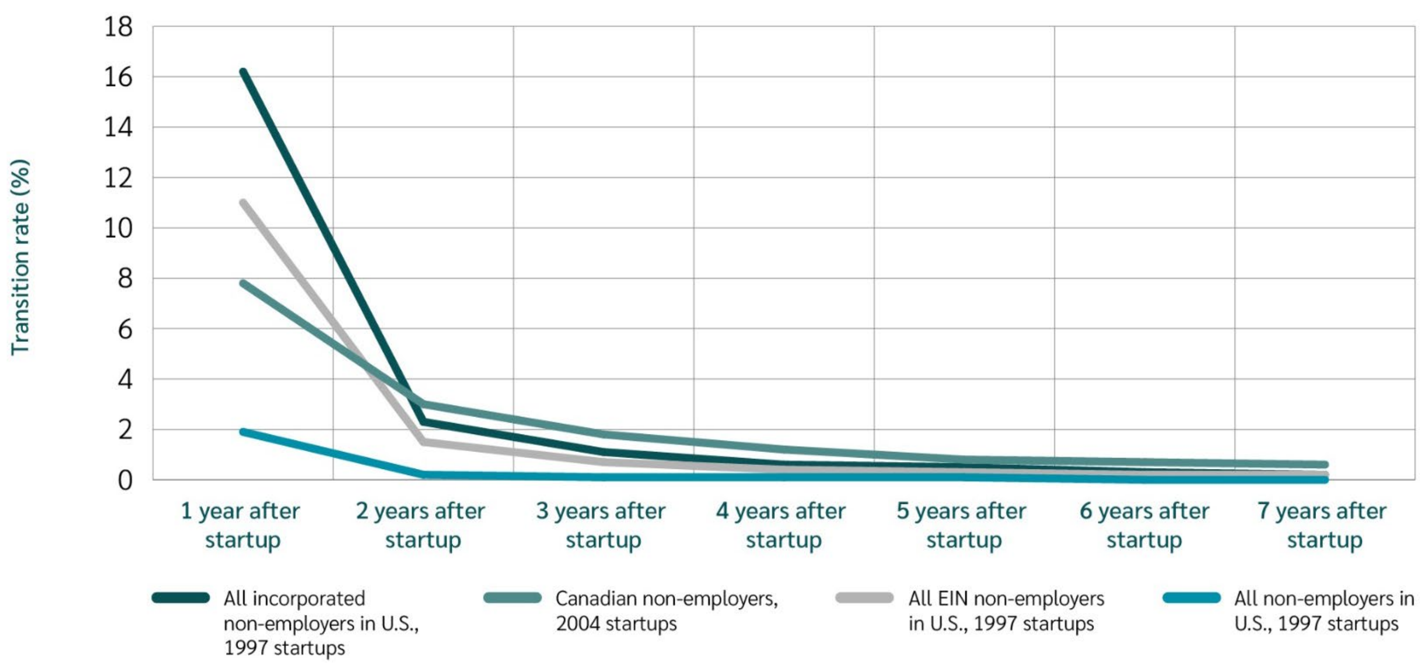
The first-hiring rate for the 2003 cohort was at its highest, 16%, in those firms' first year of operation, and declined quickly over time to under one percent in 2008, their sixth year of operation. Of the 35% of 2003 startups that hired, over 90% hired their first employee within their first five years of operation.

As noted above, the Canadian data presented above are not directly comparable with the U.S. data presented in FM, primarily due to the inclusion of first-year first hires. However, their counts of non-employer—employer transitions in the U.S., which are calculated from one year after startup and on and are analogous to the counts of first hires in the second year and on, allow for a rough comparison Canada-U.S. comparison: all Canadian firms that did not hire employees in their first year are non-employer startups, which makes the counts of second year first-hires analogous to FM's counts of U.S. transitions in the first year after startup.

Figure 2 shows, for Canada, all new incorporated non-employer businesses, and, for the U.S., all new non-employers, all new non-employers that registered for an Employee Identification Number (EIN)[16], and all new non-employers that are incorporated. With respect to the U.S. data, non-employer firms, EIN and incorporated businesses offer better comparisons than non-employer firms to incorporated businesses in Canada.

Broadly speaking, the finding that in Canada first-hires decline dramatically from the second to the third year of operation, and are decreasingly lower thereafter, parallels a comparable trend in FM's U.S. non-employer to employer transition counts, though the decline for incorporated startups and EIN startups in transitions from the first to the second year after startup is much steeper.

Figure 2: Transition rates for Canadian non-employers and U.S. non-employers

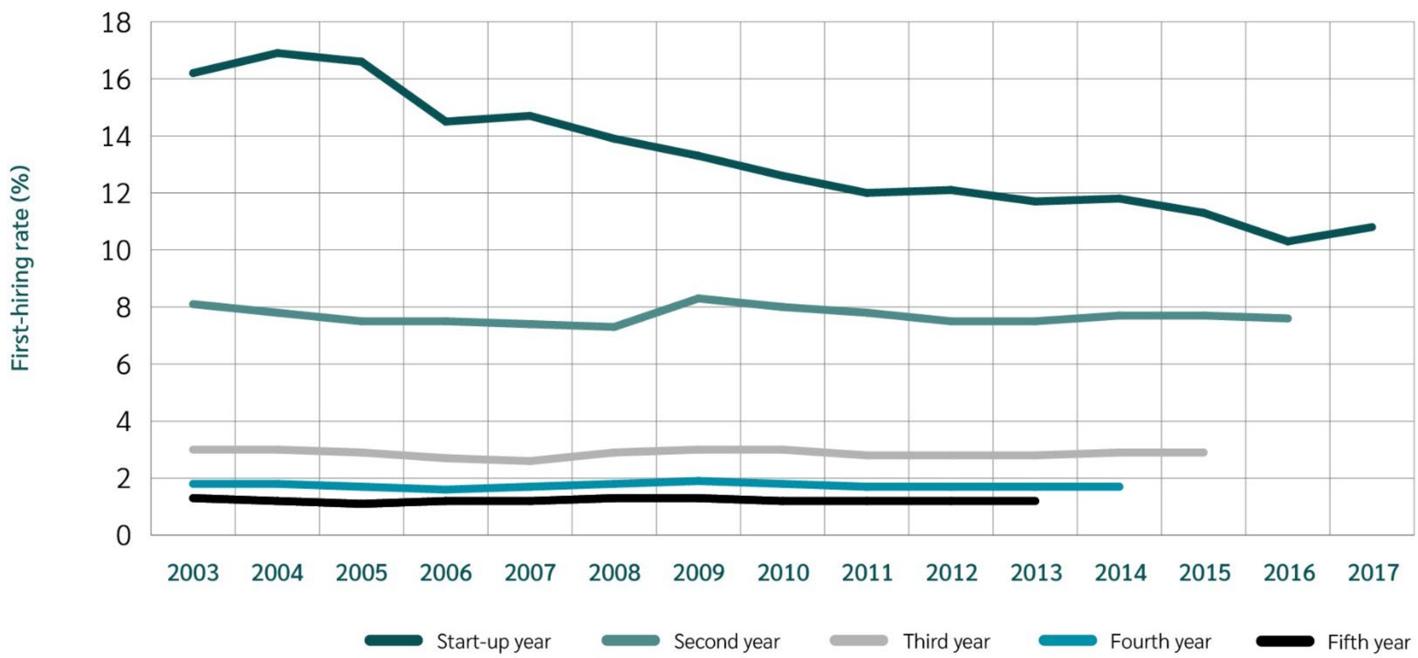


Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

[16] Among non-employer businesses in the U.S., an EIN is required for businesses that are incorporated or operate as a partnership, withhold taxes on income, have a Keogh plan (a type of tax-deferred retirement plan for self-employed and unincorporated businesses), or are involved with certain types of organizations such as trusts or estates.

Returning to the Canadian data, looking across the 2003 to 2017 startup cohorts, a particularly noteworthy trend is observed: a steady decline in the rate of startup year first-hiring over time, indicated by the (diamond) line in Figure 3. The startup year first-hiring rate is 16% for the 2003 startup cohort, dropping to under 11% for the 2017 startup cohort. As shown in Table 2, the decline is driven by a decrease in the number of firms hiring in their first year of operation, with the total number of startups trending slowly up over time.

Figure 3: First-hiring rates, by startup cohort and year of operation



Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

Table 2: First-hiring rates, first hires and total startups, by startup cohort, for startups' first year of operation

Startup cohort	First year of operation		All startups
	First-hiring rate (%)	First hires	
2003	16.2	21,135	130,165
2004	16.9	23,690	140,310
2005	16.6	25,660	154,365
2006	14.5	23,130	159,600
2007	14.7	23,720	161,505
2008	13.9	21,205	152,600
2009	13.3	17,970	135,010
2010	12.6	18,865	149,960
2011	12.0	18,565	154,925

2012	12.1	19,305	159,415
2013	11.7	18,700	159,440
2014	11.8	18,805	159,955
2015	11.3	17,740	157,350
2016	10.3	17,345	167,795
2017	10.8	16,455	151,905

Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

This decline contrasts with first-hiring rates in the years after startup: while fewer startups are hiring employees in their first year, first-hiring rates for the years after startup are remarkably stable (Figure 3).[17] Taken together, these trends, which are broadly observed across provinces and industries, imply a decrease in the overall propensity to hire employees by startups.

Although these trends are observed over a relatively short timeframe, they do appear consistent with recent research into firm entry and exit. Indeed, a downward trend in the hiring propensity of new firms may offer complementary perspectives to Leung (2015) and Cao *et al*. (2017), who respectively show that the hiring intensity of entrants, and that the entry rate of employer-firms, have fallen in recent years.

For example, a decrease in the hiring propensity of startups, all else being equal (e.g. no change in hiring intensity for startups that hire), would result in a decrease in the hiring intensity of all new firms, similar to that observed in Leung (2015).[18]

Likewise, fewer startups hiring employees in their first year, all else being equal (e.g. no change in entry of both employer and non-employer startups), would be reflected in measures of entry counting only employer-firms as a decline in entry rates, which is a trend studied by Cao *et al*. (2017).[19]

With respect to this latter trend of falling entry rates for employer-firms, the results raise the possibility that fewer new firms are hiring employees rather than that fewer firms are entering.[20]

Note that while Cao *et al*. (2017) study Canadian entry and exit trends, a similar trend of declining (employer) firm entry has been observed in the United States (Decker *et al*., 2014) and in other Organisation for Economic Co-operation and Development (OECD) countries (Criscuolo *et al*., 2014).

[17] These trends—a pronounced decline in start-up year first-hiring rates from 2003 to 2017, across industries and regions, as well as stable first-hiring rates for the years after start-up—are also observed for figures calculated using the T4 definition of hiring.
[18] Specifically, Leung (2015) describes a decline in the job creation rate of entrants over the period 2001 to 2014. This includes a fall from 2.5% in 2003 to 1.5% in 2013 (Statistics Canada, 2018).
[19] Cao et al. (2017) study the apparent secular decline in the entry rate of employer-firms from 1983 to 2012, including a decrease from 2003 to 2012.
[20] Direct comparison of the results in this report with both Leung (2015) and Cao *et al.* (2017) is precluded by important differences in the datasets used. For example, the data they use defines employment differently, and include both unincorporated and incorporated firms.

With the churn of businesses—as newer, more productive firms enter and replace older, less productive ones—linked to aggregate labour productivity growth (Decker *et al*, 2016), to the extent that declining employer firm entry may reflect decreasing propensity for new firms to hire, the trend studied in this report could have important macroeconomic implications.

Complementary perspectives aside, a trend towards fewer startups hiring also raises questions surrounding its possible causes. A decrease in startups' propensity to hire could reflect substitution away from labour due to increased productivity and technological change. Indeed, a growing body of evidence from the U.S. points to an increase in the use of robot and computer-assisted technologies as a productivity-increasing substitute for labour (e.g. Acemoglu and Restrepo, 2017).

But while in the past more productive firms expanded employment and less productive firms contracted employment, this link between firm-level productivity and hiring has weakened with time (Decker *et al*., 2016a).

Another explanation for this trend could be increased within-industry concentration, and the corresponding increase in firm size, observed since the late 1980s (Cao *et al*., 2017). Autor *et al*. (2017), for example, suggest that as within-industry concentration rises, profits increase for dominant firms and there is a reallocation of labour towards these firms. If workers are increasingly employed by larger firms, there is a smaller pool from which new entrants can hire.

More study is required to better understand the implications of and factors behind the observed decline in the startup year first-hiring rate, and whether it is a long-term and continuing trend.

