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Persistence, survival and growth: A closer look at 20 years of high growth firms in Austria

Werner Hölzl

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Abstract

This research studies the persistence of the high growth phenomenon in Austria using social security data for the years 1985 to 2007. The Eurostat-OECD definition is used to identify high growth firms (HGFs) and a modified Birch Index to identify high impact firms (HIFs). Bringing the definitions to the data confirms that the two definitions lead to the selection of different firms. We use matching as nonparametric preprocessing and estimate survival, persistence and growth regression on balanced datasets. The results show that being an HGF does not improve the likelihood of survival in future periods in excess of the size effect induced by the high growth event. For persistence and high growth we find an HGF treatment effect. For HIFs we find a significant treatment effect for survival, persistence and growth. HIFs show a much higher persistence than HGFs. The average growth rate after the high growth episode is quite modest for both HIFs and HGFs. Policy implications of the findings are discussed.

Keywords: firm growth, high growth firms
JEL codes: L11 - L25

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1 Introduction

High growth firms figure importantly in the European public policy debate. A background to this prominence of fast growing firms is the inability in Europe to generate new high technology firms such as Google, Microsoft or Apple in Europe. Empirical studies show that Europe has a lower number of new large firms (Cohen and Lorenzi, 2000; Philippon and Veron, 2008), and that the average firm dynamics are lower in most European countries than in the USA (Bartelsman, Scarpetta, and Schivardi, 2005; Hoffmann and Junge, 2006; Bravo-Biosca, 2010). This debate has also influenced the Europe 2020 strategy. The European Commissions Innovation Union Communication, one of the seven pillars of the Europe 2020 strategy, explicitly mentions the support of high-growth SMEs as a political objective. Furthermore, the share of fast-growing innovative firms has been proposed as a headline indicator to measure the progress of the Europe 2020 Strategy.

However, while much is known about the importance of fast-growing firms for job creation (Henrekson and Johansson 2010), not much is known about the fate of high growth firms after a high growth event. This paper looks at the persistence and survival patterns of high growth firms by considering the long run development of fast-growing firms in Austrian private industries based on social security data. The central research questions of the paper are:

- Are high growth firms more likely to be high growth firms at some future point in time compared to non-high growth firms?
- Is the average future growth performance of high growth firms higher compared to non-high growth firms?
- Are high growth firms less likely to exit from the market than non-high growth firms at some future point in time?

Answering these research questions should help us to better understand the processes of high growth. Whether high growth firms show persistence or not has important policy implications. If high growth firms are persistent in their growth, this would make it possible to design policy schemes for high growth firms identified by past growth. However, if they are more likely to collapse after a growth spurt, such policy measures would be a waste of money.

In order to account for different ways of measuring high growth, we use two popular methods to identify high growth firms. The first is the Eurostat-OECD definition of high growth firms as firms that achieve an annualized growth rate of 20 % over a three-year period and have more than 10 employees at the beginning of that period. The second method is a modified Birch Index. Studying the persistence and survival of high growth firms using two different measures to identify high growth firms makes it possible to draw more general conclusions.

The paper is structured as follows: The next section provides a short survey on high growth firms and the persistence of firm growth. Section 3 presents the properties of the high growth definitions used in the research. Section 4 presents the data and descriptive statistics. Section 5 outlines the econometric methodology. Section 6 presents the results and section 7 concludes the paper.

2 Setting the stage

High growth firms have recently moved onto the radar of policy makers and researchers. The interest in these firms is motivated by the fact that they are perceived as important drivers of economic dynamics and employment generation. The research on the economic importance of fast-growing firms grew out of the controversy regarding the contribution of small firms to job creation. While Birch (1979, 1981) claimed that SMEs contributed a disproportionately large share to overall job creation in the US, Davis, Haltiwanger, and Schuh (1996) challenged these results on the basis of methodological issues. During this discussion it has been observed that it is not the typical small firm that drives job creation among small firms. Job creation in small size classes is concentrated among a few high growth firms. Thus, the attention of some small business and entrepreneurship researchers has shifted towards these high growth firms. Henrekson and Johansson (2010) provide a survey of 19 studies that use a variety of methods to identify high growth firms. Despite differences in method and measurement, they find results that are remarkably robust to the definition of high growth firms, countries, time periods and coverage of firms (Henrekson and Johansson, 2010):

1. The few rapidly growing firms create the most new jobs within cohorts of firms of the same age.
2. In relation to aggregate numbers, such as total job growth in the economy, the results are less clear-cut. For some countries (e.g. US, UK), studies find that high growth firms are the central driver of overall job generation, while other studies (e.g. Sweden) find more moderate effects.
3. Although most rapidly growing firms are SMEs, there is also an important subset of large, high growth firms.
4. High growth firms tend to be younger than the average firm in the industry.
5. High growth firms exist in all industries. There is no evidence to support the view that gazelles are overrepresented in high-tech industries. If anywhere, high growth firms are overrepresented in knowledge-intensive service industries. (Almus, 2002; Henrekson and Johansson, 2010). This suggests that being a

high growth firm is primarily an economic and not a technological phenomenon (Hölzl, 2009).

Interestingly, not much is known about the persistence of high growth. In one of the few studies on the persistence of high growth firms Parker, Storey, and van Witteloostuijn (2010) find no evidence of persistence for a sample of UK high growth firms. In a strudy fo the US, Acs, Parsons, and Tracy (2008) show that the persistence of being a high growth firm is considerably smaller for small firms than for the few large firms. Thus, it is often claimed that being a high growth firm is a typically temporary phenomenon in the life of an enterprise (Hölzl, 2009). However, this conjecture is primarily based on empirical studies on firm growth. While some early studies focusing on samples of large firms found a positive autocorrelation in annual growth rates (Ijiri and Simon, 1967; Singh and Whittington, 1975), more recent work using more representative samples suggests that the autocorrelation of firm growth is rather small in magnitude (e.g. Dunne and Hughes 1994) or even negative (e.g. Goddard, Wilson, and Blandon 2002).

