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HIGH-GROWTH FIRM CHARACTERISTICS IN CANADA

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ABSTRACT

The main objective of this study is to assess the characteristics of firms that have undergone rapid growth over the period 2003–2012. More specifically, its aim is to determine the factors that may have an impact on a firm's probability of becoming a high-growth firm (HGF). This analysis uses a sample of Canadian firms from a unique dataset, the *National Accounts Longitudinal Microdata File*, developed by Statistics Canada. Empirical findings suggest that firms experiencing current rapid growth are more likely to become HGFs in the future. Moreover, this effect varies among industry sectors: being a HGF in some industry sectors increases the probability of becoming a HGF in the future more than in other sectors. For example, HGFs in the management of companies and enterprises sector are more likely to become HGFs in the future than HGFs in the agriculture, forestry, fishing and hunting sector. Also, younger firms are more likely to become a HGF in a subsequent period. Other significant predictors of HGFs include profitability, debt ratio, human capital and labour productivity. In addition, firms that spend on research and development and invest in machinery and equipment in the current period increase their probability of becoming HGFs in the future. Finally, working capital — an indicator of cash flow and firm liquidity — is negatively correlated with a firm's probability of becoming a HGF. This implies that holding liquid assets, such as cash, may not benefit fast-growing firms.

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1. INTRODUCTION

High-growth firms (HGFs) (or rapidly growing firms) have aroused the interest of government and policy-makers over the past years as they are reputed to contribute disproportionately to job creation.[1] Indeed, they usually represent a small share of total firms (e.g., 1–5 percent), but contribute to a large share of job creation (e.g., 40–75 percent).

In Canada, some studies also support those findings. For instance, results obtained by Picot and Dupuy (1998), Schreyer (2000), Halabisky et al. (2006) and Parsley and Halabisky (2008) all showed that fast-growing firms were responsible for a large share of employment creation over various periods of time.[2] More recently, Dixon and Rollin (2014) also investigated the contributions to job creation made by fast-growing firms. They found that fast-growing firms accounted for a large share of jobs created between 2000 and 2009, on the order of 38 to 47 percent depending upon the definition of HGFs that was used. Rivard (2017) shows that HGFs in 2012 with at least 10 employees in 2009, represented only 4 percent of all firms with at least 10 employees but contributed to approximately 40 percent of the total net employment change over the period 2009–2012. Furthermore, HGFs with one or more employees contributed 63 percent to the total net employment change, but only represented 1 percent of all firms with at least one employee.

There exists other stylized facts about high growth as mentioned by Coad et al. (2014). One such fact is that HGFs tend to be young. Moreno and Coad (2015) showed that, on average, HGFs are younger than non-HGFs. Moreover, HGFs are found in all industry sectors, not solely in high-technology industries. The assumption that HGFs are

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[1] See Henrekson and Johansson (2010), Daunfeldt et al. (2014) and Moreno and Coad (2015) for a literature review.

[2] Picot and Dupuy (1998) found that job creation is highly concentrated among relatively few fast-growing, continuing firms in all size groups for consecutive years between 1984 and 1988 (short-term employment change) and over the period 1983 to 1986 (long-run employment). Schreyer (2000) found similar results for firms in the manufacturing sector in Quebec, i.e., fast-growing firms accounted for a large proportion of job creation between 1990 and 1996. Halabisky et al. (2006) showed that fast-growing, continuing firms were responsible for a large share of employment creation over the period 1985 to 1999. Of 1.8 million net jobs created between 1985 and 1999, fast-growing firms were responsible for creating 1 million jobs. Moreover, these firms represented 7 percent of all firms in the private sector in 1985. Parsley and Halabisky (2008) also obtained results consistent with previous studies, i.e., fast-growing, continuing firms contribute disproportionately to job creation, being responsible for 45 percent of net jobs created between 1993 and 2003.

exclusively related to high technology is not supported by empirical data (Hölzl, 2009). Rivard (2017) observed that HGFs with at least 10 employees in 2009 were found mainly in construction (16 percent), manufacturing (12 percent), accommodation and food services (10 percent) and professional, scientific and technical services (9 percent) in 2012. Côté and Rosa (2017) obtained similar results.

From a policy point of view, picking winners by identifying those firms that will become HGFs is a particularly challenging task (Freel, 1998). One often suggested reason, among other factors, is that firm growth could be a random process and that “growth is mainly affected by purely stochastic shocks” (Marsili, 2001; Coad et al., 2014). Deschryvere (2008) also found that “firm growth is difficult to predict as it is characterised by a predominantly stochastic element.” In addition, HGFs are not concentrated in specific industry sectors and they are rare (Hölzl, 2009). HGF heterogeneity ensures that supporting any particular sector is laborious (Mason and Brown, 2013). Despite these concerns, a better understanding of the characteristics of rapidly growing firms is needed and, in Canada, there is limited information and research on this topic. This knowledge, in turn, may be used by government to develop policies that can guide or help entrepreneurs that are motivated to achieve rapid growth for their business.

The aim of this study is to analyze the determinants of HGFs in Canada over the period 2003−2012. The study leveraged a unique dataset, the *National Accounts Longitudinal Microdata File* (NALMF), developed by Statistics Canada. More specifically, it used an econometric model to assess which variables could have an impact on a firm’s probability of becoming a HGF in the next period. The methodology employed herein is largely inspired by that used by López-García and Puente (2012). One difference between this approach and that of López-García and Puente is that this study considered firms that survived over a period of time, from 2000 to 2012. One advantage of adopting this framework is that it provides another perspective by studying — during an important part of a firm’s life cycle — how various factors can influence or impact a firm’s growth process to achieve fast growth, even if HGFs tend to be young.

This paper contributes to research by widening the literature on empirical studies that examine determinants specifically related to rapidly growing firms. The literature review showed that very little research has been conducted in this area for the Canadian context.

The paper is organized into seven sections. Section 2 presents a literature review of studies on the characteristics of HGFs. Section 3 provides an overview of growth measures and HGF definitions. The data sources and data used in this study are described in Section 4. Section 5 presents the econometric model that was developed for this study, describes the set of variables that was used and provides some descriptive statistics that were gathered from the analysis. Results from the econometric model and interpretation of the findings are given in Section 6. Section 7 offers some conclusions that were derived from the study.

2. LITERATURE REVIEW

Determinants of firm growth have been abundantly studied for the international context in the literature,[3] with some studies focusing specifically on rapidly expanding firms. This section will review those papers. As mentioned by López-García and Puente (2012), only a few papers used an empirical framework to study the determinants of HGFs. However, since their work, the number of papers on this subject has increased substantially.

Hölzl (2009) analyzed the determinants of firm growth[4] using data from the third *Community Innovation Survey* (CIS-3), which covers firms' innovation activity for the period 1998–2000 in the manufacturing sector in 16 countries. The author used quantile regressions[5] over three groups of countries to take into account regional differences:

- Continental Europe (EU-cont): Austria, Germany, Belgium, Sweden and Finland
- Southern Europe (EU-South): Italy, Portugal, Greece and Spain
- New Member States (EU-NMS): Slovenia, Slovakia, Estonia, Hungary, Czech Republic, Lithuania and Latvia

Hölzl (2009) found that firm size is negatively correlated with high growth rates (95th quantile) for all three country groups. Also, the fraction of turnover due to new or improved products introduced during the 1998–2000 period had a positive impact on high growth rates for EU-cont and EU-South. Research and experimental development is positively correlated with high growth rates, but the result was significant only for EU-cont. The author showed that exports have a positive impact on high growth rates, but only for countries in EU-cont and EU-NMS. Finally, he noted that skill intensity,

[3] See Dobbs and Hamilton (2007) for a literature review.

[4] Hölzl (2009) used employment as a growth indicator. Growth is measured using the Birch–Schreyer indicator (see Section 3). High-growth firms are chosen as the 5 percent or 10 percent of firms with the highest value of the Birch–Schreyer indicator.

[5] There are various advantages of using quantile regressions instead of ordinary least squares (OLS). In particular, this allows the possibility to analyze the relationship between explanatory variables and a different quantile of the dependant variables. In this case, the dependant variable is the firm logarithmic employment growth, and fast-growing firms are considered to be at the top 5 or 10 percent of the distribution, i.e., the 95th quantile or 90th quantile respectively. In comparison, OLS estimate the mean effects of explanatory variables on a specific outcome, based upon the conditional mean $E(Y|X)$ (Cameron and Trivedi, 2005; Goedhuys and Sleuwaegen, 2010).

defined as the share of staff with tertiary education in the base year 1998, is positively correlated with high growth rates for countries in EU-cont and EU-South, but negatively correlated for countries in EU-NMS. The author did not give any explanation for this surprising result.

Stam and Wennberg (2009) used a longitudinal random sample of Dutch firms that were tracked over their first six years of operation (i.e., 1994 to 2000). Their dataset was representative of the population of start-ups. Using ordinary least squares (OLS) regression models, the authors concluded that research and development (R&D) activities and founder/entrepreneur human capital, such as leadership and industry experience, have a positive impact on firms that have undergone fast growth[6] over the period 1994–2000. They also found that the number of business partners, considered an indicator of organizational capital, was positively correlated with firms that exhibit rapid growth.

By using a sample of French firms in the manufacturing sector, with 10 to 250 employees from 1997 through 2007, Levratto et al. (2010) gathered evidence that firm age, firm size and labour cost (measured as total employment expenditure per employee) decreased the probability of becoming a fast-growing firm.[7] The authors also found that firm profits, trade debt (measured as the ratio of trade debt to total liabilities) and the fact that the firm exported increase the probability of becoming a HGF.

Goedhuys and Sleuwaegen (2010) also studied the effect of firm characteristics and entrepreneurs' attributes on high-growth firms.[8] They used a set of firms in the manufacturing sector of 11 sub-Saharan African countries from the World Bank *Investment Climate Survey*, *2006*. The survey also used employment information for

[6] Stam and Wennberg (2009) used employment as a growth indicator. Growth is measured as the rate of growth employment over the period 1994–2000. Firms in the top 10 percent of the growth distribution are considered to be high-growth firms.