5. First-hiring hazard

For the remainder of this paper, the analysis models the hazard rate of first-hiring in a duration framework, where the hazard refers to the instantaneous probability of exiting a given state. Specifically, the hazard rate of hiring a first employee (or, equivalently, of exiting the state of non-employer status) is estimated, where time is measured in years:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr\,(t \leq T < t + \Delta t | T \geq t)}{\Delta t}.$$

These estimates explore whether the apparent trend of declining hiring propensity by startups holds, controlling for observable owner and firm characteristics. The contributions of these characteristics to the log-likelihood of the estimated hazard are also evaluated.

The data used for this analysis are described below, including the sample restrictions and derivation of variables. Next, non-parametric estimates of the hazard are used to motivate the parametric analysis. Finally, the main results, from a parametric model that specifies the baseline hazard as Gompertz distributed, are discussed.

5.1. Data

This section details the data used in the duration analysis. The data cleaning and sample restrictions are explained, followed by the choice of covariates, including their importance to first-hiring decisions.

5.1.1. Data restrictions

The construction of the dataset used for the analysis that follows is shown in Table 3 below.[21]

First, 319,705 startups that entered in 2016 or 2017 are removed so that all firms in the analysis are observed for a minimum of three years.

Next, 624,485 firms that exit before hiring are removed. These startups are right-truncated since, upon exit, they are no longer at risk of first-hiring.[22] Finally, the following restrictions are further imposed, removing 459,045 new businesses[23]:

- Businesses with a change in province, North American Industrial Classification System (NAICS) code or primary owner over time, which may indicate a substantive change in the nature of the business[24];
- Businesses with more than one Business Number associated with the firm, removing firms with complex business structures;
- Businesses with missing values or data errors (e.g. negative sales) in variables of interest. The majority of these businesses are those missing information on ownership.[25]
- Businesses with startup year values of sales, assets, liabilities or employees in the 99th of their 3- or 4-digit NAICS industry,[26] or more than 200 employees. This is because such firms, which have for example $3 million in sales or more than 200 employees in their first year of operation, are unlikely to be truly new firms (i.e. such firms may not be new despite their firm identifiers appearing for the first time in the data).

[21] Counts of businesses shown in Table 3 are rounded to the nearest 5 in accordance with Statistics Canada confidentiality restrictions.
[22] An alternative treatment for right-truncated startups, to treat them as censored, is considered in the Appendix.
[23] The analysis is also conducted on a sample that does not impose this final set of restrictions and the results are qualitatively similar.
[24] For example, it is not clear from the data that a firm which began as a startup in Ontario but later moved to Quebec while keeping the same BN is still the same firm.
[25] In addition to missing information due to imperfect record linkage, or to incomplete records, both of which are common with administrative data, businesses may be missing ownership information because reporting is only required for ownership shares of 10% of more. Section compares results from a sample that includes businesses missing ownership information.
[26] For firms in the 3-digit NAICS 541 (Professional, scientific and technical services), which contains a particularly high concentration of new firms, percentiles are calculated at the 4-digit NAICS level. For all other firms, percentiles are calculated at the 3-digit NAICS level.

Table 3: Sample restrictions

Total new private sector startups between 2003 and 2015	1,975,225
Right-truncated	624,485
Change in ownership, province of operation or NAICS	107,370
More than one Business Number	2,100
Missing values or data errors	331,295
Unlikely to be startups	19,180
Zero revenues for 3 consecutive years	80,080
No GST number in start-up year	262,110
Final sample	548,605

Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

Two further restrictions are imposed. The first is designed to limit the sample to firms at similar stages of startup, while the latter excludes firms likely primarily engaged in tax optimization strategies rather than production of goods and services. These restrictions, particularly the latter, result in a sample that may be considered to be a cleaner sample, which is more likely to include only firms of policy interest.[27]

First, firms with no revenue for three or more consecutive years are excluded.[28] This removes 80,080 firms that may have incorporated but are still far-removed from being in a position to engage in economic production; comparing the first hires of a firm that generates revenues within its first two years with those of a firm that generates no revenue for several consecutive years would not be the comparison of interest.

Next, 262,110 new firms without GST/HST numbers in their first year of operation are excluded. Firms are required to charge and remit GST/HST when their annual sales exceed $30,000, so GST/HST filings indicate non-trivial amounts of production.[29]

Furthermore, all firms can register for a GST/HST number, so for firms with a GST/HST number but no sales or sales under $30,000, registration indicates the intent to sell, and likely indicates the intent or expectation that sales will grow beyond $30,000. Firms formed primarily for tax-planning ends are unlikely to be willing to fill out the additional paperwork if they do not intend to sell goods or services. The sub-population of startups with GST/HST numbers should therefore be one that excludes tax-planning firms.

[27] The results shown below are qualitatively similar to those based on a sample that does not impose these two restrictions.
[28] Changing this cutoff to 2 or 4 years does not materially affect the sample or results.
[29] GST/HST is a value-added tax levied on nearly all goods and services purchased in Canada.

5.1.2. Covariates

The analysis includes controls for firm characteristics related to first-hiring decisions, such as industry, province and firm performance. Controls for primary owner and majority ownership are also included.

5.1.2.1. Firm characteristics

In all specifications, controls for entry cohort, province and industry are included. The corresponding summary statistics, presented in the fourth, fifth and sixth panels of Table 4, clearly show important differences, between startups that hired by 2017 and those that did not, along these dimensions.

Compared to startups that did not hire, new firms that transitioned from non-employer to employer are more likely to have begun operating in earlier cohorts. While this reflects in part that later cohorts have had less time during which to hire, given the much lower rate of hiring in later years (for all cohorts), the analysis below shows that these distributional differences are driven by the trend of a declining propensity, with each cohort, to hire.[30]

To avoid discarding further observations, startups with missing province and NAICS codes are not excluded. Instead, dummy variables indicating unknown province and NAICS are created. This is particularly important for the latter variable since discarding these firms would remove nearly 9% of the sample, potentially limiting its representativeness.[31]

There are also interesting differences in the geographic distributions. Startups that hired are, relative to all new firms, overrepresented in Atlantic provinces and Quebec, and underrepresented in Alberta and Ontario.

The sectoral distributions reflect differences across industries in the importance of hiring employees. Startups that hired were more likely than new firms that did not hire to operate in the Accommodation and Food services, Construction, Other services and Trade, transportation and utilities sectors, and less likely to operate in the Finance and real estate and Professional services sectors.

Finally, variables are created for startups indicating their initial values of net income, sales and leverage, the latter of which is calculated as the ratio of liabilities to assets.[32] The bottom panel of Table 4 contains summary statistics for these measures. The average sales of firms that hired by 2017 is much higher than that of firms that did not, which is expected given that it is difficult to pay employees without sales. From a theoretical perspective, sales are a measure of a firm's production; insofar as firms with greater sales are larger and more successful, they should be more likely to hire (Piva and Vivarelli (2017)).

[30] As discussed below, regression results below indicate that the first-hiring hazard declines with year of entry, even when startups from all entry cohorts are coded as censored beyond their third year.
[31] Corresponding models are also estimated removing startups with missing province or NAICS codes. The results are qualitatively similar.
[32] Net income, sales, liabilities and assets are first deflated to 2003 values using Consumer Price Index (CPI) data.

Table 4: Summary statistics of start-up year owner characteristics

	All firms		Did not hire		Hired		H_0: Did not hire = Hired
	Mean	Standard error	Mean	Standard error	Mean	Standard error	p-value
Primary owner							
Marital status							
Single	0.222	0.415	0.219	0.414	0.224	0.417	0.000
Married/common-law	0.700	0.458	0.705	0.456	0.696	0.460	0.000
Divorced/widowed/separated	0.078	0.268	0.076	0.266	0.079	0.270	0.000
Age							
Under 30 years	0.137	0.344	0.128	0.334	0.146	0.353	0.000
30 to 65 years	0.845	0.362	0.851	0.356	0.839	0.367	0.000
Older than 65 years	0.018	0.133	0.021	0.143	0.015	0.123	0.000
Collected Employment Insurance	0.083	0.276	0.075	0.263	0.091	0.287	0.000
Dividend income from outside of firm	0.246	0.431	0.291	0.454	0.206	0.404	0.000
Majority ownership							
Gender							
Majority-male	0.665	0.372	0.669	0.470	0.660	0.474	0.000
Equal ownership	0.161	0.367	0.172	0.378	0.150	0.357	0.000
Majority-female	0.175	0.380	0.158	0.365	0.190	0.392	0.000
Immigrant status							
Majority-immigrant	0.053	0.224	0.049	0.215	0.057	0.232	0.000
Equal immigrant/Canadian-born	0.010	0.098	0.006	0.080	0.013	0.112	0.000
Majority-Canadian-born	0.937	0.243	0.945	0.228	0.930	0.255	0.000
Ownership							
Firm pays at least one owner (T4)	0.171	0.376	0.126	0.332	0.211	0.408	0.000
Industry							
Accommodation and Food services sector	0.078	0.268	0.009	0.096	0.139	0.346	0.000
Construction	0.155	0.362	0.118	0.323	0.189	0.391	0.000
Finance, insurance and real estate	0.085	0.278	0.138	0.344	0.037	0.188	0.000
Information and cultural	0.017	0.129	0.021	0.142	0.013	0.115	0.000
Management	0.012	0.108	0.02	0.141	0.004	0.063	0.000
Manufacturing	0.032	0.156	0.018	0.132	0.045	0.206	0.000

Other services	0.118	0.323	0.085	0.278	0.148	0.355	0.000
Natural resources and mining	0.026	0.159	0.029	0.169	0.023	0.150	0.000
Professional services	0.183	0.387	0.272	0.445	0.103	0.304	0.000
Retail, wholesale and transportation	0.200	0.400	0.169	0.375	0.228	0.420	0.000
Unknown (missing NAICS code)	0.094	0.292	0.121	0.326	0.070	0.256	0.000
Geographic region							
Alberta	0.191	0.393	0.224	0.417	0.162	0.368	0.000
Atlantic	0.041	0.197	0.027	0.162	0.053	0.223	0.000
British Columbia	0.147	0.354	0.132	0.339	0.160	0.367	0.000
Manitoba & Saskatchewan	0.051	0.220	0.048	0.215	0.054	0.225	0.000
Ontario	0.340	0.474	0.379	0.485	0.305	0.460	0.000
Quebec	0.228	0.420	0.188	0.391	0.264	0.441	0.000
Territories	0.002	0.042	0.001	0.034	0.002	0.047	0.000
Unknown (missing province code)	0.000	0.017	0.000	0.008	0.000	0.022	0.000
Startup cohort							
2003	0.058	0.235	0.035	0.183	0.080	0.271	0.000
2004	0.064	0.244	0.041	0.198	0.084	0.278	0.000
2005	0.069	0.253	0.051	0.219	0.085	0.279	0.000
2006	0.072	0.258	0.057	0.232	0.085	0.280	0.000
2007	0.071	0.257	0.058	0.234	0.080	0.276	0.000
2008	0.070	0.254	0.060	0.237	0.078	0.268	0.000
2009	0.064	0.245	0.057	0.231	0.071	0.257	0.000
2010	0.076	0.264	0.074	0.263	0.076	0.266	0.000
2011	0.081	0.273	0.087	0.282	0.076	0.264	0.000
2012	0.087	0.283	0.102	0.303	0.074	0.263	0.000
2013	0.091	0.287	0.110	0.313	0.073	0.260	0.000
2014	0.096	0.295	0.127	0.333	0.069	0.253	0.000
2015	0.101	0.301	0.141	0.348	0.065	0.247	0.000
Financial characteristics							
Net income ($)	11,586.26	214,046.00	23,477.70	297,063.16	860.42	85,452.55	0.000
Sales ($)	101,718.49	580,368.71	49,445.66	157,904.52	148,867.49	783,238.90	0.000
Leverage (liabilities ($)/assets ($))	5.82	410.85	5.30	403.08	6.28	417.74	0.373
N	548,605		260,165		288,440		

Notes: Where means represent proportions, p-values are calculated from a Z test statistic for the difference between two proportions; otherwise, p-values are calculated from a t test statistic for the difference between two means.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

Summary statistics suggest a negative relationship between the likelihood of having hired by 2017 and net income, which is on average much lower for hiring firms. This may reflect that, in the context of start-ups, employees are often hired before a business becomes profitable.

Research also suggests new firms are often leveraged when they borrow to pay for startup costs or to grow, though too much debt diminishes firms' viability (Huynh *et al*. (2010)). The average leverage of firms that hired is higher than that of firms that did not, though the difference is not statistically significant.