The economic empirical literature on firm growth is centered around the Law of Proportionate Effects (LPE), also known as Gibrat's Law, which holds that firm growth rates are independent of firm size. The empirical evidence suggests that Gibrat's law is often observed to fail because of a negative dependence of growth rates on size: smaller and younger firms have higher expected growth rates than older and larger firms (e.g. Mansfield 1962, Hall 1987, Hart and Oulton 1996, Lotti, Santarelli, and Vivarelli 2003, Coad 2009, Coad and Hölzl 2010). In addition the relationship between size and growth is modulated by the age of firms. Age exerts a negative effect on growth rates, but has a positive effect on the likelihood of survival (e.g. Evans 1987). In general, it has been suggested that a negative dependence of growth rates on size only holds for samples of small firms, while growth rates are independent of size for firms above a certain size threshold (e.g. Hart and Oulton 1996, Pfaffermayr 2007). Lotti, Santarelli, and Vivarelli (2009) show that Gibrat's law cannot be rejected once they account for the learning and selection processes of young, small firms. Studies using quantile regression indicate that the LPE is rejected in the tails of the distribution, especially for larger firms (e.g. Coad 2007a, Coad and Hölzl 2009, Reichstein, Dahl, Ebersberger, and Jensen 2010). Capasso, Cefis, and Sapio (2011) argue that this finding is due to the variance-size scaling in growth rates and suggest that the tails of the growth rate distribution may be more relevant for the applied researcher. The fact that the LPE holds at median or mean growth rates is related to the fact that the firms in the center of the growth rate distribution do not grow, independently of firm size.

3 Defining high growth and high impact firms

Before the publication of the Eurostat-OECD Manual on Business Demography Statistics (Eurostat-OECD, 2008) a large number of different methods were used to select high growth firms. For example, Autio, Arenius, and Wallenius (2000) and Halabisky, Dreessen, and Parsley (2006) defined high growth firms as firms obtaining at least 50 % sales growth during each of three consecutive financial years. Other studies used the Birch Index - a composite measure that takes into account relative and absolute growth - and a relative cut-off point, selecting the 5% or 10% of firms with the highest Birch index (e.g. Schreyer, 2000; Hölzl, 2009; Parker, Storey, and van Witteloostuijn, 2010).

In a recent study for Sweden, Daunfelt, Elert, and Johansson (2010) show that the selection of high growth firms using different growth measures is primarily driven by whether high growth is measured in terms of absolute or relative growth. Different growth measures, such as sales, employment or value added, are of minor importance in comparison. HGFs defined by relative growth tend to be younger and smaller than those which are fast-growing in absolute terms. This finding clearly reflects that measures of absolute (relative) growth are biased towards larger (smaller firms). To reduce the impact of firm size on the growth indicator, Birch (1987) and Schreyer (2000) used a combination of both the relative and absolute growth rates. This growth indicator, also known as the 'Birch index,' is defined as:

$$m = (E_{i,t} - E_{i,t-3}) \left(\frac{E_{i,t}}{E_{i,t-3}} \right)$$

where $E_{i,t}$ is the employment of firm i at time t and growth is measured over a three year period.

In this research we use two different definitions to select rapidly growing firms:

1. In order to select high growth firms (HGF) we use the Eurostat-OECD definition. HGFs are defined as firms that achieve a annualized growth rate of at least 20% over a three-year period and have a size of at least $E_{i,t-3} \geq 10$ at the beginning of that period. The growth requirement can be written as:

$$\left(\frac{E_t}{E_{t-3}} \right)^{\frac{1}{3}} - 1 \geq 0.2 \qquad \text{if } E_{t-3} > 10. \tag{1}$$

   The size requirement of $E_{i,t-3} \geq 10$ is used in order not to select too many very small firms that grow quickly but whose absolute contribution to growth is small.[1]

[1] It would not make any difference if we used a relative growth indicator other than arithmetic

2. In order to select high impact firms (HIF), we use a modified Birch Index. In order to compare the prevalence of HIF over time, a relative cut-off in percentage terms (e.g. the top 5% or 10%) is not useful. Therefore we modify the growth requirement so that it is equal to the requirement of a 20% annualized growth rate over three years at size $E_{i,t-3} = 20$ at the beginning of the period. Below 20 employees, the index will require a higher relative growth than the Eurostat-OECD definition and above 20 employees the relative growth requirement is relaxed. In addition we require $E_{i,t-3} > 10$ in order to avoid the selection of too many small firms. In more formal terms, after translating the growth requirement into the scale of the Birch index it can be written as:

$$(E_t - E_{t-3})\left(\frac{E_t}{E_{t-3}}\right) \geq 25.15968 \qquad \text{if } E_{t-3} > 8. \tag{2}$$

In the following we denote fast-growing firms selected using the Eurostat-OECD definition as "high growth firms" (HGFs) and firms selected using the modified Birch Index as "high impact firms" (HIFs).

Which firms will be selected as HGFs or HIFs? Figure 1 plots the minimum requirements to be an HGF or an HIF for absolute growth over a three-year period (left panel) and the relative annualized growth grate over a three-year period (right panel). The growth requirement is on the y-axis and firm size at the beginning of the period (E_{t-3}) on the x-axis. It is clearly seen that the growth requirement of the OECD-Eurostat definition preferably selects smaller firms if firm growth is not independent of firm size. On the other hand the relative growth requirement to be a high impact firm decreases with firm size and the absolute growth requirements sees only modest increases. Compared to the absolute growth requirement to be an HGF it is almost constant from size 100 onward.