[7] The results reported here are based upon the hybrid multinomial logit model that the authors used. Growth is measured as the difference between logarithms of employment over 2 years. High-growth firms are those with an average growth rate greater than or equal to 20 percent.

[8] Goedhuys and Sleuwaegen (2010) used employment as an indicator of growth. Growth is calculated as the difference between the logarithm of employment in 2005 and that in 2002. Moreover, firms with more than five employees in 2002 and an annual growth rate higher than 10 percent over the period 2002–2005 are defined as high-growth firms.

2002 and 2005. To identify factors that foster HGFs, Goedhuys and Sleuwaegen (2010) applied quantile regressions and considered the upper tail of the distribution corresponding to HGFs. They found that firm age and firm size are negatively correlated with high growth rates. They also showed evidence that there is a non-linear relationship between firm size and high growth rates with a positive and significant estimated coefficient for the square of the size variable. Interestingly, their results revealed that the introduction of a new or significantly improved production process to the market over the period 2002–2005 had a positive impact on high growth rates.

Arrighetti and Lasagni (2010) analyzed factors that can influence the probability of becoming a HGF.[9] They considered manufacturing firms in Italy from 1998 to 2003 and used probit regressions to estimate the determinants of HGFs. When employment is used as a growth indicator, the authors found that firm age decreases the probability of becoming a HGF. Human capital and demand tendencies in a specific market have a positive influence on becoming a HGF. In that study, human capital was measured as a synthetic factor based upon the ratio between managers (and administrative employees) and manual workers, the percentage of employees engaged in R&D activity and the percentage of employees holding a university degree. Demand tendencies in a specific market were measured as the index of the industrial production of the sector in which firms operate.

By considering firms from the Bank of Spain Firm Demography Database over the period 1996–2003 in all sectors, except in the agricultural and financial sectors, López-García and Puente (2012) asserted that human capital, as measured by the wage premium — the ratio of the average wage paid by the firm to that paid in other firms operating in the same sector — had a positive impact on the probability of a firm becoming a HGF.[10] However, the authors did not find a statistically significant correlation between the newness of the firm and the probability of becoming a HGF.

[9] Arrighetti and Lasagni (2010) used employment and total sales as growth indicators. Growth is measured in percentage change. Firms belonging to the top 10 percent of the fastest growing firms in a 5-year period are high-growth firms.

[10] López-García and Puente (2012) used employment as a growth indicator. Growth is measured using the Birch–Schreyer indicator (see Section 3). High-growth firms are chosen as the 10 percent of firms with the highest value of the indicator.

They did find that being a high-growth firm in the previous period $(t-1)$ increases the probability of a firm becoming a HGF in the next period (t).

Bogas and Barbosa (2013) studied the impact of region-specific characteristics on HGFs using sample firms from the *Quadros de Pessoal*, a dataset on firms in Portugal, over the period 2002–2006. They pointed out that age, industrial specialization — measured as the sum of squares of an industry's share in the region, defined as the number of employees in an industry and region by employment within an industry — and workforce qualifications have a negative impact on the probability of a firm becoming a HGF.[11] They also observed that size and share of total employment in the tertiary sector[12] could have a positive impact on the probability of becoming a HGF.

Navaretti et al. (2014) found evidence that firm age, firm size and profitability — measured as the ratio of earnings before interest, taxes, depreciation and amortization of sales — have a negative impact on firms that have experienced high growth rates.[13] Results also revealed that labour productivity, capital intensity, access to finance, the percentage of employees involved in R&D activities over the total number of employees, the percentage of university graduates over the total number of employees and being led by a chief executive officer who is less than 45 years of age all have a positive and significant influence on the probability of a firm achieving a high growth rate. Navaretti et al. (2014) observed these results employing a quantile regression approach over all growth rate distributions, including rapidly growing firms, using data obtained by merging Bureau van Dijk's Amadeus with the EU-EFIGE[14]/Bruegel-UniCredit dataset. For this study the authors used data from a sample of French, Italian and Spanish firms in the manufacturing sector with 10 or more employees over the period 2001–2008.

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[11] Bogas and Barbosa (2013) used employment as a growth indicator. Growth is measured using the Birch–Schreyer indicator (see Section 3) over a 3-year period, with firms having eight employees or more at the beginning of the period. High-growth firms are those with growth higher than 25.15968 percent.

[12] The tertiary sector is the services sector.

[13] Navaretti et al. (2014) used employment as a growth indicator. Growth is calculated as the difference of the logarithm of employment over two consecutive years. The authors also used quantile regression to study the relationship between firm age and firm growth for the entire distribution of growth rates.

[14] EFIGE stands for European Firms in a Global Economy.

Recently, Du and Temouri (2015) studied the impact, among other factors, of productivity on HGFs[15] and they show that there is empirical evidence that higher productivity growth leads to high-growth firm status. Their analysis is based upon the Fame dataset, distributed by Bureau van Dijk, which contains, in particular, information on firms in the manufacturing and services sectors in the United Kingdom[16] over the period 2001–2010. The authors' results showed evidence that productivity growth, the average level of human capital within the firm — as proxied by average wages — and intangible assets as indicators of wider innovative capacity in the previous period $(t-1)$ increase the probability of becoming a HGF in the next period (t). Du and Temouri (2015) also found that age, size and cash flow[17] in the previous period decrease the probability of becoming a HGF in the next period. The aforementioned results applied to both the manufacturing and services sectors.

Overall, some stylized facts seem to emerge from previous studies regarding the determinants of rapidly growing firms. In particular, firm age and firm size have been identified as having a negative impact on firm growth and a firm's probability of becoming a HGF, and as being negatively correlated with high growth rates. To a lesser extent, researchers also observed that human capital and firm profitability are positively correlated with high growth rates. As a consequence, these determinants, as well as other factors, will be considered in our model to see if we obtain similar results for HGFs in Canada.

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[15] Du and Temouri (2015) used sales as a growth indicator. Growth is determined using a compounding annual growth calculation. A firm is considered high growth if it grows at an average annual rate of at least 20 percent over a 3-year period and has 10 or more employees at the start of the growth period.

[16] Readers can refer to Fame for further details.

[17] Du and Temouri (2015) mentioned that financial liquidity can negatively affect a firm as it could be a sign that managers did not detect good investment opportunities.

3. IDENTIFYING HIGH-GROWTH FIRMS

Identifying rapidly growing firms is not a simple task as it depends, fundamentally, on the indicator of growth and the measures of growth chosen (Coad et al., 2014). Some researchers go further and raise the possibility that the choice of a growth indicator could have an important impact on policy implications (Daunfeldt et al., 2014). In particular, the authors compared different indicators of growth, such as employment, sales, value added and productivity. Their findings revealed that HGFs defined in terms of employment are not the same as HGFs defined in terms of productivity. As mentioned by Daunfeldt et al. (2014), "Economic policy promoting fast growth in employment may therefore come at the cost of reduced productivity growth."

In general, there are two popular indicators of growth used in the literature: total sales and total employment (number of employees). In this study, total employment was chosen as the growth indicator, given the general policy objective of supporting HGFs as a means to drive job creation.

There are many ways to measure growth, usually classified in two categories: absolute and relative change. Let x_{t-k} and x_t denote growth indicators at years $t-k$ and t to measure growth over a period of k years. Using this notation, the absolute growth is given by $(x_t - x_{t-k})$ and the relative growth is given, for example,[18] by x_t/x_{t-k}. However, both growth indicators have issues. In the case of the absolute measure, growth is biased in favour of large firms and in the case of the relative measure, growth is biased in favour of small firms (Coad et al., 2014; Côté and Rosa, 2017). To reduce the bias, another growth measure used combines the relative and absolute measures. This is known as the Birch−Schreyer index:

$$(x_t - x_{t-k}) \times \frac{x_t}{x_{t-k}}.$$

[18] As mentioned by Coad et al. (2014), there are many ways to measure relative growth: percentage change, logarithm differences, etc.

Another source for differences in what constitutes a HGF is related to the choice of a threshold level for high growth: based upon a fixed level of growth (percentage) or based upon a cut-off in a growth distribution. For example, HGFs could be chosen as those that have undergone a growth rate higher than 50 percent or they could be chosen as, say, 5 percent of firms with the highest growth rates. A methodology based upon a threshold in terms of a fixed level of growth has the advantage that results related to HGFs are comparable across time or across countries (Coad et al., 2014). Eurostat and the Organisation for Economic Co-operation and Development (OECD) propose the following definition (Eurostat–OECD, 2007).

Eurostat–OECD definition

A high-growth firm is a firm with 10 or more employees at the beginning of the period that has average annualized growth greater than 20 percent per year over a 3-year period.

Using the previous notation, a firm is considered to be a HGF at time t if $x_{t-3} \geq 10$ and if

$$\left(\frac{x_t}{x_{t-3}}\right)^{\frac{1}{3}} - 1 > 0.20.$$

One issue with the Eurostat–OECD definition is that the choice of the threshold level for growth is arbitrary (Dixon and Rollin, 2014). As mentioned by Goedhuys and Sleuwaegen (2010), this choice is "… based more on convention than on evidence."

Another major issue with the Eurostat–OECD definition is that it could exclude a non-negligible number of small firms (Coad et al., 2014; Daunfeldt et al., 2014; Daunfeldt and Halvarsson, 2015). In Canada, employer businesses with 1 to 9 employees, which would be excluded from the Eurostat–OECD calculation for HGFs, constitute approximately

74 percent of all Canadian employer business using December 2015[19] data (Innovation, Science and Economic Development Canada, 2016).

The Bureau of Labor Statistics (BLS) proposes an alternate definition based upon a "kink point" approach that includes firms with 1 to 9 employees and coincides with the Eurostat–OECD definition for firms with at least 10 employees (Clayton et al., 2013).

BLS definition

- If a firm with less than 10 employees at the beginning of the period grows by eight or more employees over a 3-year period, this firm will be classified as a high-growth firm.
- If a firm with 10 employees has average annualized growth greater than 20 percent per year over a 3-year period (or 72.8 percent over the 3-year period), this firm will be classified as a high-growth firm.