5.1.2.2. Ownership characteristics

The primary owner is defined as the owner with the highest percentage share of ownership.[33] For the primary owner, the following binary indicators are created, using initial values (i.e. values during the startup year): younger than 30 years of age, between 30 and 64 years, and 65 years or older; married or common-law status, single, and for divorced, separated or widowed; and, collected Employment Insurance in the firm's startup year. In addition, the primary owner's dividend income from all sources outside the firm, as well as their employment income (T4 filing) from all sources outside the firm, is calculated.

The top panel of Table 4 shows summary statistics for primary owner characteristics for all firms in the sample, as well as by whether the startup hired its first employee by 2017. The age and marital status of primary owners at firms that hired and of firms that did not hire are quite similar, with primary owners at hiring startups modestly more likely to be younger than 30 and less likely to be older than 65 years of age.

Coad *et al*. (2017) find some evidence that startup motivation, measured by labour market status, is important to a firm's first-hiring decisions, with necessity-based startups (whose owners were unemployed in the year they founded the firm) less likely to hire.

This analysis, similarly, includes an indicator for the collection of EI benefits to proxy for necessity-based new firms, though the summary statistics here suggest that startups that hired were modestly more likely than startups that did not hire to be owned by an individual who had collected EI benefits in the previous year.

In addition, to the extent that greater income from outside their firm indicates less necessity for primary owners to generate income within their firm, income from outside sources may capture startup motivations; alternatively, extra-firm income may support investment in growing a new firm.

To control for outside income in the parametric analysis, a variable indicating outside dividend income is included.[34] The owners of startups that transitioned to employer firms were more likely to extra-firm dividend income than those of startups that remained non-employers.

[33] Note that the highest percentage share of ownership may not be a majority owner. For firms where two or more owners have the highest percentage share (i.e. their shares are equal), one owner is chosen randomly as the primary owner. Although these assumptions result in some imprecision in the (estimated) identification of the primary owner, the advantage of this approach is that it limits the amount of missing values and dropped observations.
[34] Models including of extra-firm employment income were also estimated, yielding qualitatively similar results.

CEEDD also allows for calculation of indicators for two characteristics of majority ownership: gender and immigrant status.[35] Specifically, binary indicators are defined for the gender categories majority-male, equal, and majority-female, and for the immigrant status categories majority-immigrant, equal immigrant and Canadian-born, and majority Canadian-born status.

As shown in the second panel of Table 4, startups that hired were more likely to have been majority female owned, and less likely to have had ownership split equally between male and female owners. The distributions of the immigrant status of ownership were similar for startups that hired and those that did not.

Finally, Table 4 shows an additional ownership indicator for whether the firm paid a salary (T4) to at least one owner. New firms that hired were more likely than startups that did not hire to have paid a salary to at least one owner.

5.2. Non-parametric first-hiring hazard

The empirical hazard of these firms, the starting point of the duration analysis, is presented in Figure 4. The hazard reflects the patterns observed for first-hiring rates described above—that firms are most likely to hire in their startup year, and if firms have not hired by their third year of operation, they are unlikely to hire at all—though the hazard rates are higher for the restricted sample given the focus on a sub-population that excludes right-truncated firms, firms are earlier stages of startup and firms more likely to be tax-planning entities.

Figure 4: Empirical hazard of time until first-hiring

Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

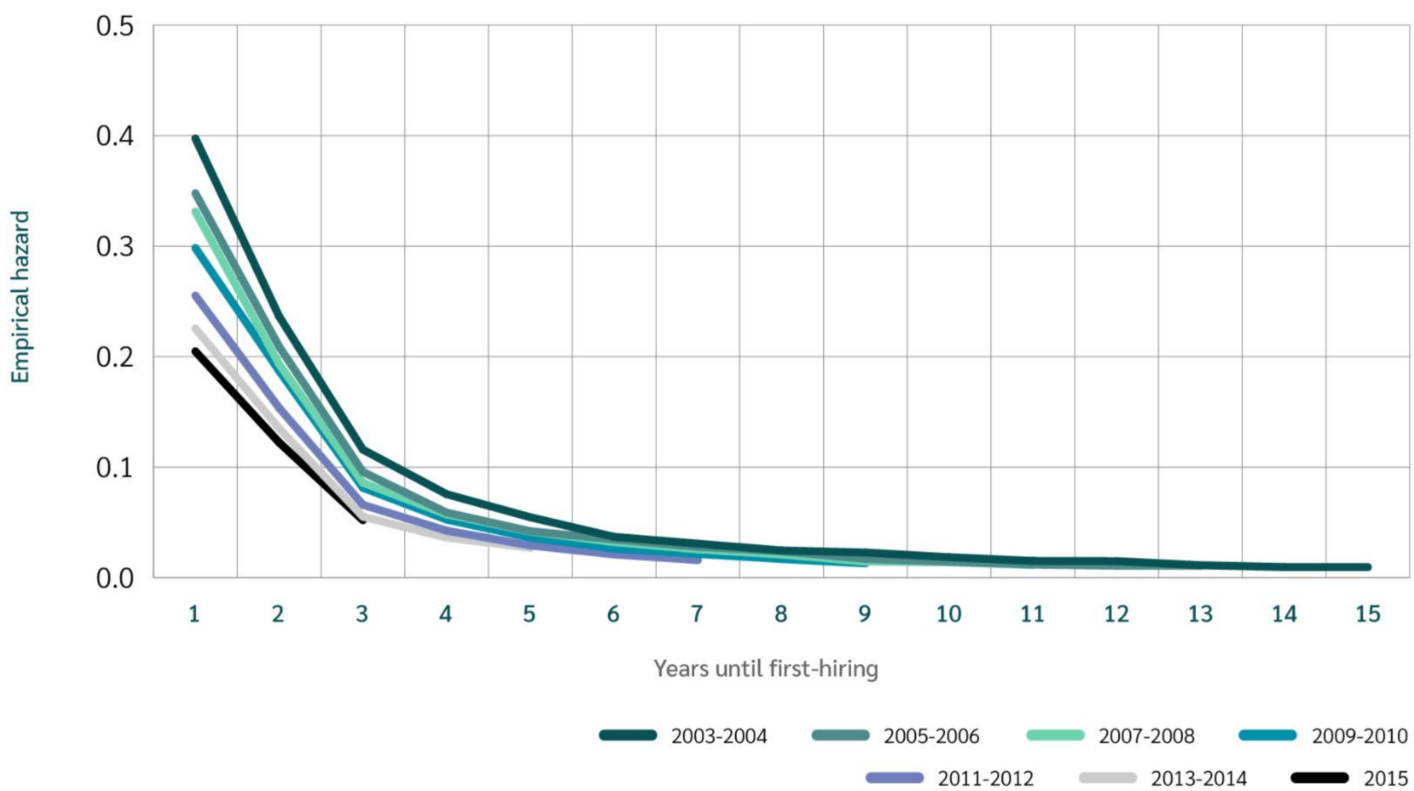
[35] For firms where identified private ownership is less than 100%, it is not always possible to identify majority ownership. Similar to the approach for primary owners, the approach used here is to estimate primary ownership as belonging to that demographic when owners belonging to that demographic hold a higher share of ownership than their demographic of comparison. For example, for a firm with only two owners identifiable from S50 filings associated with that firm, one immigrant with a 35% ownership share and the other Canadian-born with a 25% ownership share, the firm would be considered to be majority immigrant-owned.

Reflecting these trends, the hazard is characterized by negative duration dependence. In particular, the first-hiring hazard is at its highest in the startup year, and decreases rapidly in the following two years. By the third year of operation the hazard of hiring a first employee is quite low, thereafter continuing to decrease at a diminishing rate.

Broadly speaking, the hazard varies significantly (based on both Wilcoxon and Log-rank tests) by subgroups formed using the ownership and firm characteristics described above, which motivates the parametric estimation of the hazard.

Figure 5 and Figure 6 indicate, for example, important differences in firms' first-hiring hazards according to their startup year cohort and industry.[36] Figure 5 shows the hazard of first-hiring declining with successive startup cohorts, with the decline most apparent across startup years.

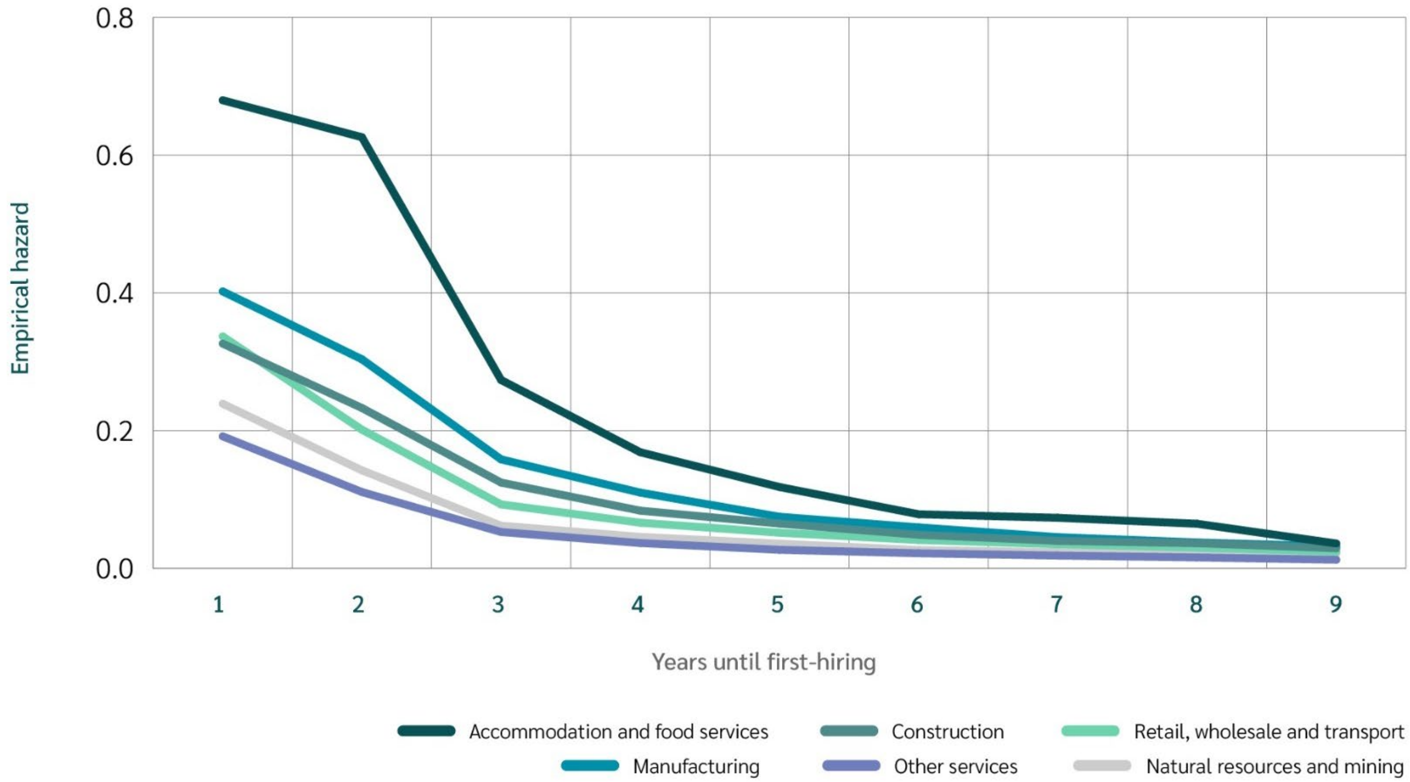
Figure 5: Empirical hazard of time until first-hiring, by startup cohort



Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

[36] Hazards for two-year cohorts are shown in Figure 4 for cleaner presentation. The hazards of one-year cohorts show the same trend.

Figure 6: Empirical hazard of time until first-hiring, by sector



Note: Hazards in Figure 6 are shown only up to nine years from startup because subsequent values for some of the hazards are considered confidential by Statistics Canada.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

Figure 6 indicates first-hiring hazards are highest for firms in the accommodation and food services sector, while those of startups in construction, retail, wholesale and transport, and manufacturing industries are similar to the empirical hazard for all firms. The hazards for startups in natural resources and mining and other service industries are relatively low. These estimates are unsurprising: the accommodation and food services sector is much more labour-intensive than retail, wholesale or transport industries, while firms in other service industries often do not hire at all.