4 Data and descriptive statistics

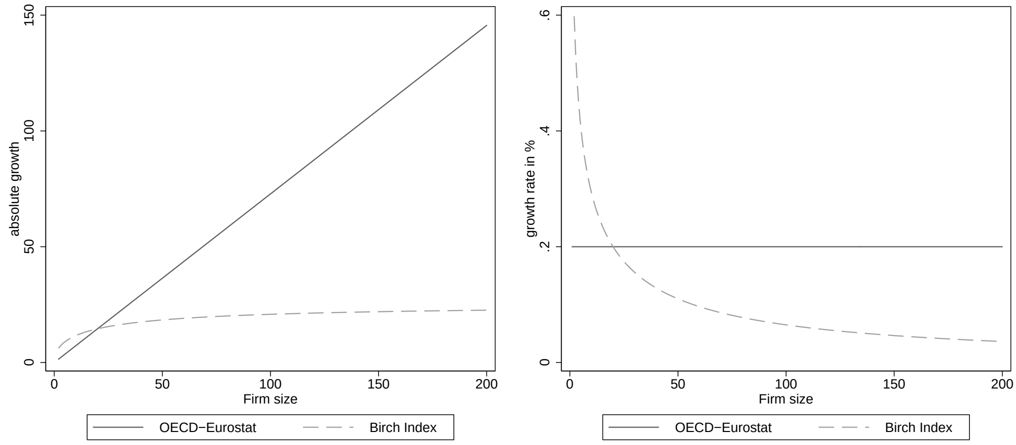
4.1 Data

The data we use to measure firm level employment stem from the Austrian Social Security files. They contain annual employment stocks for all private sector firms with at least one employee for the time period from 1972 to 2007.[2] In principle we

annualized growth. Independence of the unit of measurement is a central property of every indicator of relative change (Thornqvist, Vartia, and Vartia, 1985). Only if this property, which implies invariance to size, is violated (as with the Birch index or other indicators that give weight to absolute change) is a different set of firms selected as HGFs.

[2]See Winter-Ebmer (2003) Coad and Hölzl (2009) and Kaniovski and Peneder (2008) for papers using this data and Hofer and Winter-Ebmer (2003) for a data description.

Figure 1: Properties of the OECD-Eurostat definition and the Birch Index for selecting HGF and HIF



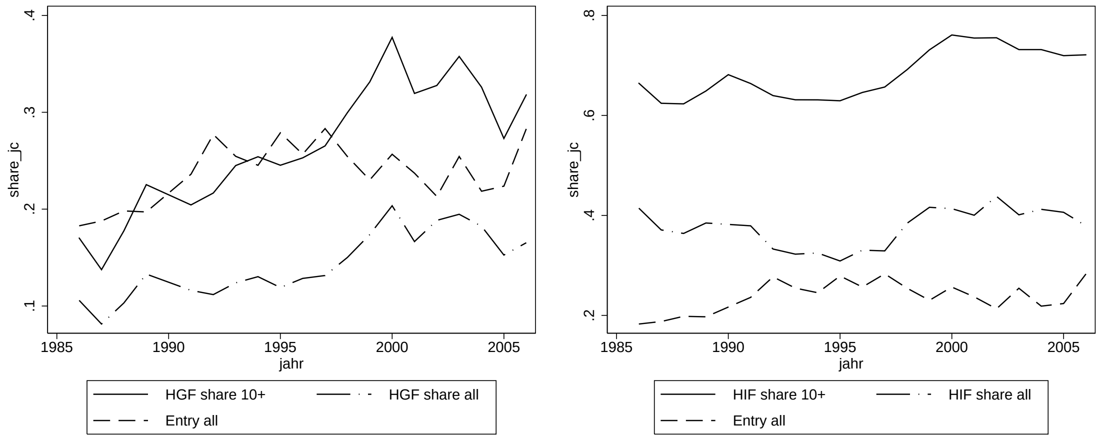
***Notes*:** Left: Absolute growth required to be a HGF or a HIF; right: Relative growth required to be a HGF or a HIF.

have information on all business units for the Austrian private sector starting from the size of one employee. However, we decided to drop sectors from our sample that are characterized by high seasonality (construction - NACE 45, hotels and restaurants - NACE 55) and are likely to follow different processes of firm growth (agriculture and mining - NACE smaller than 10, retail trade - NACE 52, all firms with NACE $\geq$ 75). The years up to 1985 were used to calculate growth rates. The time period 1985 to 1988 is the first for which we selected HGFs and HIFs. The age of the firm is only known if it entered the the dataset after 1972. Otherwise, age is censored.

This broad coverage, however, comes at the price of limited information on firms. We lack information on firms other than industry affiliation and region of operation (e.g. productivity, sales or profitability). Moreover, it is also not entirely clear whether the business units reporting are enterprises or establishments, as the anonymous firm numbers in the social security files identify administrative accounts. It is left to the discretion of the individual firm whether it chooses to report at the enterprise or establishment level (or a combination of both). Thus, this enterprise definition is not the same as that used in official statistics or commercial databases. Larger enterprises in particular typically consist of more than one business unit. However, Stiglbauer (2003) argues that the majority of the data are found at the level of the enterprise, since firms reduce their administrative burdens when reporting social security contributions. Due to the regional administrative nature of the database, firms operating in more than one Bundesland are required to use as many business units as Bundesländer where they are active. This is likely to bias the reported growth for large firms downwards and the growth indicator is clearly biased towards organic growth. Takeovers and mergers need not affect social security reporting. In this respect, it should also be noted that the definition of an enterprise is not just a practical problem. The legal definition of an enterprise does not have to be the economically relevant one (e.g. Cowling and Sudgen 1998; Pitelis and Teece 2009). Different research questions (internal capital markets, firm growth, enterprise networks, vertical integration) may necessitate different definitions of an enterprise.

To summarize, the data used in this research is not likely to be comparable to other research on the results for large firms. However, if the focus is on organic growth and not growth trough acquisition, then this dataset should provide appropriate evidence. In each case, the results should be understood as an approximation. Due to the robustness and the qualitative confirmation of stylised facts regarding the growth rate distributions, we are convinced that our results would change only quantitatively but not qualitatively if other data (e.g. enterprise register data) were used.

Figure 2: Relative job creation of High growth and high impact firms, 1985 - 2006



***Notes*:** High growth and high impact firms defined as in the text. HGF (HIF) share 10+ denotes the share of job creation of HGF (HIF) in the job creation of all firms with $E_{t-3} >= 10$. HGF (HIF) share all is share of job creation of HGF(HIF) in overall job creation. Entry all is the share of job creation due to new entrants between t and $t-3$.