Using the same notation as before, it follows that

- If $x_{t-3} < 10$ and $(x_t - x_{t-3}) \geq 8$, then the firm is a high-growth firm at t;
- If $x_{t-3} \geq 10$ and $\left(\frac{x_t}{x_{t-3}}\right)^{\frac{1}{3}} - 1 > 0.20$, then the firm is a high-growth firm at t.

In the current study described in this report, we will identify HGFs using the BLS definition.

[19] The large share of firms with 1 to 9 employees was also noted by Rivard (2017) using the *National Accounts Longitudinal Microdata File* from Statistics Canada (see Section 4 for more details). He observed that firms with 1 to 9 employees represented 88 percent of the total number of firms with at least one employee in 2009. The difference between this result and that from Innovation, Science and Economic Development Canada (2016) (88 percent versus 74 percent) may be explained by the difference in the data sources used. In the latter case, the data came from the Business Register. It is worth noting that the *National Accounts Longitudinal Microdata File* is at the enterprise level and the Business Register is at the establishment level. More details are available from the Business Register. The use of two time references (2009 versus 2015) may also play a role in the difference, but to a lesser extent.

4. DATA SOURCE

A unique dataset developed by Statistics Canada, the *National Accounts Longitudinal Microdata File*[20] was used for this study. It was created by linking multiple administrative files: T2 Corporation Income Tax Return, Goods and Services Tax, Payroll Account Deductions and Remittances (PD7) and T4 Statement of Remuneration Paid. These sources are combined through Statistics Canada's Business Register to produce a final linked file at the statistical level of the enterprise. The NALMF includes both incorporated and unincorporated businesses. Only business employers (i.e., with at least one employee) are considered in this study.

Some industry sectors are excluded from this analysis. Following the North American Industry Classification System, the excluded sectors are utilities (22), educational services (61) and public administration (91). Outliers have also been excluded from the dataset. The period covered by this analysis is 2000–2012.

Firms likely to have changed their structure over the observation period through, say, a merger, an acquisition or a spinoff are also excluded[21] from the sample. Therefore, only organic growth is considered in this study. The data have been cleaned of outliers, missing observations and inconsistencies.[22] A balanced subpanel was extracted from the initial sample. This means that the firms in the sample have observations for all variables. The balanced property of the dataset is a requirement dictated by the econometric model used in this study, namely the dynamic probit model with correlated random effects.[23] The balanced panel dataset[24] consisted of 210,714 firms per year over the period 2003–2012, for a total of 2,107,140 observations.

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[20] The NALMF is constructed using annual cross-sectional files. Firms are identified over years by an ID number. For different years, the same ID number corresponds to a unique firm. Inclusion of those firms ensures the longitudinal aspect of the dataset as a firm is identified by a unique ID number.

[21] The NALMF contains a variable that flags those firms. It is a dummy variable equal to 1 if the firm is likely to have changed its structure and 0 otherwise. Firms excluded represent a small proportion (less than 1 percent) of total firms for every year in the NALMF.

[22] A negative value for total employment payroll or for total sales of goods and services are examples of inconsistencies.

[23] See Wooldridge (2000, 2005 and 2010) and Albarran et al. (2015) for more details.

[24] In comparison, the NALMF contains more than one million employer businesses per year.

5. METHODOLOGY

5.1 ECONOMETRIC MODEL

The main objective of this study is to analyze the factors that have an impact on a firm's chance of becoming a high-growth firm. The methodology follows the work of López-García and Puente (2012). The base equation that will be estimated is given by

$$hgf^*_{it+1} = \gamma hgf_{it} + \beta \mathbf{x}_{it} + \xi_{it}, \qquad (1)$$

where $i = 1, \dots, N$, $t = 1, \dots, T$ and

$$\xi_{it} = c_i + \varepsilon_{it}.$$

In the previous equation, c_i represents unobserved heterogeneity effects, such as any unobserved characteristics specific to the firm. Also, hgf^*_{it+1} is a latent variable that represents the propensity of a firm to become a HGF. The latent variable is not directly observed in the data. However, another variable is used, denoted hgf_{it+1}, which is 1 if a firm is a HGF at $t+1$ and 0 otherwise. This dummy variable indicates in which category hgf^*_{it+1} falls:

$$hgf_{it+1} = \begin{cases} 1 & if\ hgf^*_{it+1} > 0; \\ 0 & if\ hgf^*_{it+1} \leq 0. \end{cases}$$

We will assume that ε_{it} is uncorrelated with the explanatory variables for all i and t and uncorrelated with c_i. In addition, we hypothesize that $\varepsilon_{it} \sim N(0,1)$. Equation (1) could be rewritten as

$$P(hgf_{it+1} = 1 | hgf_{it}, hgf_{it-1}, \dots, hgf_{i0}, \mathbf{x}_i, c_i) = P(hgf^*_{it+1} > 0 | hgf_{it}, hgf_{it-1}, \dots, hgf_{i0}, \mathbf{x}_i, c_i) =$$
$$\Phi(\beta \mathbf{x}_{it} + \gamma hgf_{it} + c_i), \qquad (2)$$

where $\Phi(\cdot)$ is the standard normal cumulative distribution function and $\mathbf{x}_i = \mathbf{x}_{i1}, \cdots, \mathbf{x}_{iT}$. As equation (2) shows, the lagged dependent variable is added to control for state dependence. The fact that a firm is high growth at t could have an impact on the firm's probability of becoming a HGF at $t+1$.

The model is called the dynamic probit model with correlated random effects[25] (or dynamic probit model with unobserved effects). Therefore, using this model, it is possible to estimate a firm's probability of becoming a HGF in the next period, after controlling the status in the current period (the lagged dependent variable); a set of current and lagged explanatory variables; and the unobserved heterogeneity effects.

We assume that a lag of one year for HGF status is sufficient in the context of this study. The lagged dependent variable captures the dynamics of firm growth and state dependence. This is also known in the literature as serial correlation or autocorrelation. Thus, the model may determine whether HGF status is persistent or not. This is given by the sign of the estimated coefficient of the lagged dependent variable. If the estimated coefficient is positive, there is persistence, i.e., being a HGF in one period increases the probability of being a HGF in the next period. If the estimated coefficient of the lagged dependent variable is negative, we can conclude that there is no persistence. Including the previous status for HGFs makes the model similar to a Markov chain of order one (Contoyannis et al., 2004). A Markov chain is a process that assumes that the next state of a random variable depends only upon the previous state. However, the model presented here is richer as it includes other variables that could have an impact on HGF status at $t+1$.

Estimating the coefficients of equation (1) raises many difficulties. First, the error terms ξ_{it} are certainly serially correlated as $corr(\xi_{it}, \xi_{is}) = \sigma_c^2/(1+\sigma_c^2) \neq 0$, for $s \neq t$ and where $Var(c_i) = \sigma_c^2$. Second, the presence of a lagged dependent variable introduces bias in the estimation of coefficients as it is correlated with the error terms ξ_{it} due to the unobserved effects c_i. It can be shown that $Cov(hgf_{it-1}, \xi_{it}) \approx \sigma_c^2/(1-\gamma)$ (Greene, 2012). Another issue is the well-known initial conditions problem. The initial state, denoted by hgf_{i0}, is usually unknown and is certainly highly correlated with all hgf_{it} as it determines the entire path followed by the firm, i.e., the HGF status of the firm for each year during its lifetime. (Greene, 2012). The initial state is also correlated with the unobserved

[25] As mentioned by Wooldridge (2010) in panel data models, a random effects framework means that there is no correlation between the unobserved effects c_i and the explanatory variables $\mathbf{x}_{it}$. In a fixed effects framework, correlation is allowed between c_i and $\mathbf{x}_{it}$. In a correlated random effects framework, dependence between c_i and $\mathbf{x}_{it}$ is allowed, but the dependence is modelled, i.e., given $\mathbf{x}_i = (\mathbf{x}_{i1}, \dots, \mathbf{x}_{iT})$, a distribution for c_i is specified.

heterogeneity effects c_i. For example, a firm becoming a HGF for the first time will acquire some specific characteristics. Therefore, in all cases, the strict exogeneity assumption failed.

To get unbiased estimators, Wooldridge (2000, 2005) proposed a solution by assuming that the unobserved heterogeneity effects follow a distribution that depends upon the initial state and exogenous explanatory variables over the entire time series (Bluhm et al., 2014). However, using a framework à la Chamberlain−Mundlak (Chamberlain, 1984; Mundlak, 1978), the means of the explanatory variables over time can be used instead. This can be written as

$$c_i = \alpha_0 + \alpha_1 hgf_{i0} + \alpha_2 \overline{\mathbf{x}_i} + u_i. \tag{3}$$

We will suppose[26] that $u_i \sim N(0, \sigma_u^2)$ and is independent of hgf_{i0} and $\mathbf{x}_i$.

Integrating equation (3) in equation (2), the model that will be estimated is

$$P(hgf_{it+1} = 1 | hgf_{it-1}, \dots, hgf_{i0}, \mathbf{x}_i, c_i) = \Phi(\gamma hgf_{it} + \beta \mathbf{x}_{it} + \alpha_0 + \alpha_1 hgf_{i0} + \alpha_2 \overline{\mathbf{x}_i} + u_i). \tag{4}$$

The previous equation can be estimated using a standard probit with random effects (e.g., with the command XTPROBIT in Stata). This model has been widely used in the literature (Contoyannis et al., 2004; López-García and Puente, 2012; Rivard, 2014; Du and Temouri, 2015). The dynamic probit model with correlated random effects relies on heavy assumptions, particularly on the distribution of heterogeneity effects. As mentioned by Wooldridge (2005), misspecification of the model leads to inconsistent parameter estimates.

Akay (2012) investigated the Wooldridge method in terms of robustness and performance, and found that the method is very good for panel data of a moderately long duration, i.e., 5–8 periods. Rabe-Hesketh and Skrondal (2013) also showed how to avoid the bias introduced in short panel data using the Wooldridge method.