5.3. Parametric first-hiring hazard

A general parametric regression model of the hazard of the time until first-hiring can be written as

$$h(t) = h_0(t)\phi(X\beta),$$

where $h_0(t)$ is the baseline hazard and $\phi(X\beta)$ characterizes how the hazard changes with the covariates, X.[37] Included in X are the ownership and business characteristics listed above. Since $h_0(t)$ a function of only time (t) and $\phi(X\beta)$ a function of only ownership and firm characteristics (X), the hazard becomes a function of only time when all covariates are set to zero. Time is measured in years, and treated continuously.[38]

This model is estimated parametrically and semi-parametrically, using a wide range of specifications.[39] In particular, a variety of functional forms for covariates (described below in detail) are explored, while models are also estimated by cohort, geographic region and sector. Some specifications model firm-specific unobserved heterogeneity, reducing the effect of unobservables. Because the estimated models are proportional hazard models, the results are presented as hazard ratios in order to facilitate interpretation.[40]

Note that this analysis does not support a causal interpretation of firm and ownership characteristics on the first-hiring hazard. This limitation is due in part to the structure of the data: for firms that hire in their startup year, sales made before the hire and sales made after, for example, cannot be separated. Moreover, the data—and indeed all firm-level datasets—are characterized by a significant amount of unobserved heterogeneity. The analysis, therefore, is descriptive: it offers estimates of conditional correlations between initial (startup year) ownership and firm characteristics and the first-hiring hazard.

5.3.1. Covariate specification

The majority of the covariates are categorical, and therefore specified using indicators. However, firm sales and leverage (i.e. liabilities over assets) are specified as continuous variables.[41] Recall that these variables are set to their startup year values. Choosing the appropriate functional form is important for model specification, and particularly so in the context of tests of proportional hazards for duration models, such as the Grambsch and Therneau test for non-proportionality (e.g. Radoman and Voia (2015)).

Financial variables may be non-linearly related to the first-hiring hazard for a number of reasons. As noted above, Huynh *et al*. (2010) find non-linearity in the effect of leverage on firm survival. The first-hiring hazard of firms with zero leverage, then, may be lower than that of firms with low leverage but higher than that of firms with high leverage.

[37] By convention, $\phi(X\beta)$ is specified as $exp(X\beta)$.
[38] Complementary log-log models, which treat time as discrete, were estimated as well and yield qualitatively similar predictions.
[39] The approach to duration modelling, including how the model is specified and tested for robustness, follows closely the approach taken in Radoman and Voia (2015).
[40] Average and median marginal effects are estimated but somewhat imprecisely (e.g. an average predicted survival time of 28 years, with a 95% confidence interval of [6,50], or a median predicted survival time of 9 with a 95% confidence interval of [5,12]), likely due to the high proportion of censored times.
[41] Owner extra-firm income (i.e. dividend or employment income from outside the business) are also recorded continuously but are specified as dummy variables since alternative specifications yield qualitatively similar results and model fit.

Similarly, firms with low negative net income in their startup year, which tend to spend more than they earn to expand and hire, may have higher hazards than firms with positive startup year net income, insofar as non-employers may focus more on initial profitability; conversely, high negative net income would be associated with lower hazards if it was reflective of future profits. Finally, even though sales and first hires may be expected to be positively related, the relationship may not be well-captured through a linear specification if, for example, the hazard changed differently beyond different sales thresholds.

Moreover, particularly with firm financials, the relationship to the first-hiring hazard likely varies greatly by industry. For example, profit, leverage and sales for a restaurant impact growth prospects—and first hires—differently than do to profit, leverage and sales for a manufacturer or consultancy. To the extent that firm performance depends on firms' entry years, cohort effects may be important as well. The appropriate functional form, then, should capture not only non-linearity but also industry or cohort effects.

Indeed, initial specification of these variables linearly, quadratically or in logarithms suggests more complex non-linearity in their relationships with the hazard: the coefficient estimates are near-zero but highly statistically significant. Subsequent specification using fractional polynomials confirms that non-linear (and non-quadratic) scaling yields better-fitting models.[42]

However, fractional polynomials do not capture industry and cohort effects; an additional disadvantage of fractional polynomials—or cubic spline functions, a popular alternative to fractional polynomials—is that their coefficients become less interpretable.

In order to increase interpretability and to capture non-linearity, as well as relative inter-industry and inter-cohort differences, the following approach is used. For sales, net income and leverage, indicators are calculated for each quintile, by both startup-year cohort and by 3- and 4-digit NAICS. Including indicators for each sales, leverage and net income quintile in the model captures how the hazard changes for firms in different industry/cohort quintiles. For example, the coefficient for the 5th sales quintile shows how the hazard for firms with startup year sales in the top sales quintile for their industry and cohort compares to the hazard for firms with zero sales. Estimates using these indicators yield even better-fitting models than those using fractional polynomials specifications while also offering more interpretable information.[43]

The specifications of sales and leverage are further modified by multiplying sales quintile indicators with the log value of sales, and leverage quintile indicators with the value of leverage.[44] These modifications are made, in the context of working with a confidential dataset, in order to reduce disclosure risk since regression estimates of models containing only binary variables have a higher risk of disclosure.[45]

[42] Model fit is compared using Akaike (AIC) and Bayesian Information Criteria (BIC) statistics.
[43] As above, model fit is compared using AIC and BIC.
[44] These interactions follow a similar treatment to that of Huynh, Petrunia and Voia (2010).
[45] Model fit, evaluated using AIC and BIC, with these specifications compared to specifications using only quintile dummy variables.

5.3.2. Unobserved heterogeneity

As noted above, the empirical hazard shown is characterized by negative duration dependence, with the rate of first-hiring decreasing over time. The hazard model estimated for this analysis, which does not account for unobserved heterogeneity, assumes that firms with the same values of all covariates are identical. However, if firms are heterogeneous along unobservable dimensions, there are two possible interpretations for the observed negative duration dependence. The decreasing hazard may be due to declining hazards for each firm, or to aggregating across firms with different individual hazards (e.g. even if all individuals hazards were increasing in time, the population hazard may decrease as it is increasingly comprised of firms that are less likely to hire a first employee). In the latter case, the model would be misspecified.

To account for this possibility, shared frailty models are estimated, with heterogeneity specified in bins of 10 provinces (or the territories) and 20 two-digit NAICS.[46] In this context, a shared frailty model is a random effects model where heterogeneity is common among firms in each bin (Gutierrez, 2002).

5.3.3. Time until first-hiring: results

Estimates are presented below of conditional correlations between firms' startup year ownership and firm characteristics and their hazard to hire a first employee. Three specifications are estimated. Model 1 includes only controls for industry, geographic region and startup cohort. Models 2 and 3 add to the model ownership characteristics and firm financial characteristics, respectively. Model 4 adds shared frailty to covariates included in Model 3.

Qualitatively, the estimates are largely similar across all models, with a few differences between Models 3 and 4. Since the estimated models are proportional hazard models, estimated hazard ratios, which allow for straightforward interpretation, are shown rather than coefficient estimates. Focus is given to the results for Model 3, which has straightforwardly interpretable hazard ratios in contrast to Model 4.[47]

To account for the possibility of intra-class correlation in Models 1, 2 and 3, estimated standard errors are clustered by province/territory, by startup cohort and by 2-digit NAICS. The former two sets are qualitatively similar to the unadjusted standard errors. By contrast, clustering by industry yields standard errors which tend to be larger than their unadjusted counterparts. For more conservative inference, these standard errors (i.e. clustered by 2-digit NAICS) are presented.[48]

---

[46] The shared frailty model is similar to heterogeneity clustering to obtain more efficient standard errors (Huynh et al., 2010). Models with individual-level frailty are also estimated; however, the estimated frailty variance is not statistically different from zero, suggesting there may be no role for modelling unshared frailty in this context.

[47] In hazard models with frailty, reported hazard ratios retain the usual interpretation only conditional on a given value of α (the parameter introduced to represent heterogeneity in the model), or at $t = 0$.

[48] Models are estimated using the command *streg* in Stata, which does not allow for multi-way clustering. The post-estimation command *boottest* is used to estimate test-statistics assuming clustering by 2-digit NAICS and province, and by 2-digit NAICS and startup cohort. Assuming multi-way clustering does not qualitatively change inference described above.

The choice of distribution for the baseline hazard is determined using Akaike (AIC) and Bayesian Information Criteria (BIC). The Generalized Gamma model fails to converge. Between other distributions, AIC and BIC suggest the baseline hazard specified as Gompertz yields the best-fitting model, as shown in Table A2.[49] Model selection is discussed further in the Appendix.

Table 5 presents the estimated hazard ratios from all four models. The top three panels of Table 5 contain the estimated hazard ratios for indicators of cohort, region and industry sector, which have as their reference categories 2003 startup cohort, Ontario and Manufacturing, respectively.

Table 5: Time until first-hiring results, Gompertz

	M1	M2	M3	M4
Startup cohort				
2003	0.949***	0.951***	0.969**	0.982**
2004	0.864***	0.892***	0.775***	0.822***
2005	0.827***	0.854***	0.743***	0.786***
2006	0.817***	0.835***	0.735***	0.776***
2007	0.770***	0.793***	0.701***	0.732***
2008	0.744***	0.772***	0.689***	0.707***
2009	0.671***	0.695***	0.629***	0.651***
2010	0.624***	0.648***	0.592***	0.620***
2011	0.567***	0.589***	0.541***	0.571***
2012	0.551***	0.573***	0.530***	0.562***
2013	0.521***	0.543***	0.506***	0.539***
2014	0.530***	0.553***	0.521***	0.555***
2015	0.949***	0.951***	0.969**	0.982**
Geographic region				
Alberta	0.934	0.919	0.969	0.982
Atlantic	1.845***	1.794***	1.788***	1.756***
British Columbia	1.338***	1.325***	1.280***	1.188*
Manitoba/Saskatchewan	1.294***	1.285***	1.284***	1.303***
Quebec	1.375***	1.352***	1.419***	1.400***
Territories	1.708***	1.666***	2.182***	2.184***
Unknown (missing province code)	5.341***	5.200***	8.844***	6.836***

[49] Although Table A2 shows AIC and BIC statistics only for Model 3, Gompertz is preferred by information criteria for Models 1 and 2.

Industry				
Accommodation and food services	2.130***	2.056***	2.036***	1.719***
Construction	0.802***	0.802***	0.841**	0.776**
Finance, insurance and real estate	0.200***	0.207***	0.236***	0.211***
Information and cultural	0.439***	0.439***	0.441***	0.527***
Management	0.124***	0.129***	0.158***	0.148***
Natural resources and mining	0.494***	0.496***	0.535***	0.521***
Other services	0.858	0.836**	0.853*	0.748***
Professional services	0.280***	0.271***	0.292***	0.262***
Retail, wholesale and transportation	0.749	0.74	0.711	0.698***
Unknown (missing NAICS code)	0.484***	0.485***	0.473***	0.474***
Primary owner				
Marital status				
Married/common-law		1.046**	1.047**	1.054***
Divorced/widowed/separated		1.057**	1.065***	1.080***
Age				
Under 30 years		1.001	1.064	1.098***
Older than 65 years		1.054	1.062	1.041***
Collected Employment Insurance		0.996	1.01	1.007
Dividend income from outside firm		0.962	0.897**	0.879***
Ownership — general				
Firm pays at least one owner (T4)		1.540***	1.121**	1.122***
Majority ownership				
Gender				
Equal ownership		0.984	0.975	0.940***
Majority-female		1.243***	1.238***	1.157***
Immigrant status				
Equal immigrant/Canadian-born		1.234***	1.117***	1.072***
Majority-immigrant		0.772**	0.835**	0.861***
Financial characteristics				
Log sales				
1st (NAICS/cohort) quintile			0.903***	0.972

2nd (NAICS/cohort) quintile			1.007	1.004***
3rd (NAICS/cohort) quintile			1.039***	1.034***
4th (NAICS/cohort) quintile			1.069***	1.065***
5th (NAICS/cohort) quintile			1.111***	1.108***
Leverage				
1st (NAICS/cohort) quintile			3.720**	2.304***
2nd (NAICS/cohort) quintile			1.578***	1.351***
3rd (NAICS/cohort) quintile			1.208***	1.135***
4th (NAICS/cohort) quintile			1.003	0.984***
5th (NAICS/cohort) quintile			1.000	1.000
Net income				
2nd (NAICS/cohort) quintile			0.760***	0.736***
3rd (NAICS/cohort) quintile			0.775***	0.722***
4th (NAICS/cohort) quintile			0.577***	0.612***
5th (NAICS/cohort) quintile			0.471***	0.490***
N		548,605		
γ	0.687***	0.691***	0.718***	0.728***
θ (variance of γ)	-	-	-	0.078***
Δlog L (v M1)	0	4,419	32,535	11,191

Note: Estimates statistically significant at the 0.1, 0.05 and 0.01 levels are indicated, respectively, by *, ** and ***.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

The results for startup cohorts are similar across models and, correspondingly with the non-parametric estimates, point to declining rates of first-hiring with successive startup cohorts. Notably, these estimates show that this finding holds even controlling for a wide array of other ownership and firm characteristics related to first-hiring. The hazard ratios for cohorts that entered in 2010 or later indicate that these firms are, relative to new firms that entered in 2003, over 30% less likely to hire a first employee; the estimates for the 2015 cohort suggest that 2015 startups are between 44% and 48% less likely to hire a first employee than their 2003 counterparts.