4.2 Descriptive statistics

The descriptive statistics reported here are set up with reference to the sample used and are therefore not representative for the entire Austrian private sector. The fact that important segments have been excluded from consideration should be taken into account when interpreting the findings.

Figure 2 provides evidence on the economic importance of HGFs and HIFs by plotting the job creation of HGFs (right panel) and HIFs (left panel) from 1985 to 2006. The shares are measured in annual terms, covering a different set of firms in each year. While job creation is measured annually, the selection of HGFs and HIFs is based on three-year periods. This implies that some of the HGFs (HIFs) may not experience extensive job creation in a particular year.

The shares of the job creation of HGFs (HIFs) are expressed as shares in the population of all potential high growth firms ($E_{t-3} \geq 10$ - denotes as 10+) and in overall job creation. HIFs account for about 40% of the overall job creation and HGFs for less than 20%. The shares in the 10+ population are higher than the shares in overall job creation: HIFs account for more than 60% and HGFs for 15% to 35%. For reference, we also plot the annual share in overall job creation of entrants which is between 20% and 25%, on average. It is higher than the job creation of HGFs, but lower than the job creation of HIFs.[3]

4.2.1 Growth rates, size and age distributions

Table 1 reports the distribution of job creation and share of firms for firms with positive growth rates. Job creation is defined following the labour market literature as the employment generation of expanding firms.[4] The growth requirement to be a HGF is $g \geq 0.2$. Thus, all HGFs are located in one growth class. HIFs are distributed across different growth classes. A HIF needs not be a HGF. Only a subset of 35% to 50% of HIFs are also HGFs. These firms account for approximately 30% to 50 % of job creation of HIFs. Among the HIFs a number of firms has medium growth rates. These are larger firms that report modest relative growth rates but large absolute changes in employment.

Figure 3 reports the log size distribution at time $t-3$ for all firms in the reference population (firms with more than 5 employees at the beginning and the end of the three-year period)[5], HGFs, and HIFs for the years 1988, 1994 and 2000. The kernel density estimates for the different years show that the firm size distributions are quite stable over time. The size distribution of HGFs seems to be similar to the size

[3]If job creation is measured over a three-year period, the share of entrants increases to 40% to 50%, as the job creation of three-year-old firms would then also be classified as job creation of entrants.

[4]The overall firm growth distribution follows the tent-shaped form (e.g. Bottazzi and Secchi 2003, Dosi 2007).

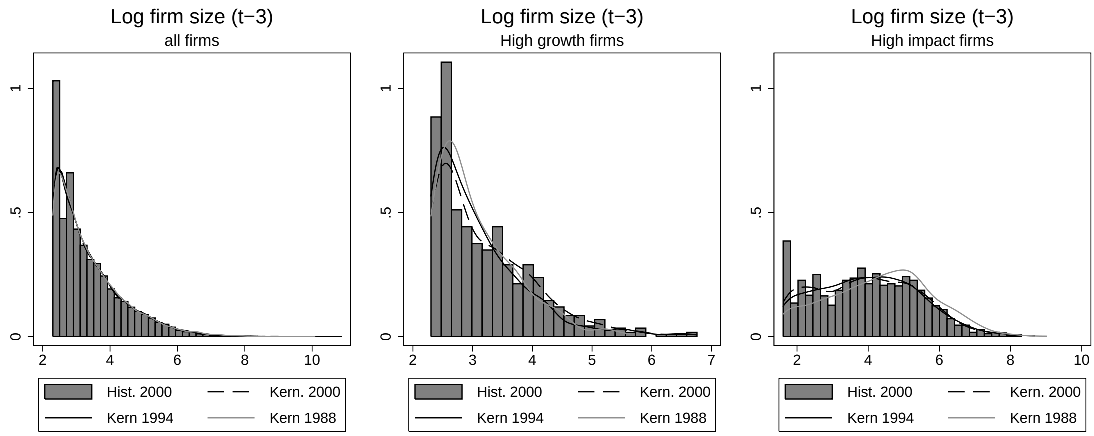
[5]This censoring is motivated by the fact that at a size of 5 employees it is possible to correct for purely administrative exits and re-entries.

Table 1: Growth rate distribution ($g >= -0.01$) for HIF and HGF

		$-0.01 > g < 0.01$	$0.01 \geq g < 0.05$	$0.05 \geq g < 0.1$	$0.1 \geq g < 0.15$	$0.15 \geq g < 0.2$	$0.2 \geq g$
				1988			
HGF	Job creation	-	-	-	-	-	1.00
	Firms	-	-	-	-	-	1.00
HIF	Job creation	0.00	0.17	0.26	0.18	0.08	0.31
	Firms	0.00	0.16	0.23	0.17	0.08	0.35
all +5	Job creation	0.01	0.23	0.29	0.18	0.08	0.21
	Firms	0.32	0.26	0.22	0.11	0.04	0.05
				1994			
HGF	Job creation	-	-	-	-	-	1.00
	Firms	-	-	-	-	-	1.00
HIF	Job creation	0.00	0.12	0.18	0.15	0.13	0.42
	Firms	0.00	0.10	0.17	0.16	0.12	0.45
all +5	Job creation	0.01	0.19	0.23	0.17	0.12	0.28
	Firms	0.31	0.24	0.22	0.11	0.05	0.06
				2000			
HGF	Job creation	-	-	-	-	-	1.00
	Firms	-	-	-	-	-	1.00
HIF	Job creation	0.00	0.07	0.17	0.14	0.10	0.52
	Firms	0.00	0.09	0.18	0.13	0.10	0.50
all +5	Job creation	0.00	0.13	0.21	0.16	0.10	0.40
	Firms	0.30	0.23	0.21	0.13	0.05	0.09

***Notes*:** HIF are high impact firms (Birch Index), HGF are high growth firms (OECD-Eurostat), all +5 denotes all firms with more than 5 employees at t and $t-3$ in the sample

Figure 3: Log size distributions 1988, 1994 and 2000



***Notes*:** Kernel density estimates using the Gaussian kernel with bandwidth suggested by the heuristic by Silverman (1986) and implemented in Stata.

distribution of the overall population of firms at first sight but a closer look reveals that HGFs are in general younger firms. The size distribution of HIFs is different.