Any empiricial work has its own limitations and the present analysis is no exception. Some drawbacks concerning the applied methodology could be identified. As

[26] Given the specification of c_i, σ_u will be estimated instead of σ_c (see Wooldridge (2010), p. 616).

mentioned in the last section, we extracted a balanced subpanel from the dataset. The major inconvenience of extracting a balanced subpanel is the loss of efficiency[27] as observations are dropped (Baltagi, 2013). Moreover, the results may suffer from selection bias. In general, smaller start-ups are less likely to survive over a long period and firms in the sample could be larger for that reason. As a consequence, this study focuses on surviving firms and their behaviour over a period of time. The sample, therefore, might not be representative of the population of businesses in Canada.[28]

Also, the variables hgf_{it+1} and hgf_{it} are highly correlated by construction: hgf_{it+1} is defined over the period $t-2$ to t and hgf_{it} over the period $t-3$ to t. Thus, the variables are defined over overlapping time periods. As a consequence, interpretation of the estimated coefficient $\hat{\gamma}$ may suggest growth duration or a growth spurt instead of the persistence of high growth.[29] The result should be robust, however, as unobserved firm heterogeneity is controlled for.

Another disadvantage of the methodology used in this paper is that it excludes start-ups, except at the beginning of the period, and no start-ups appear thereafter as the sample is balanced. In particular, to determine if a firm is high growth, the BLS definition that was used considers a 3-year period. As a consequence, firms are at least 3 years old. High-growth firms are known to be young (Coad et al., 2014). This could be one of the limitations of the present study. However, the study has the advantage of following a group of surviving firms and allows us to study their transitional phase in terms of HGFs, as well as factors that could have a positive or negative impact on firms' probability of growing rapidly. Finally, results obtained in this study have to be interpreted in the context of firms surviving over the period 2000−2012.

[27] Mátyás and Lovrics (1991) showed, by using Monte Carlo experiments and comparing the unbalanced panel and the balanced subpanel, that the loss of efficiency is negligible when $NT>250$ and serious when $NT<150$. Their findings apply for the fixed effects models and feasible generalized least-squares models.

[28] We compared the distribution of firms by industry sector and province before and after making the dataset balanced, and we obtained similar results. Therefore, the economic structure might have been preserved.

[29] For example, let us assume that the size of a firm at $t-3$ and $t-2$ is constant and denoted by x and that $x > 10$. Suppose that the firm's size is $2x$ at t and $t+1$, i.e., the firm's size doubled. Then, the firm qualified as a high-growth firm at t and $t+1$, as $(2x/x)^{1/3}-1 = 2^{1/3}-1 \approx 0.26 > 0.20$ for both time periods, but there is no rapid growth between the two periods. The notion of high-growth firm is based upon the past, over a 3-year period, and, consequently, persistence of high growth within this context has to be interpreted with caution.

5.2 VARIABLES

5.2.1 DEPENDENT VARIABLE

The dependent variable is a dummy variable, which is equal to 1 if a firm is high growth over the period $(t-2, t+1)$ and 0 otherwise. The variable will be denoted by hgf_{t+1}. The BLS definition is used to define a high-growth firm in the model.

5.2.2 EXPLANATORY VARIABLES

To study the determinants of HGFs, many control variables that could be important to explain future HGF status have been included in the model given in equation (1) and those variables are related to firm characteristics. We essentially follow the literature on this topic. Those variables include firm age, firm size, profitability, labour productivity, debt ratio, human capital and the working capital ratio. Dummy variables also control for industry sector, location, and expenditures on R&D and machinery and equipment (M&E). Table 1 describes the variables used in the model.

Almost all of the variables in the model are given at t and some include a lagged period at $t-1$. Thus, in comparison with the dependent variable (given at $t+1$), the explanatory variables are lagged, which ensures that there is no endogeneity issue due to simultaneity.

The first variable that we control for is firm age, in logarithmic terms. We also add into the model the natural logarithm of firm size and its quadratic term. We expect a non-linear relationship taking an inverted-U form between firm size and the firm's probability of becoming a HGF in the next period. As mentioned in Section 2, this has been observed by Goedhuys and Sleuwaegen (2010) for firm growth and firm size.

Variables related to the capital structure of the firm are also added into the model. These include the return on assets, debt ratio and the working capital ratio. Return on assets is an indicator of a firm's profitability. Debt ratio is included as a measure of the firm's leverage and its financial position. Debt ratio is defined as total liabilities over total assets. Within this context, total liabilities are used as a proxy for the firm's debt.

Furthermore, debt ratio can be seen as a proxy for access to financing. As mentioned by López-García and Puente (2012), higher debt ratio means that the firm has lower financing constraints. Indeed, as noticed by McVanel and Perevalov (2008), "… at some point, the firm was able to borrow." On the other hand, there is a certain limit to this being true as a debt ratio that is too high can impede the capacity of the firm to borrow.

Another variable that could have an important impact on a firm's probability of becoming a HGF is the firm's working capital ratio. Working capital is associated with cash flow and firm liquidity or firm financial health. It is the ratio of the firm's current assets divided by its current liabilities. However, an abnormally high working capital ratio may have negative implications on performance as it shows that the firm does not invest enough of its excess cash into its business.

Labour productivity and human capital are included in the model as they could have considerable influence on a firm's probability of becoming a HGF in the next period. The variable associated with human capital has to be considered as a proxy, and is calculated as the total wages paid to employees in a firm divided by the average of total wages paid to employees by firms operating in the same industry sector.[30] Higher values of this variable could indicate that employees of a firm are paid more in comparison with other firms in the same industry sector due to higher levels of relative experience or education. Wagner (2012) presented empirical evidence on the quality of the average wage in a firm as a proxy variable for the qualifications of the employees. However, this variable could also represent firm labour costs (Levratto et al., 2010). Therefore, this variable's effect on HGF status may be mixed and have a positive or a negative impact on a firm's probability of becoming a HGF.

Expenditures on R&D and M&E could have a positive influence on a firm's probability of becoming a HGF in the next period. These variables could have a major impact on firm growth as they are often related to innovation, efficiency and productivity. For example, a firm conducting R&D could develop new products and have access to new

[30] This variable has been frequently used in the empirical literature as a proxy for human capital. See, for example, López-García and Puente (2012) and Du and Temouri (2015).

markets. Also, expenditures on M&E could reduce firm costs and make the firm more competitive.

Finally, a set of dummy variables captures firm characteristics related to industry sector and location. Time dummy variables are introduced to control for economic cycles. Interaction terms between industry sectors with hgf_{it} are also added into the model. The impact of HGF status at t could differ from the probability of becoming a HGF at $t+1$ among industry sectors.

TABLE 1: DESCRIPTION OF EXPLANATORY VARIABLES

Variable	Description
Age (lnage)	The number of years the firm has been incorporated. For firms without an incorporation date, the first year the firm appeared in the Business Register was used as a proxy for age. The natural logarithm of age is used in the econometric model.
Size (lnsize)	The average number of employees during a year. The natural logarithm of size is used in the econometric model.
Return on assets (ROA)	Net income (or loss) divided by total assets.
Debt ratio (debt)	Total liabilities divided by total assets.
Labour productivity (lab_prod)	Total sales of goods and services, expressed in hundreds of thousands of dollars, divided by the number of employees (size).
Working capital ratio (w_cap)	Total current assets divided by total current liabilities.
Human capital (HC)	Total wages paid to employees divided by the average of total wages paid to employees within an industry sector.
Research and development (RD)	Equal to 1 if total expenditures on R&D are greater than zero and 0 otherwise.
Machinery and equipment (ME)	Equal to 1 if expenditures on M&E are greater than zero and 0 otherwise.
Province (reference category: Ontario)	Equal to 1 if firm is located in a province or territory and 0 otherwise; Newfoundland and Labrador, New Brunswick, Nova Scotia, Prince Edward Island, Quebec, Ontario, Manitoba, Saskatchewan, Alberta, British Columbia, Territories (Northwest Territories, Nunavut and Yukon).
Industry sector (reference category: retail trade)	Equal to 1 if the firm is in the industry sector and 0 otherwise; agriculture, forestry, fishing and hunting (agr), mining, quarrying, and oil and gas extraction (mining), manufacturing (manuf), construction (construc), wholesale trade (whole), retail trade (retail), transportation and warehousing (transp), information and cultural industries (info), finance and insurance (fin), real estate and rental and leasing (real_est), professional, scientific and technical services (prof), management of companies and enterprises (manag), administrative and support, waste management and remediation services (admin), health care and social assistance (health), arts, entertainment and recreation (art), accommodation and food services (accom), other services (other).

5.3 DESCRIPTIVE STATISTICS

As the firms in this study are tracked over the period 2003−2012 — due to the fact that a balanced dataset is required for the model — firms aged within the sample. In fact, the observation period is actually longer as size information is needed in 2000 to determine if a firm is high growth over the period 2000−2003. There are no start-ups in the dataset except for those firms that started in 2000. Furthermore, all the firms in the dataset survived for the entire 2000–2012 observation period. The study's results have to be considered in this context.

The data include 210,714 firms (N) per year over the period 2004−2011 ($T = 8$), for a total of 1,685,712 observations ($N \times T$) in the model. Because the model uses lagged explanatory variables and a lead dependent variable, only observations covering the 2004–2011 period are analyzed by the model. Descriptive statistics are generated for that period.

Table 2 presents the mean values for various variables in the analysis. The mean values are calculated from the data associated with all the sample firms over the 2004−2011 period.