The first-hiring hazard also varies significantly by region and sector, with the estimates hazard ratios qualitatively similar across models. Compared to startups in Ontario, new firms in most other regions, particularly the territories and Atlantic region, have higher rates of transitioning to employer firms. First-hiring rates for new firms in Alberta are not significantly different from those observed in Ontario.

In comparison to startups in the Manufacturing sector, those in Accommodation and Food services, a particularly labour-intensive industry, are between 72% and 113% more like to hire a first employee. New firms in all other sectors, particularly in the Management, Finance, insurance and real estate and Professional services sectors, are less likely to hire than Manufacturing startups.

The middle panel of Table 5 presents results from Model 2, Model 3 and Model 4, which add ownership characteristics to model, and show interesting relationships between ownership and first-hiring.

Results for marital status and age of the primary owner on first-hiring are mixed. Compared to the reference category of firms founded by single primary owners, firms whose primary owners were previously or currently in married or in common-law relationships are significantly more likely to hire first employees.

In contrast to Coad *et al*. (2017), who find a quadratic relationship between owner age and the likelihood of first-hiring, the evidence presented here is mixed, with the estimated hazard ratios for young and older primary owners, relative to the reference category of working-age owners, significant only in Model 4.

Owner motivation may also be captured by indicators (measured in firms' startup years) for the collection of Employment Insurance and for outside income, as noted above: entrepreneurs transitioning from unemployment or with low extra-firm income may be more motivated to grow their businesses and generate income, while higher extra-firm income may suggest less need to do so. The results here indicate that having collected Employment Insurance does not significantly predict first-hiring.

Owners with outside dividend income are less likely to hire. Specifically, compared to startups whose primary owners have no dividend income, those whose primary owners have some dividend income are over 10% less likely to hire first employees; this is consistent with the hypothesis that necessity is negatively related to hiring.[50]

Paying a salary to at least one of the owners in a new firm's startup year may relate to that firm's future viability, insofar as startups facing early challenges may have less capacity to pay their owners. The estimated hazard ratios for this indicator suggest that firms that pay their owners are more likely to become employer firms.

There are significant differences between the estimated hazard ratios for majority ownership by gender and immigrant status. Firms that are majority female-owned are between 16% and 24% more likely to hire a first employee than are majority male-owned firms (the reference category). The results for startups equally owned by male and female owners, are mixed, with some evidence (M4) that these new firms are less likely to hire than male-owned firms. This contrasts with previous findings (e.g. Coad *et al*. (2017), FM (2017) and Burke *et al*. (2000)), who find that female owners are less likely than male owners to hire.

The difference may be due in part to the measurement of gender ownership for the majority ownership rather than the primary owner, of firms; in fact, when the gender only of the primary owner is alternatively controlled for, the hazard ratio is insignificant or indicates a small but negative relationship.

[50] Alternative specifications with extra-firm dividend income measured continuously yield qualitatively similar results. Note that a previous version of this paper included controls for extra-firm employment income. The decision to exclude them here was made because these controls seemed, both intuitively and empirically, somewhat redundant when also controlling for extra-firm dividend income; moreover, the other estimates were not qualitatively impacted with its exclusion.

Immigrant-owned firms are significantly less likely to hire than new firms with Canadian-born owners (the reference category). By contrast, compared to firms majority owned by Canadian-born individuals, firms equally owned by immigrant and Canadian-born owners are significantly more likely to hire first employees.

Finally, the bottom panel of Table 5 shows the estimated hazard ratios for sales, leverage and net income. Recall that these variables are measured for firms' startup years, and based on sales, leverage and net income relative to industry and cohort peers. These additional controls give a relatively greater yet still modest improvement in log-likelihood.

The hazard ratios for sales are significant, and show the greater a startup's initial sales performance, the higher the startup's probability of hiring its first employee. As noted above, an intuitive explanation for this could be that firms without sales will have difficulty paying their employees.

The results suggest that first-hiring rates decrease with leverage, with modestly leveraged startups more likely to hire relative to firms with higher leverage. To the extent that firm survival and first-hiring decisions correlate, this result aligns with Huynh *et al*. (2010), who find that some debt signals firm success compared to high debt.

Perhaps surprisingly, the results for net income point to a negative relationship between first-hiring and startup year profitability. Relative to firms with net income in the first quintile relative to their sectoral and startup cohort (the reference category), firms with net income in higher quintiles are increasingly less likely to hire a first employee. One explanation for this could be that startups that transition to employer are more focused on growth than profitability when they begin operation.[51]

5.3.4. Model likelihood decomposition

A decomposition of the partial log-likelihood is undertaken in order to evaluate the role of different groups of variables, following the approach used by Huynh *et al*. (2010). The model likelihood decomposition is conducted as follows:

1. Estimate the intercept-only model (i.e. model with no covariates). The likelihood for the intercept-only model is treated as the lower bound. Estimate the full model (M4), which includes controls for startup cohort, geographic region, industry, ownership, firm financials and unobserved heterogeneity. The likelihood for the full model is treated as the upper bound.

2. Quantify the contribution to the partial log-likelihood of a given group of variables as the change in the likelihood from adding that group while moving from the intercept-only model to the full model (M4).[52]

[51] Alternatively, given that these estimates indicate correlations rather than causal relationships, it may be that startups that hire have higher labour costs, resulting in decreased profit.

[52] The order in which groups of variables are added does not substantively change the likelihood contributions.

The middle and right columns of Table 6 show the likelihood contributions in levels and percentages, respectively. Industry controls (45.4%) and firm financial variables (28.3%) have the largest contributions to the partial log-likelihood. Unobserved heterogeneity and startup cohort controls accounts for 9.8% and 7.2% of the likelihood, respectively. Region controls and ownership have the smallest likelihood contributions.

Table 6: Model (M4) likelihood decomposition

	Log-likelihood	Δlog L	% Δlog L
Intercept-only	-772,478	-	-
Startup cohort	-764,210	8,268	7.2
Geographic region	-757,939	6,270	5.5
Industry	-705,786	52,153	45.4
Ownership (primary owner, majority ownership, ownership)	-701,367	4,419	3.8
Firm financials	-668,832	32,535	28.3
Unobserved heterogeneity	-657,624	11,208	9.8

Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

5.3.5. Split sample test of endogeneity

To assess whether endogeneity should be a consideration in interpreting the estimates, the split sample test proposed by Huynh *et al*. (2010) is conducted. The split sample test is conducted as follows:

1. Randomly split the sample into two equal parts, Group 1 ($x^{(1)}$) and Group 2 ($x^{(2)}$).

2. Estimate Model 3 as a function of time until first-hiring (i.e. with the model specified as an accelerated time-failure model rather than a hazard model) using Group 1 ($x^{(1)}$). Retrieve the estimated coefficients, $\hat{\beta}^{(1)}$.

3. Generate predicted durations as the product of the estimated coefficients from Step 2 and the data from Group 2: $\widehat{\log t^{(2)}} = x'^{(2)}\hat{\beta}^{(1)}$. Calculate the difference between actual and predicted durations: $dif(t) = \log t^{(2)} - \widehat{\log t^{(2)}}$.

4. Regress the difference calculated in Step 3 against the covariates of Model 3, using the data from Group 2: $dif(t) = -x'^{(2)}\beta^{(2)} + \log(u^{(2)})$.

5. Test the null hypothesis of no systemic bias: H_0: $\beta^{(2)} = 0$.

Intuitively this test, by approximating Model 3 as a linear (accelerated time-failure) specification, and proxying for unobserved heterogeneity as the difference between actual and predicted durations, tests for statistically significant relationships between heterogeneity and the covariates. Note that the results of this test give, roughly, an upper bound for bias due to endogeneity.

The majority of coefficients (from step 4) are significant at the 1% of 5% level of significance, and all coefficients are jointly significant at the 1% level. This points to systemic bias for most covariates individually, as well as all covariates jointly, implying a strong possibility that unobserved heterogeneity biases the coefficient estimates. This precludes causal interpretation of the results; as noted above, the estimates should be interpreted as conditional correlations.

5.3.6. Declining first-hiring rates by startup cohort: results by sector and by province

To explore the possibility of sectoral or regional heterogeneity in the finding of declining first-hiring rates across entry cohorts, this section estimates Model 3 separately for sectors and for regions. Standard errors are estimated as heteroskedasticity-robust.

As shown in Table 7, the results suggest that first-hiring hazard decreases with successive startup cohorts in most sectors, with declines observed in the estimated hazard ratios for startups in the every sector except for Accommodation and food services. Taking the 2015 entry cohort as an example, the estimated hazard ratios imply that new firms that began operations in 2015 in the Construction, Retail, wholesale and transportation, Manufacturing, Other services and Natural resources and mining sectors were 44.7%, 62.2%, 29.6%, 56.6% and 49.6% less likely than their 2003 counterparts to hire, respectively. There are particularly pronounced drops from the 2004 to the 2005 entry cohort, relative to their corresponding 2003 entry cohorts, in the Retail, wholesale and transportation and the Other services sectors.

By contrast, this type of steady decline is not apparent for startups in the Accommodation and food services sector, for which the estimates imply a 14.4% decrease in first-hiring for a firm in the 2005 entry cohort relative to a firm entering in 2003; however, the hazard ratios for succeeding cohorts remain relatively steady.

Table 7: Time until first-hiring results (Model 3), by industry sector

	Accommodation and food services	Construction	Retail, wholesale and transportation	Manufacturing	Other services	Natural resources and mining
Startup cohort						
2004	0.983	0.940***	0.918***	1.038	0.949***	0.957
2005	0.866***	0.795***	0.666***	0.926*	0.594***	0.850**
2006	0.825***	0.759***	0.644***	0.882***	0.567***	0.728***
2007	0.837***	0.732***	0.615***	0.867***	0.557***	0.695***

2008	0.822***	0.679***	0.597***	0.717***	0.537***	0.575***
2009	0.852***	0.656***	0.592***	0.725***	0.551***	0.574***
2010	0.807***	0.629***	0.545***	0.721***	0.496***	0.514***
2011	0.846***	0.589***	0.517***	0.718***	0.458***	0.569***
2012	0.803***	0.553***	0.448***	0.704***	0.429***	0.505***
2013	0.812***	0.569***	0.429***	0.692***	0.424***	0.484***
2014	0.825***	0.519***	0.393***	0.615***	0.415***	0.500***
2015	0.846***	0.553***	0.378***	0.704***	0.434***	0.504***
Industry controls	x	x	x	x	x	x
Geographic controls	x	x	x	x	x	x
Primary owner, majority ownership and ownership controls	x	x	x	x	x	x
Firm financial controls	x	x	x	x	x	x
N	42,620	85,200	109,820	17,470	227,420	14,285

Note: Estimates statistically significant at the 0.1, 0.05 and 0.01 levels are indicated, respectively, by *, ** and ***.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

Likewise, as shown in Table 8, estimates across regions point to declining first-hiring rates in all parts of Canada.[53] The declines are surprisingly uniform, with a substantive drop in the hazard of first-hiring, for all provinces and regions, from the 2004 to the 2005 entry cohort, and steady declines for subsequent entry cohorts. The estimated hazard ratios for the 2015 entry cohorts suggest that startups in the 2015 cohort in Alberta, British Colombia, the prairie provinces, the Atlantic region, Ontario and Quebec are 50.0%, 51.0%, 53.7%, 41.0%, 49.7% and 44.5% likely to transition to employer firms, respectively, relative to firms in their corresponding 2003 cohorts.

Table 8: Time until first-hiring results (Model 3), by region

	Alberta	British Columbia	Manitoba/ Saskatchewan	Atlantic provinces	Ontario	Quebec
Startup cohort						
2004	0.990	0.966	0.972	1.008	0.957***	0.961**
2005	0.802***	0.772***	0.729***	0.801***	0.749***	0.790***
2006	0.743***	0.748***	0.701***	0.784***	0.721***	0.760***
2007	0.745***	0.752***	0.671***	0.786***	0.706***	0.739***
2008	0.699***	0.688***	0.671***	0.690***	0.716***	0.691***

[53] Estimates for the territories are not shown as they are considered confidential by Statistics Canada.