Table 2 displays the age distribution for the reference population, HGF and HIF for the years 1988, 1994 and 2000. While the distribution of job creation of age by HIFs is quite similar to the job creation by age in the reference population, the average HIF is younger than the average firm in the reference group. The average HGF is considerably younger than both the average HIF and the average firm in the reference population.

Overall the evidence shows that HGFs are on average younger and smaller than HIFs and the overall population of firms, and that HIFs are on average larger than the non-HIFs and HGFs but also younger than non-HIFs.

Table 2: Age distributions for HIF and HGF

		HIF			HGF			all +5	
age	0-3	4-10	11+	0-3	4-10	11+	0-3	4-10	11+
		1988			1988			1988	
job creation	0.11	0.20	0.69	0.24	0.27	0.49	0.11	0.21	0.68
firms	0.18	0.21	0.61	0.31	0.31	0.38	0.09	0.19	0.72
		1994			1994			1994	
job creation	0.20	0.18	0.61	0.33	0.20	0.47	0.19	0.19	0.62
firms	0.24	0.20	0.56	0.35	0.25	0.40	0.13	0.18	0.69
		2000			2000			2000	
job creation	0.22	0.25	0.53	0.28	0.38	0.34	0.20	0.26	0.54
firms	0.27	0.23	0.50	0.34	0.30	0.36	0.12	0.22	0.66

***Notes*:** HIF are high impact firms (Birch Index), HGF are high growth firms (OECD-Eurostat), all +5 denotes all firms with more than 5 employees at t and $t-3$ in the sample

4.3 Transition matrices

In oder have a first look at the questions outlined in the introduction we study transition matrices with three different states: (1) the firm is a HGF (HIF), (2) the firm is a surviving firm or a new entry at time $t-1$ or $t-3$, and (3) the firm closed down (exit).

Table 3 presents the transition matrices. The left panels are for HGF and right panels for HIF for different time scales (one or three year transitions) and definitions of population (all firms that existed at time t and $t-\tau$ or firms with more than 10 employees at time $t-\tau$ with $\tau = \{1, 3\}$. The results clearly show that:

1. The probability of being an HGF or an HIF is quite small. In panel a) the probability of a surviving firm becoming an HGF is 0.3% and panel b) shows that the probability becoming anh HIF is only slightly higher (0.5%). On a three-year scale (panels c and d) this probability is only slightly higher (0.5%

Table 3: Transition matrices: all firms

a) HGF all firms - 1 year

	exit	surv.	HGF
exit	1,000	0,000	0,000
surv.	0,094	0,903	0,003
HGF	0,024	0,541	0,434

b) HIF all firms - 1 year

	exit	surv.	HIF
exit	1,000	0,000	0,000
surv.	0,094	0,901	0,005
HIF	0,015	0,370	0,616

c) HGF all firms - 3 years

	exit	surv.	HGF
exit	1,000	0,000	0,000
surv.	0,217	0,778	0,005
HGF	0,092	0,832	0,076

d) HIF all firms - 3 years

	exit	surv.	HIF
exit	1,000	0,000	0,000
surv.	0,218	0,774	0,008
HIF	0,065	0,648	0,287

e) HGF $\geq$ 10 - 3 years

	exit	surv.	HGF
exit	1,000	0,000	0,000
surv.	0,087	0,885	0,029
HGF	0,092	0,832	0,076

f) HIF $\geq$ 10 - 3 years

	exit	surv.	HIF
exit	1,000	0,000	0,000
surv.	0,088	0,860	0,052
HIF	0,065	0,648	0,287

***Notes*:** Transition matrices are calculated using frequencies; exit denotes the fact that the firm discharged the last employee and does not re-enter; surv. denotes all firms that neither exited nor were HGF(HIF). All firms denotes all firms (controlled for re-entries), $\geq$ 10 denotes firms that only at least 10 employees at the beginning of the period were considered.

for HGF and 0.8% for HIF). Only if we restrict our attention to firms with at least 10 employees (panels e and f) does the probability increase to 2.9% for becoming a HGF and 5.2% for becoming a HIF.

2. The persistence of being an HGF (HIF) is much higher for HIFs than for HGFs. In the very short run (panels a and b) 43.4% of HGFs and 62,6% of HIFs can retain this status. Over a three-year period (panels c and d), the probability declines to 7.6% for HGFs and 28,7% for HIFs.

3. The probability of an exit is higher for HGFs than for HIFs. Panels a and b show that HGFs have a 2.4% probability of exit and HIFs a 1.5% probability of exit after one year. After three years this probability increases to 9.2% for HGFs and to 6.5% for HIFs.

Table 4.3 presents transition matrices for young (up to 3 years old at $t-3$), old (older than 10 years at $t-3$), small (10 to 49 employees at $t-3$) and large firms (more than 249 employees at $t-3$). The results show that there are significant differences between young and old firms (panels a to d). For surviving firms as well as HGFs and HIFs the probability of exit declines with firm age. With regard to the persistence of being an HGF or HIF. the results show that younger firms are much more likely to achieve the status of being an HGF than older firms. The likelihood of becoming a HIF also decreases with age, but the probability of remaining an HIF