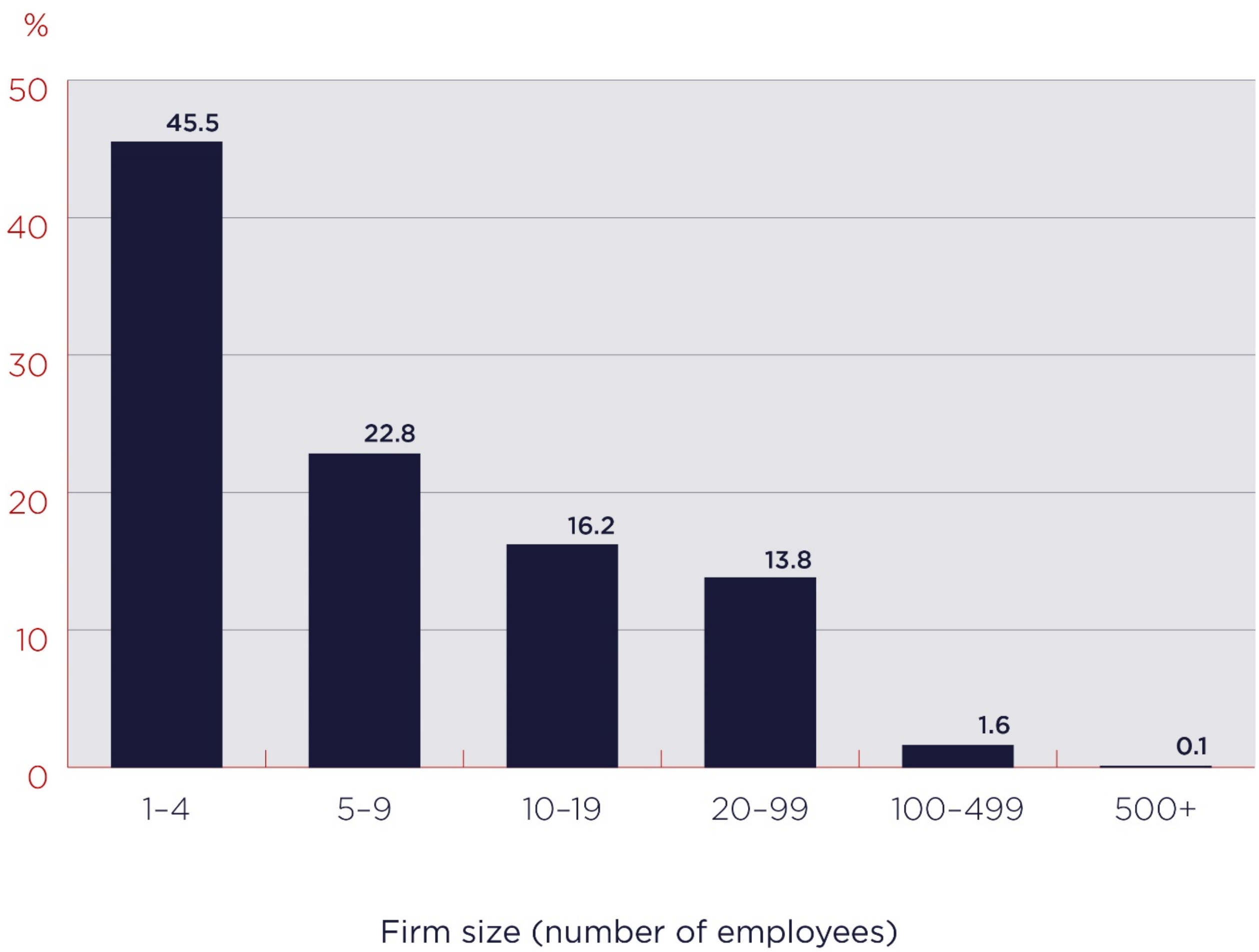
TABLE 2: FIRM-LEVEL SUMMARY STATISTICS, 2004–2011

Variable	Mean Value
Age (years)	19
Size (number of employees)	15
Return on assets	0.08
Debt ratio	0.69
Labour productivity	1.75
Working capital ratio	3.97
Human capital	1.16
Research and development (%)	4.41
Machinery and equipment (%)	57.64

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.
Note: For dummy variables, the mean corresponds to the proportion of firms over the period 2004–2011.

Figure 1 shows the distribution in percentage of firms by firm size category over the period 2004–2011.[31]

FIGURE 1: DISTRIBUTION OF OBSERVATIONS BY FIRM SIZE CATEGORY, 2004–2011



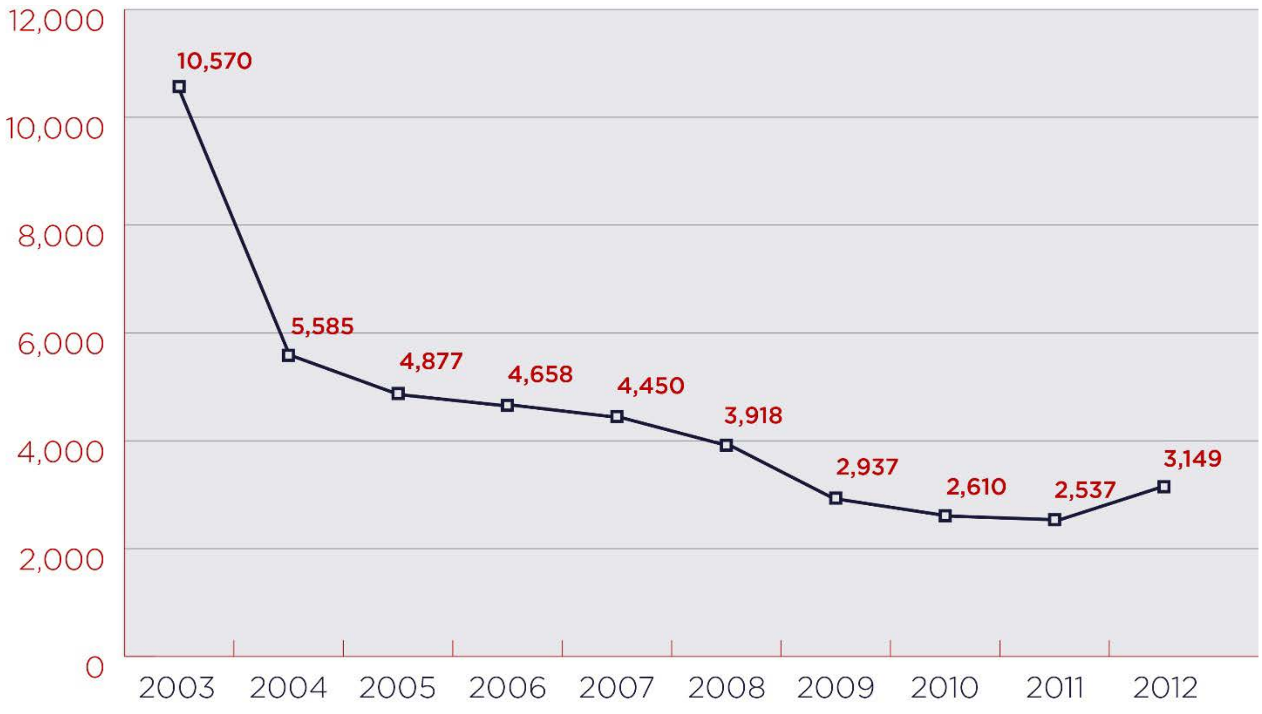
Sources: Statistics Canada, *National Accounts Longitudinal Microdata File,* 2000–2012; and author's calculations

About 68 percent of firms had 1 to 9 employees over the period 2004–2011. About 98 percent were small firms (1–99 employees), 1.6 percent were medium-sized firms (100–499 employees) and 0.1 percent were large firms (500+ employees).

[31] Distribution of firms by year and size gives results similar to those illustrated in FIGURE 1.

Figure 2 shows a decline in the number of HGFs between 2003 and 2011, followed by a slight increase in 2012.

FIGURE 2: NUMBER OF HGFS BY YEAR, 2003–2012



Sources: Statistics Canada, *National Accounts Longitudinal Microdata File,* 2000–2012; and author's calculations.

Tables 3 and 4 show the distribution of firms by province and industry sector respectively.

TABLE 3: DISTRIBUTION OF FIRMS AND HGFS BY PROVINCE/TERRITORY, 2004–2011

Province/Territory (P/T)	Number of HGFs in the P/T	Percentage of Firms in the P/T that were HGFs	Total Number of Firms in the P/T	Percentage of Canadian Firms from the P/T
Newfoundland and Labrador	504	2.02	24,444	1.48
New Brunswick	700	1.79	39,160	2.32
Nova Scotia	607	1.37	44,336	2.63
Prince Edward Island	128	1.66	7,704	0.46
Quebec	7,847	1.77	444,120	26.35
Ontario	9,497	1.76	539,552	32.01
Manitoba	908	1.84	49,256	2.92
Saskatchewan	888	1.92	46,240	2.74
Alberta	4,759	2.14	222,232	13.18
British Columbia	5,575	2.12	263,336	15.62
Northwest Territories	88	4.45	1,976	0.12
Nunavut	41	6.17	664	0.04
Yukon	30	1.37	2,192	0.13
Total	**31,572**	**1.87**	**1,685,712**	**100**

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author’s calculations.

TABLE 4: DISTRIBUTION OF FIRMS AND HGFS BY INDUSTRY SECTOR, 2004–2011

Industry Sector (IS)	Number of HGFs from the IS	Percentage of Canadian HGFs from the IS	Total Number of Firms in the IS	Percentage of Canadian Firms from the IS
Agriculture, forestry, fishing and hunting	617	1.95	38,512	2.28
Mining, quarrying, and oil and gas extraction	418	1.32	13,336	0.79
Construction	6,472	20.50	259,912	15.42
Manufacturing	3,792	12.01	164,456	9.76
Wholesale trade	2,497	7.91	146,184	8.67
Retail trade	3,420	10.83	243,376	14.44
Transportation and warehousing	1,790	5.67	84,712	5.03
Information and cultural industries	648	2.05	19,864	1.18
Finance and insurance	589	1.87	44,464	2.64
Real estate and rental and leasing	761	2.41	57,224	3.39
Professional, scientific and technical services	2,456	7.78	149,312	8.86
Management of companies and enterprises	178	0.56	14,728	0.87
Administrative and support, waste management and remediation services	2,334	7.39	82,968	4.92
Health care and social assistance	1,433	4.54	85,880	5.09
Arts, entertainment and recreation	588	1.86	26,824	1.59
Accommodation and food services	2,359	7.47	112,632	6.68
Other services	1,220	3.86	141,328	8.38
Total	**31,572**	**100**	**1,685,712**	**100**

Note: Percentages may not add up to 100 percent due to rounding.

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.

It is worth noting that HGFs are found mainly in construction (20.5 percent), manufacturing (12.0 percent) and retail trade (10.8 percent), as indicated in Table 4.