2009	0.724***	0.667***	0.631***	0.709***	0.688***	0.671***
2010	0.637***	0.616***	0.598***	0.655***	0.625***	0.626***
2011	0.542***	0.594***	0.570***	0.629***	0.593***	0.612***
2012	0.504***	0.550***	0.494***	0.550***	0.552***	0.544***
2013	0.503***	0.527***	0.505***	0.567***	0.528***	0.540***
2014	0.444***	0.502***	0.443***	0.546***	0.510***	0.545***
2015	0.500***	0.490***	0.463***	0.590***	0.503***	0.555***
Industry controls	x	x	x	x	x	x
Geographic controls	x	x	x	x	x	x
Primary owner, majority ownership and ownership controls	x	x	x	x	x	x
Firm financial controls	x	x	x	x	x	x
N	104,920	80,680	28,070	22,230	186,490	125,100

Note: Estimates statistically significant at the 0.1, 0.05 and 0.01 levels are indicated, respectively, by *, ** and ***.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

6. Conclusion

This research documents first-hiring trends among the universe of Canadian-controlled private corporations, and to estimate relationships between ownership and firm characteristics and the hazard of first-hiring.

First-hiring rates are at their highest in new firms' first year of operation, and decline sharply in each subsequent year. Specifically, between 16.9% and 10.3% of incorporated firms hire their first employee in their startup year; the rate drops in the four subsequent years to roughly 8%, 3%, 2% and 1%, continuing its decline thereafter. One implication of this is that the majority of new firms, roughly 60%, do not hire. These patterns are observed across entry cohorts, provinces and industries.

One first-hiring trend observed over time is particularly intriguing: the startup year first-hiring rate declines steadily from 2003 to 2017, from 16.2% for the 2003 startup cohort to 10.8% for the 2017 startup cohort. This contrasts with first-hiring rates for all subsequent years, which are stable across cohorts. These two trends, which are observed across provinces and industries, imply a decrease in startups' propensity to hire employees. The factors driving this decline are unclear but may include rapid technological change or increased industry concentration.

To quantify relationships between first-hiring and ownership or firm characteristics, first-hiring is modelled using a duration framework, estimating the hazard of first-hiring. The results, which are interpreted as conditional correlations, show that the trend of declining first-hiring rates with successive entry cohorts holds even when controlling for ownership and firm characteristics related to the first-hiring decision. This finding holds across most sectors and all regions when the hazard model is estimated for separate industry sectors and geographic regions.

The estimates also indicate that the hazard varies significantly along other dimensions, including industry and geography. For example, new firms in the Food and Accommodation sector are more than twice as likely as firms in the Manufacturing sector to hire a first employee, while startups in the Territories have a higher probability of first-hiring than do startups in Ontario.

Ownership and firm characteristics also factor into first-hiring decisions. Significant differences are observed in the first-hiring hazard by age and marital status and extra-firm income. The gender and immigrant status of majority ownership also play a role: for example, female-owned firms have a higher probability of hiring a first employee than do male-owned firms, while immigrant-owned firms are less likely than firms owned by individuals born in Canada.

Startups performance in their first year of operation, measured in sales, leverage and profits, also significantly predicts first-hiring. The likelihood of first-hiring increases with sales, decreases with leverage and decreases with net income, where these variables are measured in firms' first year of operation, relative to industry and cohort peers.

These results offer three main contributions to the literature on nonemployee-employer transitions.

First, the finding of declining rates of first-hiring with successive entry cohorts is to the author's knowledge, the first documentation of a trend that could have important macroeconomic implications. Furthermore, this analysis is the first analysis of non-employer—employer transitions in Canada. Moreover, the analysis adds to the sparse literature on this important entrepreneurial milestone by exploiting the richness of the dataset to show both that the finding of declining rates of first-hiring holds when controlling for owner and firm characteristics that factor significantly in first-hiring decisions, and to offer a rich analysis quantifying how those characteristics relate to first-hiring for a sub-population of new firms of policy interest.

Second, the duration analysis provides an alternative perspective to the methodological approach used in previous studies on first-hiring. One potential advantage to modelling the first-hiring decision as a hazard model over a logit or probit model is that, in accounting for the timing of the decision, yields more precise estimates.

Finally, the research question in this analysis is broader in scope than the research of Fairlie and Miranda (2017). Specifically, the first hires of all new incorporated businesses are included in the analysis, not only transitions by non-employers; this research additionally studies firms that hire in their first year of operation. Although this limits comparability between the results here and those presented in FM, the importance of including in the analysis firms that hire in their first year of operation is underlined by the fact that most firms that hire do so in their first year. Studying only non-employer—employer transitions, then, would exclude the majority of first hires. This is particularly important in light of the trend of declining startup year first hires, which pattern is only observed when including first-hires taking place in firms' first year of operation.

This research also has limitations. Specifically, while the analysis quantifies interesting conditional correlations, it does not address directionality. Furthermore, endogeneity testing suggests significant unobservable heterogeneity in the hazard model estimates.

These are issues, however, common to the majority of econometric analyses, particularly those of firms, which are highly heterogeneous across a number of dimensions, including industry, size and ownership.

Appendix

A.1. Right-censoring or right-truncated?

As described in Section 5.1, firms that exited before first-hiring are right-truncated: a firm that has exited at time t-1 is no longer be at risk of hiring a first employee at time t. As such, right-truncated firms are removed from the analysis.

An alternative treatment would be to consider such firms as right-censored, coding their hiring indicator to 0 at the time they exit and retaining these firms in the analysis. This section focuses on whether the first-hiring hazard declines with successive entry cohorts when firms that exit before hiring are treated as right-censored, rather than right-truncated.

As above the analysis here begins with non-parametric estimates of the first-hiring hazard, by cohort. These estimates are shown for the full sample (RC sample) in Figure A1 below, while the corresponding estimates for the full sample excluding right-truncated firms (RT sample) are shown below in Figure A2, for comparison.

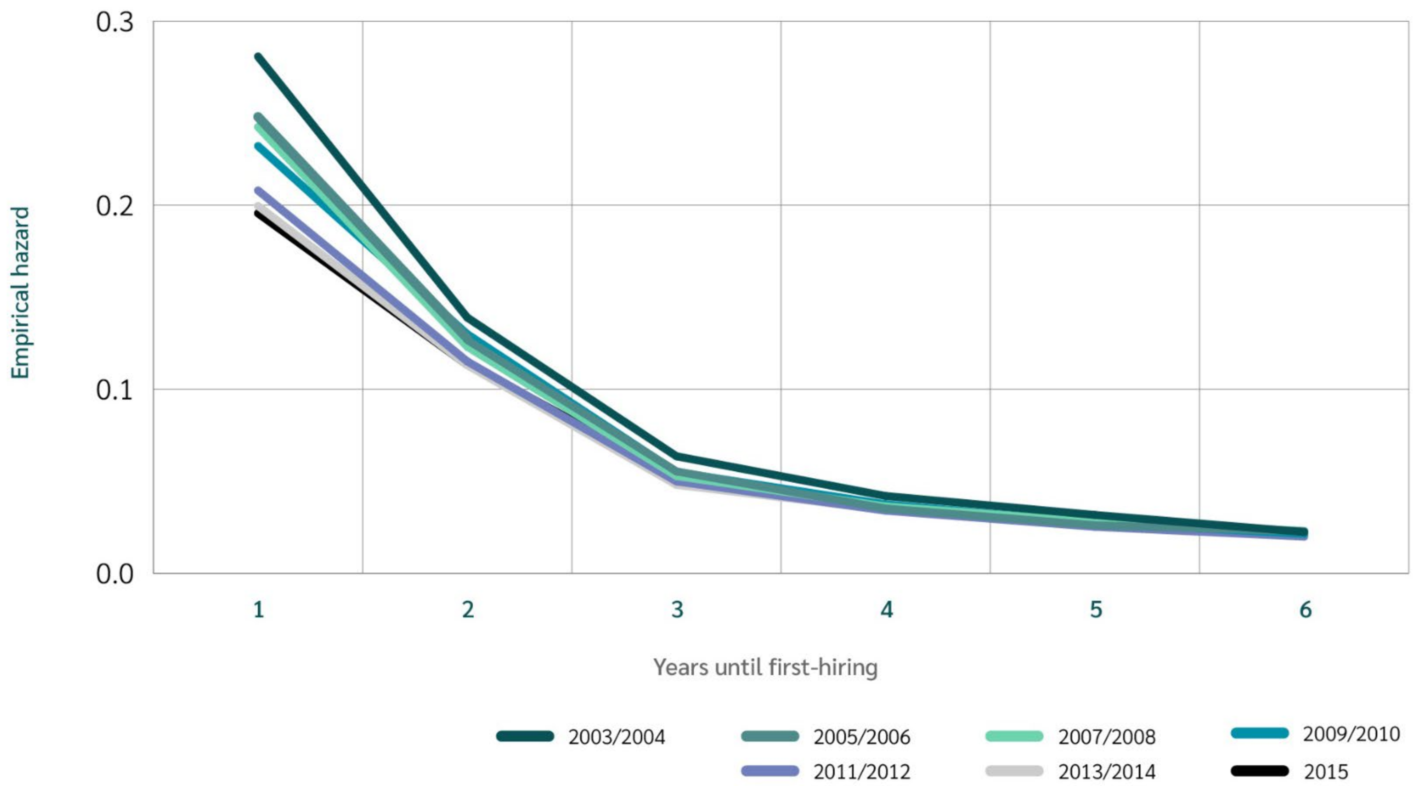
Similar to the corresponding RT sample estimates, the RC sample non-parametric hazards show startup year first-hiring hazards declining with successive entry cohorts. Also notable are two key differences. First, the RC sample hazards rates are substantively lower, since retaining right-truncated firms increases the size of the risk pool in every period.

Second, in contrast to the hazards for the RT sample, the RC sample hazards for all entry cohorts converge starting in each cohorts' second year of operation such that the shape of the hazards, across cohorts, corresponds to the trends observed in Section 4, where the data show substantive differences primarily across startup year first-hiring rates, while first-hiring rates for years t+2 and beyond are visually difficult to distinguish across entry cohorts.[54]

[54] Note that differences in hazards across entry cohorts, while not economically significant, are statistically significant even when, for example, excluding the first four years of first-hiring outcomes (implying that differences at t+4 and beyond are statistically significant).

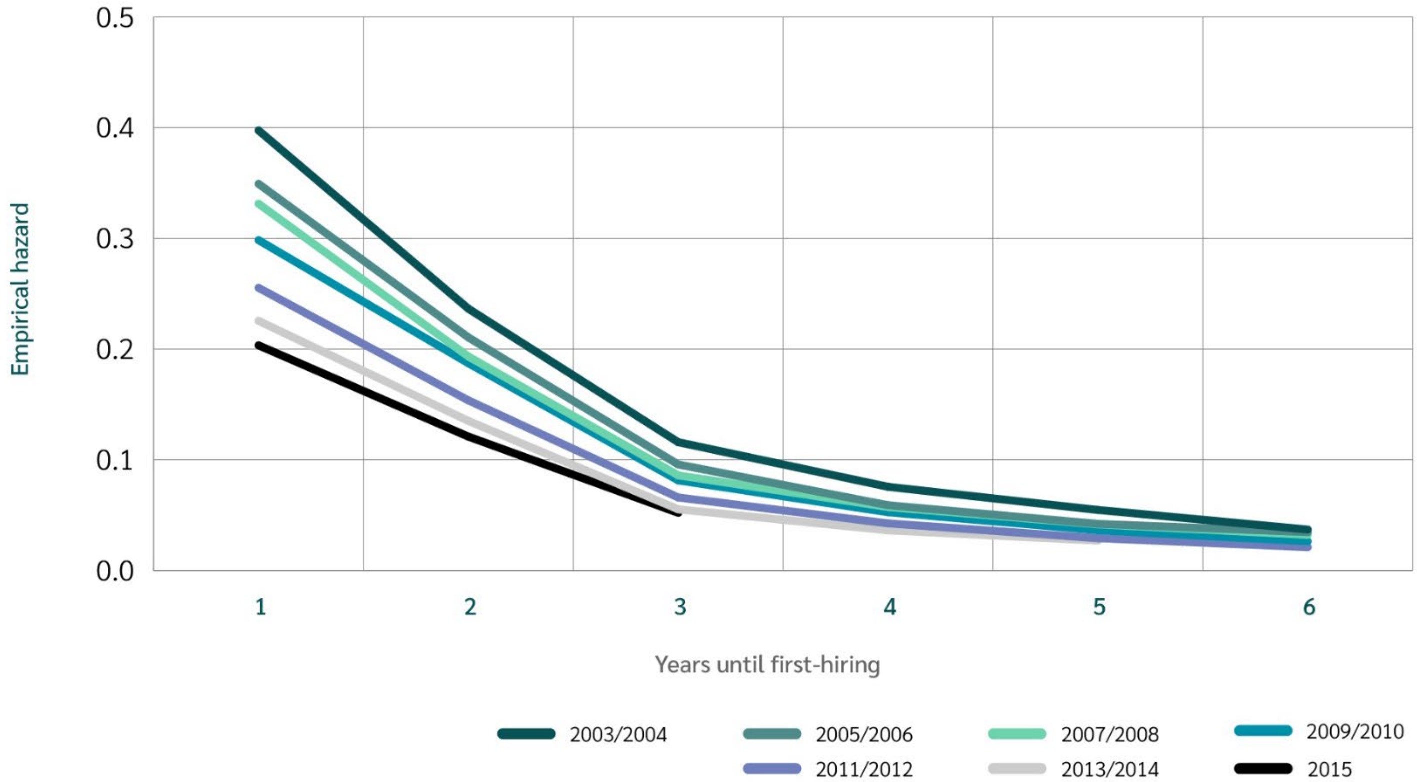
This suggests that, in treating firms that exit before hiring as right-censored, the parametric hazard models used in Section 5 may not be well-suited to an analysis of whether first-hiring rates are declining with successive entry cohorts. A given hazard ratio provides a comparative measure of first-hiring over the entire period; if first-hiring rate differences are substantial in the startup year but not in latter years, the hazard ratio for a particular entry cohort forces both the substantial differences in the startup year and the insubstantial differences in latter years into a single metric.[55]