Table 4: Transition matrices: young vs. old and small vs. large

a) HGF ≥ 10; young; 3 years

	exit	surv.	HGF
exit	1.000	0.000	0.000
surv.	0.175	0.738	0.087
HGF	0.123	0.779	0.098

b) HIF ≥ 10; young; 3 years

	exit	surv.	HIF
exit	1.000	0.000	0.000
surv.	0.176	0.711	0.114
HIF	0.109	0.616	0.274

c) HGFs ≥ 10; old; 3 years

	exit	surv.	HGF
exit	1,000	0,000	0,000
surv.	0,065	0,921	0,014
HGF	0,068	0,879	0,053

d) HIF ≥ 10; old; 3 years

	exit	surv.	HIF
exit	1,000	0,000	0,000
surv.	0,067	0,895	0,038
HIF	0,045	0,664	0,292

e) HGF ≥ 10; small 3 years

	exit	surv.	HGF
exit	1,000	0,000	0,000
surv.	0,093	0,876	0,032
HGF	0,102	0,818	0,080

f) HIF ≥ 10; small; 3 years

	exit	surv.	HIF
exit	1,000	0,000	0,000
surv.	0,093	0,875	0,033
HIF	0,101	0,749	0,150

g) HGF ≥ 10; large, 3 years

	exit	surv.	HGF
exit	1,000	0,000	0,000
surv.	0,045	0,946	0,009
HGF	0,070	0,880	0,050

h) HIF ≥ 10; large; 3 years

	exit	surv.	HIF
exit	1,000	0,000	0,000
surv.	0,052	0,738	0,211
HIF	0,038	0,557	0,406

Notes: Transition matrices are calculated using frequencies; exit denotes the fact that the firm discharged the last employee and does not re-enter; surv. denotes all firms that neither exited nor were HGF(HIF). young denotes young firms (up to 3 years old at $t-3$), old denotes old firms (older than 10 years at $t-3$), small denotes small firms (10 to 49 employees at $t-3$) and large denotes large firms (more than 249 employees at $t-3$. ≥ 10 denotes firms that only at least 10 employees at the beginning of the period were considered.

is almost the same for young and old firms. With regard to firm size we observe similar patterns. Older firms have a lower probability of exit than younger firms but also a lower probability of becoming an HGF. However, the probability of becoming an HIF increases with firm size. While small non-HIFs have a probability of 3.3% of becoming an HIF, the probability is 21.1% for large firms. Large firms also have a higher persistence of the HIF status than smaller firms (40.6% compared to 15%). This clearly shows the bias of the HIF definition towards selecting large firms, while the likelihood of selecting small firms is approximately the same for the HIF and HGF definition.

Approximately 40 to 50% of the firms selected as HGFs in the base year are HGFs only once. This is a surprisingly low value given that being a HGF is calculated on the basis of a three-year period. This suggests very low persistence over time. Among the HIFs, only 25% of the firms selected find themselves in the state of being an HIF only once. The transition matrices show that the proportional growth requirement of being an HGF makes it successively more difficult to repeat high growth. This suggests that the use of the OECD-Eurostat measure makes the selection of new, small firms easier. In contrast, the absolute growth requirement makes it easier for larger firms to display persistence in the status of being an HIF.

5 Econometric methodology

The transition matrices provided a first look at the answers to the research questions outlined in the introduction:

- Are high growth firms are more likely to be high growth firms at some future point in time compared to non-high growth firms?
- Is the average future growth performance of high growth firms higher compared to non-high growth firms?
- Are high growth firms less likely to exit from the market than non-high growth firms at some future point intime?

The finding that HGF, HIF and the reference population have different characteristics with regard to their age and size distributions makes the study of these three research questions tricky to answer. The problem arises from the fact that being an HGF (HIF) can be considered a treatment effect. If selection into the group of HGFs or HIFs depends on size and age and the control group is randomly selected from the non-HGFs (HIFs), then the estimation of the treatment effect is likely to be biased. The question is closely related to the question of determination of the relevant population (control group) to which the performance of HGFs (HIFs) should be compared. The fact that firm age and firm size are important determinants of firm growth suggests that differences in the age and size distribution of HGFs (HIFs) and the control group will affect the estimation of the "treatment effect" of being a HGFs (HIFs). Thus, a more meaningful population of comparison are firms that are similar in size and age to HGFs (HIFs).

5.1 Matching as preprocessing

Matching refers to a broad range of techniques used to match treatment and control individuals for causal interference in order to be able to estimate treatment effects without bias (e.g. see Heckman, Ichimura, and Todd 1998, Rubin 2006). The basic idea is to replicate the conditions of randomized experiments with observational data. This requires breaking the link between the treatment (in our case, being an HGF or an HIF) and a set of characteristics of the firms denoted by X. In randomized experiments, randomization breaks the link - in observational studies matching can be used to find "statistical twins".

For a causal interpretation a number of conditions are required to hold. The first condition is the stable unit-treatment value assumption (SUTVA) that requires the state of being an HGF (HIF) to be independent of the treatment participation of other firms. This implies that there should be only minor feedback effects due to the interaction between the firms. In a market context this is not entirely plausible. If more efficient firms grow faster than less efficient firms, this requirement is violated. However, there is some evidence that firm growth is only weakly related to firm performance such as productivity or profitability, even within sectors (e.g. Coad 2007b; Bottazzi, Dosi, Jacoby, Secchi, and Tamagni 2010). This suggests that interaction effects are likely to present a minor problem. A second problem is self-selection into treatment. The decision to grow fast is a decision made by the owner/manager of the firm and as we have seen from the descriptive statistics influenced by the size and the age of a firm. Thus, being an HGF (HIF) is likely affected by firm characteristics.

Matching is one of the methods used to establish the SUTVA condition and to make the treatment variable exogenous to covariates. Matching as causal method requires additional assumptions in order to identify the causal effect: the conditional independence assumption (CIA) and the common support condition (CSC). The CIA requires, that the potential outcomes and the assignment to treatment are independent, conditional on the covariates. This allows the the construction of counterfactual means. The CSC requires that for each observation there is a positive probability of belonging to the treatment and to the control group, conditional on the same covariates. Thus, CSC ensures that the construction of the control group is well-defined. These assumptions are very strong, as they require that selection is based only on observables and that all relevant variables that affect the assignment to a treatment and outcomes are observed by the researcher.

Having only information on firm age and firm size makes it impossible to fulfill the CIA assumption in any strong capacity. We do not have enough relevant information to come close to reasonably assuming to have all variables that affect the assignment of a firm to the treatment of being a HGF or HIF. Therefore our analysis cannot be seen as making very strong causal statements about differences between HGFs (HIFs) and non-HGFs (non-HIFs). However, the construction of a matched control group makes it possible to answer the question whether HGFs (HIFs) are different from firms that are similar in size and age.