To have a better understanding of the key factors that distinguish firms that become HGFs and those that do not, Table 5 provides descriptive statistics on variables at t for two groups: firms that become high growth in the next period $(t+1)$ and firms that do not. Interestingly, we can observe major differences between the two groups. In general, the differences are statistically significant.[32]

TABLE 5: MEAN OF KEY VARIABLES OVER 2004–2011 (at t) FOR HGFS AND NON-HGFS IN THE NEXT PERIOD (at $t+1$)

Variable	HGF	Non-HGF
Age (years)	17	19
Size (number of employees)	41	14
Return on assets	0.09	0.08
Profits ($)	333,555.08	166,860.43
Total assets ($)	8,845,405.70	3,218,868.70
Total current assets ($)	4,339,844.30	1,630,037.70
Debt ratio	0.72	0.69
Total liabilities ($)	5,735,283.80	2,168,475.70
Total current liabilities ($)	2,987,941.70	1,248,975.00
Total sales of goods and services ($)	7,283,001.10	2,800,822.70
Labour productivity	1.99	1.75
Working capital ratio	2.09	4.01
Human capital	1.25	1.16
Total R&D expenditures ($)	50,608.65	9,794.40
M&E expenditures ($)	541,802.53	298,995.01

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.

[32] We use the ttest command in Stata with the option *unequal*. Basically, it is a t-test using Student's t-distribution, which compares the means of two different groups and where we suppose that the data have unequal variances.

Firms that become HGFs at $t+1$ tend to be younger and larger[33] at t than those that do not become HGFs. Also, HGFs tend to have higher returns on assets, profits, total and current assets, and total and current liabilities at t. At the same time, they have less working capital than non-HGFs. HGFs have higher total sales of goods and services in the previous period. They spend more on R&D and M&E at t than firms that do not become HGFs at $t+1$. Moreover, HGFs tend to have a higher ratio of human capital at t than non-HGFs. Finally, firms that become HGFs in the next period tend to have higher labour productivity than those firms that do not become HGFs.

[33] This could be due to the fact that we follow firms over a 10-year period and start-ups are excluded. Instead of using the average over the 2004–2011 period, we obtain similar results for every year between 2004 and 2011. In the unbalanced dataset, in general, results remain qualitatively similar. Also, we examine the variables presented in Table 5 among firms that have never been HGFs over the period 2004–2011 and firms that have been HGFs at least once. As a result, the same conclusions apply in terms of differences between the two groups for every variable in terms of magnitude.

6. RESULTS

The estimated coefficients of the dynamic probit model with correlated random effects are presented in Table 6.

TABLE 6: RESULTS OF THE DYNAMIC PROBIT MODEL WITH CORRELATED RANDOM EFFECTS

Variable	Coefficient
Dependent variable	
hgf_{t+1}	
Explanatory variable	
hgf_t	1.928*** (0.026)
$lnsize_t$	1.504*** (0.030)
$lnsize_t^2$	-0.239*** (0.005)
$lnage_t$	-0.191*** (0.039)
ROA_t	0.227*** (0.022)
ROA_{t-1}	0.064*** (0.022)
$debt_t$	0.060*** (0.013)
$debt_{t-1}$	-0.008 (0.013)
HC_t	-0.083*** (0.014)
HC_{t-1}	0.18*** (0.012)
lab_prod_t	0.029*** (0.004)
lab_prod_{t-1}	0.108*** (0.004)
w_cap_t	-0.011*** (0.001)

w_cap_{t-1}	0.005*** (0.001)
RD_t	0.162*** (0.022)
RD_{t-1}	-0.014 (0.022)
ME_t	0.03** (0.015)
ME_{t-1}	-0.017 (0.015)
$agr \times hgf_t$	-0.478*** (0.064)
$mining \times hgf_t$	-0.279*** (0.079)
$manuf \times hgf_t$	-0.232*** (0.035)
$construc \times hgf_t$	-0.464*** (0.031)
$whole \times hgf_t$	-0.044 (0.039)
$transp \times hgf_t$	-0.173*** (0.044)
$info \times hgf_t$	-0.127* (0.067)
$fin \times hgf_t$	-0.065 (0.067)
$real\_est \times hgf_t$	-0.190** (0.059)
$prof \times hgf_t$	-0.213*** (0.040)
$manag \times hgf_t$	-0.150 (0.113)
$admin \times hgf_t$	-0.237*** (0.040)
$health \times hgf_t$	-0.088* (0.047)
$art \times hgf_t$	-0.362*** (0.066)
$accom \times hgf_t$	-0.109** (0.039)
$other \times hgf_t$	-0.092***

	(0.049)
Observations $(N \times T)$	1,685,712
Log-likelihood	-94,348.938
σ_u	0.277
ρ	0.071

Note 1: Standard errors are in parentheses. Robust standard errors were estimated to control for heteroskedasticity and within-panel serial correlation. They were similar to the standard errors shown in Table 6, and the significance of the variables is the same in both cases.

Note 2: The regression includes dummy variables for the year, industry sector and province.

Note 3: *** Statistically significant at the 1 percent level; **statistically significant at the 5 percent level; *statistically significant at the 10 percent level.

Note 4: σ_u denotes the standard deviation of u_i from equation (3).

Note 5: ρ denotes the proportion of the total variance contributed by the panel-level variance component and is given by $\sigma_u^2/(\sigma_u^2+1)$.

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.

The results show that there is a positive and strong state dependence between current and future high-growth state as shown by the positive and significant estimated coefficient for the lagged dependent variable.[34] In other words, being a HGF at t increases a firm's probability of becoming a HGF at $t+1$. Strong positive autocorrelation between past and current fast growth was also observed by López-García and Puente (2012). The authors mentioned that this result is robust as unobserved firm heterogeneity is controlled for. However, there is no consensus in the literature on HGF persistence and, more generally, on the autocorrelation of firm growth. Empirical studies show mixed results: some have obtained positive autocorrelation and others have found negative autocorrelation or even significant autocorrelation (Coad, 2006). Researchers tend to believe that autocorrelation of firm growth is negative and high growth is not persistent (Coad et al. 2014). We are inclined to agree with Hölzl (2014) that empirical studies provide a rather "ambiguous" answer to this question.

However, the result has to be interpreted with caution. The variables hgf_{t+1} and hgf_t are highly correlated due to their construction. The variable hgf_{t+1} is defined over the period $t-2$ to $t+1$ and hgf_t over the period $t-3$ to t. As a consequence, both variables

34 This result is also supported by an examination of transition matrices, as more than one third of firms that are HGFs at t become HGFs at $t+1$, for every year.

are defined over an overlapping period. This implies that instead of showing persistence of high growth, they may only show growth duration or a growth spurt.

Also, the effect differs among industry sectors, as revealed by the interaction terms of HGF status and industry sector. To quantify the impact, we calculated the average partial effects[35] (Table 7). For an industry sector, the average partial effects give the average variation among observations of a firm's probability of becoming a HGF at $t+1$ when a firm is a HGF at t compared with the case when a firm is not a HGF at t, relative to a firm in the retail trade sector.

TABLE 7: AVERAGE PARTIAL EFFECTS OF hgf_t BY INDUSTRY SECTOR

Variable	Coefficient
agr	0.1453*** (0.012)
$mining$	0.2089*** (0.023)
$manuf$	0.1523*** (0.004)
$construc$	0.1631*** (0.003)
$whole$	0.1862*** (0.010)
$transp$	0.1963*** (0.007)
$info$	0.2089*** (0.014)
fin	0.2052*** (0.019)
$real\_est$	0.1915*** (0.015)
$prof$	0.1899*** (0.008)
$manag$	0.2100*** (0.022)
$admin$	0.1980*** (0.009)

[35] See Rivard (2014) for more details on average partial effects.

$health$	0.1951*** (0.010)
$arts$	0.1595*** (0.012)
$accom$	0.1648*** (0.010)
$other$	0.1708*** (0.007)
Observations $(N \times T)$	1,685,712

Note 1: Standard errors are in parentheses. Standard errors of average partial effects were calculated using the bootstrap method.

Note 2: *** Statistically significant at the 1 percent level; **statistically significant at the 5 percent level; *statistically significant at the 10 percent level.

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.

For example, as shown in Table 7, the probability of becoming a HGF at $t+1$ for a firm in the manufacturing sector is 15 percentage points higher if the firm is a HGF at t than if it is not. State dependence is stronger for firms in the management of companies and enterprises sector as the probability of becoming a HGF at $t+1$ is 21 percentage points higher if the firm is a HGF at t than if it is not. On the other hand, agriculture, forestry, fishing and hunting is the industry sector that is least affected by the HGF status of the firm at t. The probability of becoming a HGF at $t+1$ is 14 percentage points higher if the firm is a HGF at t than if it is not.

The results from Table 6 show that older firms are less likely to be HGFs in the next period. This was largely observed in the literature. Our assumption of a non-linear relationship between size and becoming a HGF is confirmed in our model as we obtained a significant estimated coefficient for the quadratic term. This relationship takes the form of an inverted-U curve. Therefore, the probability of becoming a HGF in the next period increases with firm size until a certain threshold is reached (we estimated this threshold to be around 23 employees), after which the probability of becoming a HGF in the next period decreases with firm size. This is confirmed by the statistics presented in Table 5 as firms that become HGFs at $t+1$ are larger, on average (about 41 employees), in the previous period compared with those that do not become HGFs at $t+1$. However, they are still considered small businesses (1–99 employees).

Table 8 presents the average partial effects for some of the continuous variables used in the econometric model.

TABLE 8: AVERAGE PARTIAL EFFECTS FOR CONTINUOUS VARIABLES

Variable	Coefficient
ROA_t	0.0062*** (0.00053)
ROA_{t-1}	0.0018 (0.000455)
$debt_t$	0.0017*** (0.000401)
$debt_{t-1}$	-0.0002 (0.000471)
HC_t	-0.00227*** (0.000563)
HC_{t-1}	0.004945*** (0.000368)
lab_prod_t	0.0008*** (0.000111)
lab_prod_{t-1}	0.0030*** (0.000123)
w_cap_t	-0.0003*** (0.000064)
w_cap_{t-1}	0.0001*** (0.000021)
Observations $(N \times T)$	1,685,712

Note 1: Robust standard errors are in parentheses.