Figure A1: Empirical hazard of time until first-hiring, RC sample (firms that exit before hiring treated as right-censored)



[55] Notably, this issue is distinct from a failure of the proportional hazards assumption. Indeed, tests of the proportional hazards assumption for the entry cohort dummies indicate the this assumption is satisfied.

Figure A2: Empirical hazard of time until first-hiring, RT sample (firms that exit before hiring treated as right-truncated)



Notes: In Figure A1, the hazard only shown up to 6 years from startup because the hazard rate for the RC sample for subsequent years considered confidential by Statistics Canada. The hazard in Figure A2 shows up to 6 years to correspond with Figure A1.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

This is evident in comparing the estimated non-parametric hazards with estimates from a parametric hazard model, shown below in Table A1. The former show significant declines in the startup year hazard rate for entry cohorts up to the 2014 cohort, with a slight increase for the 2015 entry cohort, while the latter—even for the model containing only dummy variables for entry cohort—would imply significant declines in the hazard (over all periods) with successive startup cohorts up to the 2012 cohort, and subsequent increases, of a greater magnitude, up to the 2015 entry cohort.

Table A1: Time until first-hiring results, RC sample (treating firms that exit before hiring as right-censored)

	Hazard model (time until first-hiring)		Logit model (first-hiring within first 3 years)	
	M1	M3	M1	M3
Startup cohort				
2004	0.954***	0.969*	0.923***	0.956
2005	0.885***	0.769***	0.830***	0.719***
2006	0.869***	0.757***	0.818***	0.713***
2007	0.902***	0.779***	0.861***	0.744***
2008	0.886***	0.774***	0.854***	0.751***
2009	0.887***	0.783***	0.866***	0.766***
2010	0.825***	0.736***	0.785***	0.699***
2011	0.784***	0.711***	0.719***	0.648***
2012	0.748***	0.677***	0.664***	0.597***
2013	0.761***	0.692***	0.662***	0.595***
2014	0.764***	0.699***	0.644***	0.584***
2015	0.827***	0.761***	0.664***	0.610***
Industry controls	x	x	x	x
Geographic controls	x	x	x	x
Primary owner, majority ownership and ownership controls	-	x	-	x
Firm financial controls	-	x	-	x
N	737,883			

Note: Estimates statistically significant at the 0.1, 0.05 and 0.01 levels are indicated, respectively, by *, ** and ***.
Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

In this context—where the goal is to include firms that exit before hiring—logit models may be more appropriate for evaluating whether the first-hiring rates decrease over entry cohorts. Logit models provide estimates for the unconditional probability of first-hiring at any point in time during the observation period, which circumvents the issue of forcing substantial differences (across cohorts in their startup years) and insubstantial differences (across cohorts in later years) in a single metric of the first-hiring rate over the entire period since the metric estimated by logit models does not account for the exact timing of the first-hiring. Furthermore, unlike hazard models, logit models do not condition on having not yet hired at each year, which precludes the issue of increasing the risk pool at each period with firms that have exited and are consequently no longer at risk of first-hiring.

Estimates from a logit model of the probability of hiring a first-employee within a new firm's first three years are presented in Table A1.[56] The estimates from the model containing only entry cohort dummies are consistent with the trend of declining rates of start-up year first-hiring over entry cohorts' observed in the non-parametric hazard estimates (from the RT sample) shown above. Correspondingly, estimates of the entry cohort dummies are qualitatively similar in the fully specified model.

While the parametric hazard model estimates do not point to a continued trend of declining first-hiring rates over time, it is difficult to say whether this is due to the methodological issues noted above or whether retaining firms that exit before hiring actually changes the trend observed. In contrast, estimates from a logit model—which model avoids those methodological issues—point to the trend of declining first-hiring likelihood over entry cohorts. However, the logit model estimates the probability of first-hiring, which is not directly comparable with the estimated hazard of first-hiring.

To the extent that interest is in answering whether the trend of declining first-hiring is observed in the RC sample, both approaches fail to provide clear answers: treating right-truncated firms as right-censored in a duration analysis framework raises methodological issues, while using a logit analysis framework changes the question being asked, thereby confounding direct comparison.

One consideration here is how differences in estimates of first-hiring rates across cohorts might be interpreted with each treatment. Putting aside whether hazard models should be used for the RC sample, it is clear that the trend of declining first-hiring rates across successive cohorts is evident in the RT sample, which excludes firms that exit before hiring. By contrast, the trend of declining first-hiring rates across successive cohorts is not clearly shown in the RC sample, which includes firms that exit before hiring.

Within both the RC sample and the RT sample, this trend is stronger (i.e. the estimated decrease is greater with successive cohorts) when firms that do not have a GST number in their startup year, or have zero revenues for three consecutive years are excluded.

Firms that exit before hiring, do not have a GST number and do not have revenue for three consecutive years might broadly be characterized as firms that are of less interest to policymakers since such firms are more likely to include, for example, firms which are more focussed on tax efficiencies than on economic production (i.e. selling goods and services). One takeaway, then, may be that when focusing on firms that are of greater policy interest (e.g. excluding firms that might be considered to be more likely to statistically noisy in the context of this analysis), the trend of declining rates of first-hiring is more evident.

[56] Estimated standard errors are clustered by 2-digit NAICS. Estimates from logit models of the probability of first-hiring within a firm's startup year, and of the probability of first-hiring at any time over the period of analysis (i.e. up to 2017), are qualitatively similar to those shown here.

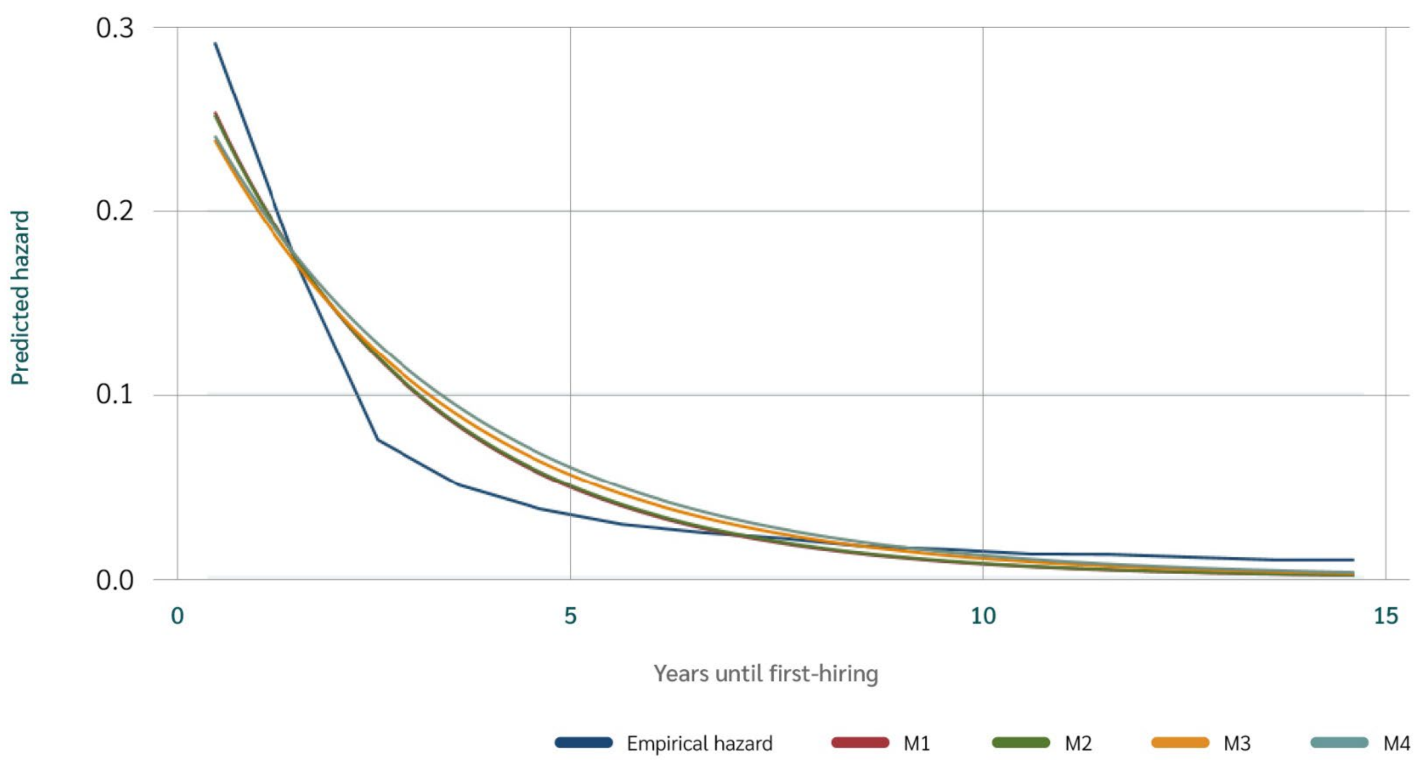
A.2. Model selection

Comparing results, the estimates of industry, region and cohort effects are quite stable across Models 1, 2 and 3. With the addition of shared frailty in Model 4, which controls for heterogeneity across industry and province bins, the coefficients for province and industry controls show qualitative differences relative to those of the first three models.

Similarly, while the estimated coefficients for primary owner, majority ownership and ownership covariates are relatively similar across Model 2 and Model 3, the introduction of shared frailty in Model 4 results in qualitative differences in the age and majority ownership effects. The estimates of firm financial coefficients in Models 3 and 4 are qualitatively similar, though do appear to be quantitatively different.

The increase in log-likelihood from Model 1 to Model 4 suggests model performance increases with additional variables, the predicted hazards in Figure A3 show evidence of overfitting: Model 4, in comparison with Models 1 through 3, appears to generate a predicted hazard farther away from the empirical hazard. The differences between all models, however, are not large; overall, all four models generate reasonable predictions.