Firm size and firm age have been identified as the most important determinants of firm growth. Other variables that would be observable in other datasets, such as productivity, R&D or profits, may turn out to be statistically significant in growth regressions, but they do not explain much of the variation in firm growth (Coad, 2009).[6] This makes random growth models (e.g. Gibrat's Law or modifications that account for size and age effects) attractive tools for empirical and theoretical research and suggests that some kind of randomization is at work, which may be of help in the identification of average treatment effects, provided the dataset is large.

We use matching in the spirit of Ho, Imai, King, and Stuart (2007) as nonparametric preprocessing of the data. In order to avoid the comparison of apples to oranges (i.e. populations of young and small firms with population of old and large firms), we adjust the data before performing our parametric analysis in such a way that the relationship between the treatment and important covariates is substantially reduced and little bias and inefficiency is induced. The requirement is that the sample of HGFs (HIFs) and the associated control groups have the same background characteristics, so that the following holds for the observed empirical density $D(.)$ and background characteristics X (Ho, Imai, King, and Stuart, 2007):

$$D(X|HGF = 1) = D(X|HGF = 0),$$

and equivalently for HIFs. Thus, the matched dataset is a dataset where unmatched control units and treatment units for which no match has been found are eliminated from the sample. The view of nonparametric preprocessing is that matching is not a method of analysis but a method of preparation of the data to improve the similarity of treatment and control covariate distribution without loosing too many observations. This helps us to obtain more accurate causal estimates by reducing bias and variance. We use the Mahalanobis distance in order to compare the similarity of treatment and non-treatment observations. It is defined as

$$M = \sqrt{(x_{nt} - x_t)' S^{-1} (x_{nt} - x_t)}$$

where x_{nt} is a vector of covariates of a non-treatment firm, x_t a vector of covariates of a treatment firm (HGF or HIF) and S is the covariance matrix.[7]

5.2 The matching protocol

We implement the matching for the years 1988, 1991, 1994, 1997, 2000 and 2003. The whole dataset spans the period from 1985 to 2006. The three-year distances are motivated by the fact that the HGF (HIF) definition is based on a three-year

[6] The limited success achieved in identifying the determinants of growth may reflect difficulties in generalizing across firms and the complexity of the task of managing a firm. The evidence on the 'within' and 'between' variation of firm growth suggests that more than half of the variation of firm growth is within individual firms over time (Geroski and Gugler, 2004).

[7] The use of propensity score matching based on predicted probabilities to form a classification regression was not satisfactory. The explanatory power of the probit was low and the matching did not lead to a satisfactory balance of the distributions of treated and non-treated firms.

period. In order to avoid the possible duplication of observations and to reduce computational cost, we selected every third year. For each of the years, the following matching protocol was implemented:

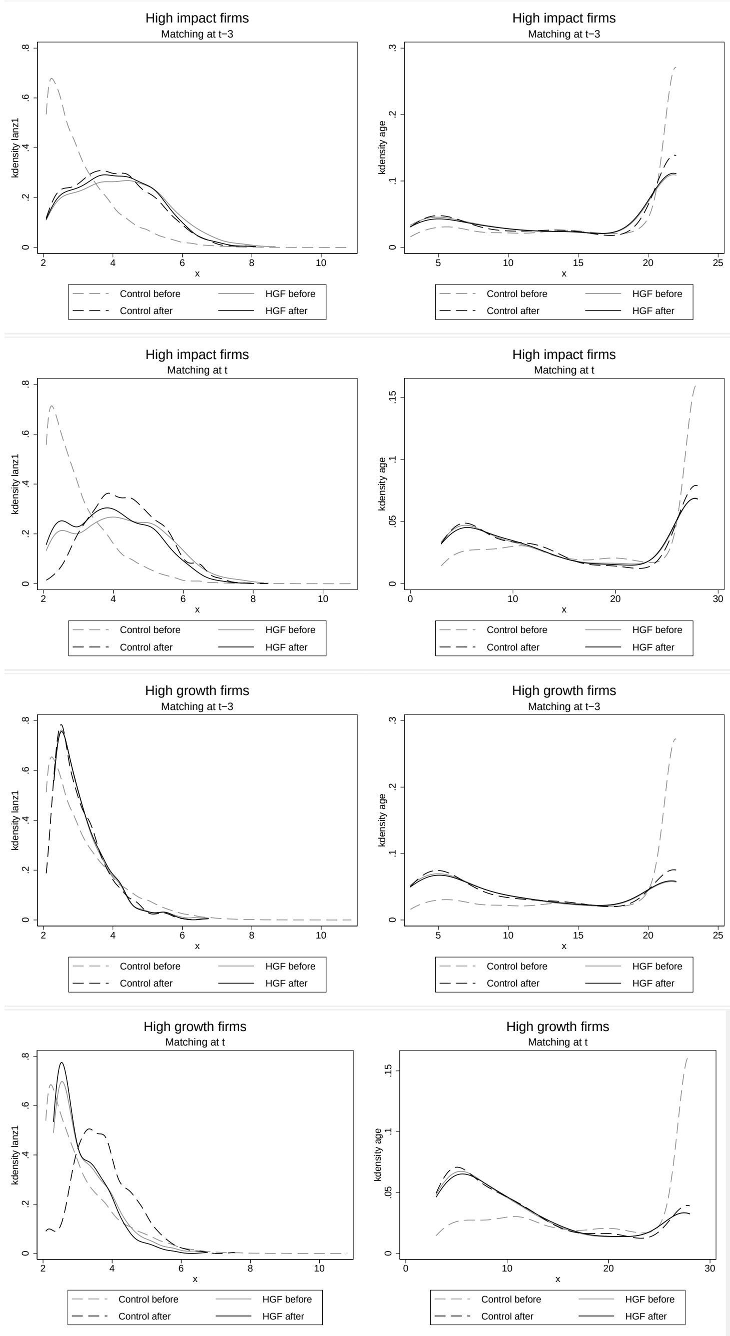
1. Identify the HGFs and HIFs.
2. Select firms in the control group based the following covariates: log firm size, log firm size squared, firm age, NACE 3-digit. In addition we impose exact matching on NACE two-digit industries by dividing the population into subgroups.
3. Perform the matching for HGFs (HIFs) twice in order to get a control group for firms that had the same size at the begin of the HGF (HIF) selection period (E_{t-3}) and a second control group for firms that had the same size at the end of the HGF (HIF) selection period (E_t). This allows allows us to study whether the effect of being a HGF (HIF) is reducible to the effect of increased size, or whether HGFs (HIFs) are in fact in an unobservable way different from non-HGFs (non-HIFs). For each HGF (HIF) we select up to four firms in the control group (non- HGFs (non-HIFs)) using the Mahalanobis distance as measure of similarity. In addition, we imposed a caliper of 1.3 on the distance in order to ensure that we select similar firms. For some HGFs no matches or fewer than four firms were selected. Each match from the control group was assigned a weight according to the number matches.