Note 2: *** Statistically significant at the 1 percent level; **statistically significant at the 5 percent level; *statistically significant at the 10 percent level.

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.

Current return on assets (ROA), which is related to firm profitability, is positively correlated with being a HGF in the next period. The estimated coefficient of ROA at $t-1$ is also significant in the model, which means that firm profitability has a positive lag effect on firm growth. Combining the impact of the current and the lagged average partial effects,[36] we show that ROA has a positive impact on the firm's probability of becoming a HGF in the next period. This result is in line with the work of Davidsson et al. (2009), in which the authors show that profitable firms are more likely to reach a state of high growth and high profitability. In other words, profitability is a precondition for growth. Rivard (2014) also found that higher profitability leads to higher performance in terms of growth and profitability.[37] Seens (2013) also found similar results, but related to sustainable growth.[38]

Estimates summarized in Table 6 from the dynamic probit model with correlated random effects indicate that debt ratio has a positive impact upon a firm's probability of becoming a HGF in the next period. As a proxy for access to financing, this means that firms that are able to borrow increase their chance of rapid growth. This phenomenon is also supported by the statistics reported in Table 5 as firms that become HGFs in the next period have higher levels of total liabilities and greater debt ratios in the previous period than firms that do not become HGFs. However, this may be true to some extent as an abnormally high debt ratio could impede a firm's capacity to borrow.

The effect of the working capital ratio on the probability of becoming a HGF is interesting. The estimated coefficient of the current working capital ratio (w_cap_t) is negative, which implies that having a high working capital ratio has a negative impact on the probability of becoming a HGF in the next period. This suggests that a firm possessing a considerable amount of current assets could negatively impact its ability to grow. Perhaps high levels of current assets may indicate low levels of investment in the business. If so, holding on to liquid assets, such as cash, may not benefit fast-growing firms. On the other hand, the lagged working capital ratio (w_cap_{t-1}) has a positive impact on the probability of becoming a HGF at $t+1$. This result makes sense as it means that firms with higher working capital ratios have probably accumulated

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[36] The cumulative effect of the current and lagged variables is calculated by adding their average partial effects. As shown in TABLE 8, the average partial effect of the lagged variable ROA is not significant, but the estimated coefficient is. In this case, we consider the inference on the estimated coefficient, as suggested by Greene (2009).

[37] Rivard (2014) adopted three measures of growth: total sales of goods and services, employment and total assets. He obtained similar results independently of the measure used.

[38] Seens (2013) used sales as a measure of growth.

current assets at $t-1$ that might be used for future investment. Overall, the working capital ratio has a negative impact on a firm's probability of becoming a HGF in the next period, after combining the average partial effect of the current and lagged working capital ratio variables.

Current and lagged labour productivity produce a positive impact on a firm's probability of becoming a HGF in the subsequent period as firms that may want to expand could invest in more efficient methods of production. Table 8 also shows that the cumulative effect of labour productivity is positive, by adding the average partial effect of the lagged and current variables.

For human capital, we obtain different results for the sign of the estimated coefficients for the current and lagged variables. Human capital at $t-1$ is positively correlated with becoming a HGF at $t+1$. However, human capital at t is negatively related to the probability of becoming a HGF at $t+1$. This suggests that human capital does not have an immediate impact on a firm's likelihood of becoming a rapidly growing firm, but a delayed effect instead. The variable that we used to proxy human capital — the ratio of the average wage per employee paid by the firm to the average wages per employee paid by firms within the same industry sector — may also be related to a firm's labour cost. Higher wages paid per employee could negatively impact growth in the short term as it adds higher costs until that investment generates return in the longer term. Overall, the combined effect of the lagged and current average partial effects of human capital is positive.

Estimates summarized in Table 6 from the dynamic probit model with correlated random effects also suggest that current expenditures on R&D, as well as on M&E, positively influence the probability of a firm becoming a HGF at $t+1$. Furthermore, considering the average partial effects, as shown in Table 9, a firm's probability of becoming a HGF at $t+1$ increases by 0.5 percentage points if the firm has spent on R&D at t as opposed to if it has not, and by 0.08 percentage points if a firm has spent on M&E compared with if it has not. The model shows that R&D and M&E have highly significant and positive estimated coefficients, but the effect on a firm's probability of becoming a HGF in the next period is relatively small. However, the results obtained are in line with the statistics reported in Table 5, which show that there is a significant difference in the amount spent on R&D and M&E in the current period by those firms that become HGFs in the next period and those that do not. Indeed, firms that become HGFs at $t+1$ have higher expenditures on R&D than those that do not. The same phenomenon is observed for expenditures on M&E, where firms that become HGFs in the next period spend more on M&E than those that do not.

TABLE 9: AVERAGE PARTIAL EFFECTS FOR R&D AND M&E

Variable	Coefficient
RD_t	0.0050*** (0.00042)
RD_{t-1}	-0.0004 (0.00051)
ME_t	0.0008*** (0.00023)
ME_{t-1}	-0.0005 (0.00040)
Observations $(N \times T)$	1,685,712

Note 1: Robust standard errors are in parentheses.

Note 2: *** Statistically significant at the 1 percent level; **statistically significant at the 5 percent level; *statistically significant at the 10 percent level.

Sources: Statistics Canada, *National Accounts Longitudinal Microdata File*, 2000–2012; and author's calculations.

It should be noted that other models were used to test the robustness of the results. In particular, the analysis related to the persistence of HGFs was investigated further. We applied the methodology used by López-García and Puente (2012), which used the Birch−Schreyer indicator as a growth measure, along with a different definition for HGF, namely that a firm was considered to be a HGF if it was in the top 10 percent of firms with the highest growth rates. We found that the estimated coefficient of the lagged dependent variable was positive and significant. López-García and Puente (2012) found the same result.

Also, we estimated several probit models where the dependent variable was hgf_{it} and with hgf_{it-3} among the explanatory variables[39] for different time periods (2003–2006, 2004–2007, etc.). We observed that the estimated coefficient of the lagged dependent variables was positive and significant in all cases except for the period 2003–2006, where the coefficient was positive but not significant. Those models suggest that HGF status is persistent, that is, firms that experienced high growth are more likely to exhibit rapid growth 3 years later. The result is also supported by an examination of transition matrices, for HGFs and non-HGFs, over a 3-year period for years between 2003 and 2012. We observed that businesses that were HGFs at t were more likely to become HGFs at $t+3$ than those that were non-HGFs at t. The variables presented in Table 1 were also added into these other econometric models. The results were similar to those obtained using the main dynamic probit model with correlated random effects in terms of the sign and the statistical significance of the results.

We carried out other robustness checks by applying previous methodologies (main model *xtprobit*, probit with a 3-year period, probit with the Birch–Schreyer indicator) to industry sectors. Generally, we found persistence of HGFs within industry sectors. For the most part, we obtained the same results for the other explanatory variables with regard to sign and statistical significance of the estimated coefficients.

It is worth mentioning a few limitations of this analysis. They are related more specifically to the structure of the sample as we extracted a balanced dataset from the original sample. In the present study, this means that we followed firms over a 12-year period (from 2000 to 2012). As a consequence, only surviving firms are included in this analysis and start-ups are excluded (except at the beginning of the period). Thus, the estimated results could suffer from selection bias. The results generally apply to firms that survived during a long period of time and became or did not become HGFs. However, this study has the advantage of providing insights on firm behaviour and the HGF status of firms over a meaningful period of time.

[39] Lagged explanatory variables were also added into the models.

Due to the HGF definition used in this study, construction of the current and lagged dependent variable (which overlapped for $t-1$ and t) may explain the result on status dependence as they are highly correlated. However, the results obtained in this study from the use of other econometric models and an analysis of transition matrices over 3-year periods confirmed that firms that experienced high growth are more likely to become high-growth firms 3 years later compared with firms that were not initially HGFs. This study presented evidence that suggests that there is persistence in the growth of HGFs.

7. CONCLUSIONS

This paper's main aim is to identify the factors that influence a firm's probability of becoming a high-growth firm (HGF). To do this, we used a unique dataset, the *National Accounts Longitudinal Microdata File,* developed by Statistics Canada.

Our framework is largely inspired by the work of López-García and Puente (2012), in which the authors employed a dynamic probit model with correlated random effects. We estimated the probability that a firm will become a HGF in the next period, controlling for the lagged dependent variable, which is the current HGF status of the firm, and other relevant explanatory variables. By considering surviving firms over a long period, which in this case is from 2000 to 2012, this framework allows us to determine the factors that could have played an important role in producing HGFs. Moreover, this analysis provides useful information on the behaviour of firms or, more specifically, their growth status over time.

Our results show that firms experiencing rapid growth are more likely to achieve a high-growth status in the future, which suggests that there is state dependence. Furthermore, the impact on future HGF status varies across industry sectors. The state dependence result is similar to results obtained by López-García and Puente (2012). However, it contradicts other results from the literature (Coad, 2006; Daunfeldt and Halvarsson, 2015; Goedhuys and Sleuwaegen, 2015).

This paper also highlights that some variables related to firm characteristics are significant determinants of HGFs. Younger firms are more likely to become HGFs in the next period compared with older firms. We found that there is an inverted-U relationship between HGF status and firm size, meaning that firms are more likely to grow, as they approach an estimated size of 23 employees, and then the probability that the firm becomes a HGF lowers as the firm becomes larger.

Many variables related to the capital structure of the firm are significant determinants of HGFs. Among those variables, we noted that current and past profitability have a positive impact on a firm's probability of becoming a HGF. Debt ratio is positively correlated to the probability that the firm becomes a HGF. Interestingly, we found that the overall impact of working capital on a firm's probability to undergo fast growth is negative. This shows that holding cash might not be beneficial to firms that want to growth rapidly. Another finding is that the overall effect of human capital is positively correlated with a firm's probability of becoming a future HGF. Labour productivity is also a significant determinant that acts positively on a firm's probability of becoming a HGF in the next period.

Finally, we also found that firms that have spent on R&D in the current period increase their probability of becoming HGFs in the next period. Furthermore, the same phenomenon was observed for firms that spend on M&E in the current period. However, these effects are relatively small.