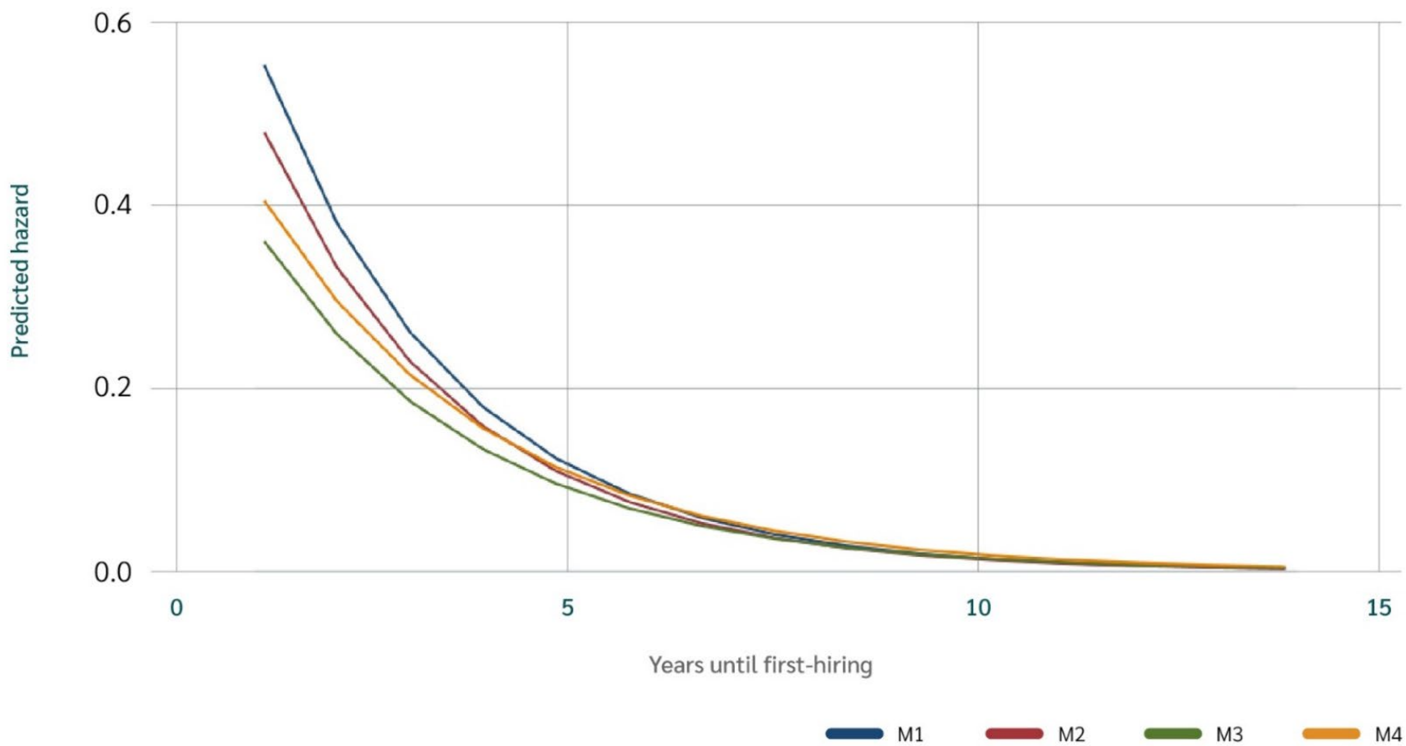
Figure A3: Gompertz baseline hazard estimates for time until first-hires



Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

In addition, as shown in Figure A4, all three models predict baseline hazards which exhibit negative state dependence consistent with the empirical hazard. Accurately modelling the underlying time dependency suggests that the parametric estimates of the Gompertz models yield more precise results than would be obtained leaving the baseline hazard unspecified using, for example, a semi-parametric Cox proportional hazards model.

Figure A4: Gompertz baseline hazard estimates for time until first-hires



Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

A Cox analog of Models 3 and 4 is explored but this alternative specification appears unsatisfactory. First, Schoenfeld residual-based tests suggest the proportional hazards assumption is violated both for individual covariates and globally.[57] Second, the hazard estimated using an analogous Cox model does not predict the empirical hazard well, particularly in comparison with the predictions from the Gompertz models. Finally, a Vuong test for discriminating between rival non-nested models suggests our Gompertz model is preferred to an alternative Cox analog.[58]

[57] In particular, under the null hypothesis of proportional hazards, a graph of Schoenfeld residuals against time should have zero slope; nonzero slope, therefore, indicates a violation of the null.

[58] Specifically, the test follows the approach used in Radoman and Voia (2015), calculating a Vuong test statistic for comparing non-nested models. The Vuong test compares the normalized likelihoods of Model 3 and its Cox analog, testing the null hypothesis that the normalized log-likelihood ratio is equal to zero against the one-sided alternatives that it is negative or positive. The statistic, equal to 555.220, is large, positive and statistically significant, indicating that Model 3 is preferred.

Model 3, then, seems to offer the most balance between additional quantification, given interest in relationships between ownership and firm characteristics and the first-hiring hazard, and accuracy of prediction.

A.3. Tables

Table A1: AIC and BIC statistics for Model 3, by distribution of baseline hazard

Distribution	AIC	BIC
Exponential	1,471,979	1,472,181
Weibull	1,439,208	1,439,410
Loglogistic	1,387,677	1,387,879
Lognormal	1,377,234	1,377,436
Gompertz	1,337,701	1,337,903

Sources: Statistics Canada, *Canadian Employer-Employee Dynamics Database*; and author's calculations.

References

Acemoglu, Daron and P. Restrepo (2017). “Robots and jobs: evidence from US labor markets.” NBER working paper, no. 23285.

Allison, Paul D. (2010). “*Survival analysis using SAS: a practical guide*.” 2nd Ed., Cary, NC: SAS Institute Inc.

Autor, David, D. Dorn, L. F. Katz, C. Patterson and J. V. Reenen (2017). “Concentrating on the fall of the labor share.” NBER working paper, no. 23108.

Baldwin, John, L. Bian, R. Dupuy, G. Gellatly (2000). “Failure rates for new Canadian firms: new perspectives on entry and exit.” Ottawa: Statistics Canada.

Cockx, Bart and S. Desiere (2023). “Labour costs and the decision to hire the first employee.” *IZA Discussion Papers 16122*, Institute of Labor Economics (IZA).

Birch, David L. (1979). “The Job Generation Process.” Cambridge, MA: MIT Program on Neighborhood and Regional Change.

Bogliacino, Francesco and M. Pianta (2010). “Innovation and employment: a reinvestigation using revised Pavitt classes.” *Research Policy*, 39, p. 799–809.

Burke, Andrew E., F. R. FitzRoy and M. A. Nolan (2000). “When less is more: distinguishing between entrepreneurial choice and performance.” *Oxford Bulletin of Economics and Statistics*, 62(5), p. 565–587.

Burke, Andrew E., F. R. FitzRoy and M. A. Nolan (2002). “Self-employment wealth and job creation: the roles of gender, non-pecuniary motivation and entrepreneurial ability.” *Small Business Economics*, 19, p. 255–270.

Cao, Shutao, M. Salameh, M. Seki, P. St-Amant (2017). “Trends in firm entry and new entrepreneurship in Canada.” *Canadian Public Policy*, 43(3), p. 190–201.

Caliendo, Marco, F. M. Fossen and A. S. Kritikos (2019). “What makes an employer?” *IZA Discussion Papers 12742*, Institute of Labor Economics (IZA).

Carroll, Robert, D. Holtz-Eakin, M. Rider, and H. S. Rosen (2000). “Income Taxes and Entrepreneurs’ Use of Labor.” *Journal of Labor Economics*, 18(2), p. 324–351.

Clementi, Gian L. and B. Palazzo (2016). “Entry, exit, firm dynamics and aggregate fluctuations.” *American Economic Journal: Macroeconomics*, 8(3), p. 1–41.

Criscuolo, Chiara, P. N. Gal, C. Menon (2014). “The dynamics of employment growth: new evidence from 18 countries.” *OECD Science, Technology and Industry Policy Papers,* No. 14, Paris: OECD Publishing.

Coad, Alex, S.-O. Daunfeldt, W. Holzl, D. Johansson, and P. Nightingale (2014). "High-growth firms: introduction to the special section." *Industrial and Corporate Change*, 23(1), p. 91–112.

Congregado, Emilio, J. M. Millán and C. Román (2010). "From own-account worker to job creator." *International Review of Entrepreneurship*, 8(4), p. 277–302.

Cowling, Marc, M. Taylor and P. Mitchell (2004). "Job creators." *The Manchester School*, 72(5), p. 601–617.

Decker, Ryan, J. Haltiwanger, R. S. Jarmin and J. Miranda (2014). "The role of entrepreneurship in US job creation and economic development." *Journal of Economic Perspectives*, 28(3), p. 3—24.

Decker, Ryan A., J. Haltiwanger, R. S. Jarmin and J. Miranda (2016a). "Declining business dynamism: implications for productivity?" Hutchins Center Working Paper, no. 23, Washington DC: Brookings Institute.

Decker, Ryan A., J. Haltiwanger, R. S. Jarmin and J. Miranda (2016b). "Where has all the skewness gone? The decline in high-growth (young) firms in the U.S." *European Economic Review*, 86(C), p. 4–23.

Dixon, Jay and A.-M. Rollin (2014). "The distribution of employment growth rates in Canada: The role of high-growth and rapidly shrinking firms." Ottawa: Statistics Canada.

Fairlie, Robert W. and J. Miranda (2017). "Taking the leap: the determinants of entrepreneurs hiring their first employee." *Journal of Economics and Management Strategy*, 26(1), p. 3–34.

Fabling, Richard (2018). "Entrepreneurial beginnings: transitions to self-employment and the creation of jobs." *Motu Working Paper 18-12*, Motu Economic and Public Policy Research.

Green, David A., H. Liu, Y. Ostrovsky and G. Picot (2016). "Immigration, business ownership and employment in Canada." Ottawa: Statistics Canada.

Grekou, Douwere and H. Liu (2018). "The entry into and exit out of self-employment and business ownership in Canada." Ottawa: Statistics Canada.

Gutierrez, Roberto G. (2002). "Parametric frailty and shared frailty survival models." *The Stata Journal*, 2(1), p. 22–44.

Haltiwanger, John, R. S. Jarmin and J. Miranda (2013). "Who Creates Jobs: Small vs Large vs Young." *Review of Economics and Statistics*, 95(2), p. 347–361.

Henley, Andrew (2005). "Job creation by the self-employed: the roles of entrepreneurial and financial capital." *Small Business Economics*, 25, p. 175–196.

Huynh, Kim P., R. J. Petrunia and M. Voia (2010). "The impact of initial financial state on firm duration across entry cohorts." *The Journal of Industrial Economics*, 55(3), p. 661–689.

Innovation, Science and Economic Development Canada. (2016). Automotive, Transportation and Digital Technologies Branch. *Canadian ICT Sector Profile*. Ottawa : Innovation, Science and Economic Development Canada.

Innovation, Science and Economic Development Canada. (2016). Small Business Branch. *Key Small Business Statistics—June 2016 edition*. Ottawa: Innovation, Science and Economic Development Canada.

Kihlstrom, Richard E. and J.-J. Laffont (1979). "A general equilibrium entrepreneurial theory of firm formation based on risk aversion." *Journal of Political Economy*, 87(4), p.719—748.

Klette, Tor and S. Kortum (2004). "Innovating firms and aggregate innovation." *Journal of Political Economy*, 112(5), p. 986—1018.

Leung, Danny (2015). "Quarterly business and employment dynamics: experimental estimates, first quarter 2001 to third quarter 2014." Ottawa: Statistics Canada.

Levine, Ross and Y. Rubinstein (2017). "Smart and illicit: who becomes an entrepreneur and do they earn more?" *The Quarterly Journal of Economics*, 132(2), p. 963—1018.

Lucas, Robert E. (1978). "On the size distribution of business firms." *Bell Journal of Economics*, 9(2), p. 508—523.

Melitz, Marc (2003). "The impact of trade on intra-industry reallocations and aggregate industry productivity." *Econometrica*, 71(6), p 1695—1725.

Millán, Ana, J. M. Millán, C. Román and A. van Stel (2013). "How does employment protection legislation influence hiring and firing decisions by the smallest firms?" *Economics Letters*, 121, p. 444–448.

Neumark, David, B. Wall and J. Zhang (2011). "Do Small Businesses Create More Jobs? New Evidence for the United States from the National Establishment Time Series." *Review of Economics and Statistics*, 93(1), 16–29.

Parker, Simon C. (2009). "The economics of entrepreneurship." Cambridge: Cambridge University Press.

Piva, Mariacristina and M. Vivarelli (2017). "Is R&D good for employment? Microeconometric evidence from the EU." IZA Discussion Papers, no. 10581, Bonn: IZA.

Radoman, Mihailo and M. C. Voia (2015). "Youth training programs and their impact on career and spell duration of professional soccer players." *Review of Labor Economics and Industrial Relations*, 29(2), p. 163-193.

Statistics Canada (2018). CANSIM Table 282-0012, Labour force survey estimates (LFS), employment by class of worker, North American Industry Classification System (NAICS) and sex. Retrieved from http://www.statcan.gc.ca/.

Statistics Canada (2018). *CANSIM Table 527-0013, Experimental quarterly estimates of business entry and exit*. Retrieved from http://www.statcan.gc.ca/.

Wolfson, Michael, M. Veall, N. Brooks and B. Murphy (2016). "Piercing the Veil: Private Corporations and the Income of the Affluent." *Canadian Tax Journal*, 64(1), p. 1–30.