The results from this study provide clues for policies that can stimulate rapid company growth. In particular, measures that promote investment in human capital by firms or improve firm access to financing may help firms achieve rapid growth. Moreover, implementing policies that promote firm level investments in R&D and M&E may definitely play a role, although a small one, in rapid firm growth. Other strategies to promote growth may lie in policies that can increase entrepreneurs' awareness of the effects of profitability as a precondition to future fast growth and that operating with a relatively high current working capital ratio — perhaps by holding on to high levels of cash — may hamper growth.

The study of HGFs presents interesting opportunities for additional research to gain a better understanding of their characteristics, specifically in Canada where there are only a few studies on HGFs. For example, a study on the journey followed by firms that become HGFs could answer questions relative to how many times a firm can achieve this state or what happens after the firm reaches HGF status. As well, while much of the focus on HGFs is their disproportionate contribution to net employment growth, more research can be conducted to focus on their contribution to economic drivers, such as productivity or gross output. This was studied by Haltiwanger et al. (2016), but to the best of our knowledge, no similar studies have been conducted for the Canadian context.

REFERENCES

Akay, A. (2012). Finite-sample comparison of alternative methods for estimating dynamic panel data models. *Journal of Applied Econometrics*, 27(7), 1189–1204.

Albarran, P., Carrasco, R., and Carro, J. M. (2015). *Estimation of Dynamic Nonlinear Random Effects Models with Unbalanced Panels.* Universidad Carlos III De Madrid Working Papers.

Arrighetti, A., and Lasagni, A. (2010). *Assessing the Determinants of Fast Growth in Italy.* Department of Economics, Parma University, Working Papers.

Baltagi, B. H. (2013). *Econometric Analysis of Panel Data* (5th edition). John Wiley & Sons.

Bluhm, R., De Crombrugghe, D., and Szirmai, A. (May 8, 2014). The Dynamics of Stagnation. *Macroeconomic Dynamics*.

Bogas, P., and Barbosa, N. (2013). High-Growth Firms: What Is the Impact of Region-Specific Characteristics? NIPE Working Paper.

Cameron, A. C., and Trivedi, P. K. (2005). *Microeconometrics: Methods and Applications.* New York: Cambridge University Press.

Chamberlain, G. (1984). Panel Data. In Z. Griliches and M. D. Intriligator, eds., *Handbook of Econometrics* (Vol. 2, pp. 1247–1318). Elsevier Science Publishers.

Clayton, R. L., Sadeghi, A., Spletzer, J. R., and Talan, D. M. (2013). High-employment-growth firms: Defining and counting them. *Monthly Labor Review*, 136, 3–12.

Coad, A. (2006). *A Closer Look at Serial Growth Rate Correlation.* Laboratory of Economics and Management Working Paper Series No. 2006/29.

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

Contoyannis, P., Jones, A. M., and Rice, N. (2004). The dynamics of health in the British Household Panel Survey. *Journal of Applied Econometrics*, 19(4), 473–503.

Côté, S., and Rosa, J. M. (2017). *Comparing Different Measures of High-Growth Enterprises: A Canadian Case Study.* Ottawa: Innovation, Science and Economic Development Canada.

Daunfeldt, S.-O., and Halvarsson, D. (2015). Are high-growth firms one-hit wonders? Evidence from Sweden. *Small Business Economics,* 44(2), 361–383.

Daunfeldt, S.-O., Elert, N., and Johansson, D. (2014). The economic contribution of high-growth firms: Do policy implications depend on the choice of growth indicator? *Journal of Industry, Competition and Trade*, 14(3), 337–365.

Davidsson, P., Steffens, P., and Fitzsimmons, J. (2009). Growing profitable or growing from profits: Putting the horse in front of the cart? *Journal of Business Venturing,* 24(4), 388–406.

Deschryvere, M. (2008). *High Growth Firms and Job Creation in Finland.* Research Institute of the Finnish Economy, ETLA Discussion Paper 1144.

Dixon, J., and Rollin, A.-M. (2014). The Distribution of Employment Growth Rates in Canada: The Role of High-Growth and Rapidly Shrinking Firms. Ottawa: Statistics Canada, Economic Analysis Division.

Dobbs, M., and Hamilton, R. T. (2007). Small business growth: Recent evidence and new directions. *International Journal of Entrepreneurial Behaviour & Research*, 13(5), 296–322.

Du, J., and Temouri, Y. (2015). High-growth firms and productivity: Evidence from the United Kingdom. *Small Business Economics*, 44(1), 123–143.

Eurostat–OECD. (2007). *Eurostat−OECD Manual on Business Demography Statistics.* Luxembourg: Office for Official Publications of the European Communities.

Freel, M. F. (1998). Policy, prediction and growth: Picking start-up winners? *Journal of Small Business and Enterprise Development,* 5(1), 19–32.

Goedhuys, M., and Sleuwaegen, L. (2010). High-growth entrepreneurial firms in Africa: A quantile regression approach. *Small Business Economics*, 34(1), 31–51.

Goedhuys, M., and Sleuwaegen, L. (2015). *Human Capital, Innovation and the Distribution of Firm Growth Rates.* Maastricht: The Netherlands: UNU-MERIT Working Papers 2015-013.

Greene, W. (2009). Discrete Choice Modeling. In T. Mills and K. Patterson, eds., *Handbook of Econometrics — Volume 2: Applied Econometrics* (pp. 473–556). London: Palgrave Macmillan.

Greene, W. (2012). *Econometric Analysis.* Upper Saddle River, New Jersey: Prentice Hall.

Halabisky, D., Dreessen, E., and Parsley, C. (2006). Growth in firms in Canada, 1985–1999. *Journal of Small Business & Entrepreneurship*, 19(6), 255–267.

Haltiwanger, J., Jarmin, R. S., Kulick, R., and Miranda, J. (2016). High Growth Young Firms: Contribution to Job, Output, and Productivity Growth. In *Measuring*

Entrepreneurial Businesses: Current Knowledge and Challenges. University of Chicago Press.

Henrekson, M., and Johansson, D. (2010). Gazelles as job creators: A survy and interpretation of the evidence. *Small Business Economics*, 35(2), 227–244.

Hölzl, W. (2009). Is the R&D behaviour of fast-growing SMEs different? Evidence from CIS III data for 16 countries. *Small Business Economics*, 33(1), 59–75.

Hölzl, W. (2014). Persistence, survival, and growth: A closer look at 20 years of fast-growing firms in Austria. *Industrial and Corporate Change*, 23(1), 199–231.

Innovation, Science and Economic Development Canada. (June 2016). *Key Small Business Statistics.*

Levratto, N., Tessier, L., and Zouikri, M. (2010). The Determinants of Growth for SMEs — A Longitudinal Study from French Manufacturing Firms. SSRN Electronic Journal, 1780466.

López-García, P., and Puente, S. (2012). What makes a high-growth firm? A dynamic probit analysis using Spanish firm-level data. *Small Business Economics*, 39(4), 1029−1041.

Marsili, O. (2001). The Anatomy and Evolution of Industries: Technological Change and Industrial Dynamics. Cheltenham, United Kingdom: Edward Elgar Publishing Ltd.

Mason, C., and Brown, R. (2013). Creating good public policy to support high-growth firms. *Small Business Economics*, 40(2), 211–225.

Mátyás, L., and Lovrics, L. (1991). Missing observations and panel data: A Monte-Carlo analysis. *Economics Letters,* 37(1), 39–44.

McVanel, D., and Perevalov, N. (2008). *Financial Constraints and the Cash-Holding Behaviour of Canadian Firms.* Bank of Canada, Discussion Paper 2008-16.

Moreno, F., and Coad, A. (2015). High-Growth Firms: Stylized Facts and Conflicting Results. In Entrepreneurial Growth: Individual, Firm, and Region. Advances in Entrepreneurship, Firm Emergence and Growth (Vol. 17, pp. 187−230). Emerald Group Publishing Limited.

Mundlak, Y. (1978). On the pooling of time series and cross section data. *Econometrica,* 46(1), 69–85.

Navaretti, G. B., Castellani, D., and Pieri, F. (2014). Age and firm growth: Evidence from three European countries. *Small Business Economics*, 43(4), 823–837.

Parsley, C., and Halabisky, D. (2008). *Profile of Growth Firms: A Summary of Industry Canada Research*. Ottawa: Industry Canada.

Picot, G., and Dupuy, R. (1998). Job creation by company size class: The magnitude, concentration and persistence of job gains and losses in Canada. *Small Business Economics*, 10(2), 117–139.

Rabe-Hesketh, S., and Skrondal, A. (2013). Avoiding biased versions of Wooldridge's simple solution to the initial conditions problem. *Economics Letters*, 120(2), 346–349.

Rivard, P. (2014). Growth or Profitability First? The Case of Small and Medium-Sized Enterprises in Canada. Ottawa: Industry Canada.

Rivard, P. (2017). *The Contribution to Canadian Net Employment Change by High-Growth Firms.* Ottawa: Innovation, Science and Economic Development Canada.

Schreyer, P. (2000). *High-Growth Firms and Employment.* Paris: OECD Science, Technology and Industry Working Papers.

Seens, D. (2013). Small and Medium-Sized Enterprises Growth Study: Actual vs. Sustainable Growth. Ottawa: Industry Canada.

Stam, E., and Wennberg, K. (2009). The roles of R&D in new firm growth. *Small Business Economics,* 33(1), 77–89.

Wagner, J. (2012). Average wage, qualification of the workfoce and export performance in German enterprises: Evidence from KombiFiD data. *Journal for Labour Market Research*, 45, 161–170.

Wooldridge, J. M. (2000). A framework for estimating dynamic, unobserved effects panel data models with possible feedback to future explanatory variables. *Economics Letters*, 68(3), 245–250.

Wooldridge, J. M. (2005). Simple solutions to the initial conditions problem in dynamic, nonlinear panel data models with unobserved heterogeneity. *Journal of Applied Econometrics*, 20(1), 39–54.

Wooldridge, J. M. (2010). *Correlated Random Effects Models with Unbalanced Panels.* Manuscript (version May 2010), Michigan State University.