We assess the achieved balance $D(X|HGF = 1) = D(X|HGF = 0)$ by using kernel density regressions and elementary tests of common support. Figure 4 shows the differences in the distribution of the covariates between HGFs and HIFs and the control group before and after matching, respectively. The figures show the effect of the elimination of observations where no match could be found. The distributions of age and log size become more similar by applying the matching protocol. Mean tests for common support (table 11 in the appendix) show that matching leads to a substantial reduction of bias and that the balance is much better for age than for firm size.

5.3 Parametric Analysis

Following Ho, Imai, King, and Stuart (2007), we use the matched samples to perform parametric regression analysis. In our case, the use of a parametric model is justified on methodological grounds. We want to study the performance of HGFs (HIFs) 3, 6 and 9 years after they were identified as such. This naturally suggests the use of a parametric regression model instead of a mean test to control for additional covariates. Ho, Imai, King, and Stuart (2007) assert that using parametric methods

Figure 4: Differences in the distribution of covariates before and after matching, 1994 and 2000



***Notes*:** Kernel densities for log size and age before and after matching. The kernel is Gaussian with the bandwidth suggested by Silverman (1986) and implemented in Stata. The upper four graphs display matching for HIF. The lower four graphs matching for HGF. $t-3$ and t refers to firm size at begin or the end of the period. Columns 1 and 3 display results for 1994, columns 2 and 4 for 2000.

in the second stage instead of testing the difference in means provides an opportunity to eliminate remaining bias. In our case, the evidence from mean tests for common support suggests that there is still potential for correcting the bias for firm size, especially for the matched samples with firm size measured at time $t-3$. Our parametric model for studying the likelihood of survival, the persistence of being a HGF (HIF) and the growth performance after 3, 6 and 9 years is:

$$y_{i,t+\tau} = \alpha + \beta_1 T_{i,t} + \beta_2 X_{i,t*} + \beta_3 X_{j,t} + \beta_4 X_{j,t+\tau}, \tag{3}$$

where $y_{i,t}$ is an outcome variable at time $t + tau$ for firm i. τ refers to time after selection into the HGF (HIF) group, $\tau = \{3, 6, 9\}$. $T_{i,t*}$ is the treatment (HGF or HIF) at time t. $X_{i,t*}$ are firm specific covariates at time $t*$. $t*$ is equal to t for the matched sample based on the end period and equal to $t-3$ for the matched sample based on the begin period. $X_{j,t}$ are industry-specific covariates for industry j at time t and $X_{j,t+\tau}$ are industry-specific covariates for industry j at time $t+\tau$. β_1 is the treatment effect to be estimated, and α, β_2 and β_3 and β_4 are coefficients to be estimated.

The covariates used in the parametric stage are:

1. Firm age at the time when the firm was selected as an HGF (HIF) or placed into the respective control group.
2. Firm size at the time when the firm was selected as an HGF (HIF) or placed into the respective control group.
3. Industry size in employment at time t.
4. Average industry growth from time t to time $t+\tau$ in order to control for the effect of industry growth on survival, persistence and firm growth.
5. The average of the excess job creation rate in the industry from time t to time $t+\tau$. The excess job creation rate is defined as

   $$XJCR_t = \frac{JC_t + JD_t - |JC_t - JD_t|}{0.5 * (E_t + E_{t-1})},$$

   where JC_t is job creation and JD_t is job destruction during time t and $t-1$. This indicator captures two interrelated effects. It captures volatility at the firm level and excessive turnover of employment that is not related to growth or decline the of jobs in the industry. This connects nicely to exit and sunk costs, which play a central role in the theory and empirics of industrial dynamics, firm growth and entry and exit (see e.g. Sutton 1998; Cabral 1995; Hölzl 2005). Contestable markets should be characterized by higher volatility and lower firm size. When exit costs are associated with intangible capital there should be less turnover in employment and more opportunities for sustained growth. Efficient firm size depends on the exploitation of tangible and intangible assets, which are associated with exit costs. Higher exit or sunk costs should therefore decrease the amount of volatile growth and increase growth opportunities. The expected sign is negative.

6 Results

6.1 Survival

The first question we tackle is whether being a HGF or HIF indeed increases the probability of survival. We construct the dependent variable by recording whether the firm survived the next 3, 6 or 9 years. We code survival as 1 and exit as 0. Thus our dependent variable is binary. As we are only interested in mean effects, we follow the suggestion of Angrist and Pischke (2008) and estimate a linear probability model (LPM) instead of a nonlinear probit or logit model. Angrist and Pischke (2008) argue that if one is interested in the mean effect $E(Y = 1|X)$ and not the whole distribution then the LPM with robust standard errors is an appropriate choice. They show that in several empirical applications, there is little difference between the marginal effects estimated with limited dependent variable models and linear probability models. Probit and logit estimates would require the computation of marginal effects at the mean.[8]

Table 5 reports the results for HGFs and HIFs. We report the estimates based on the unmatched sample (denoted by all) and the matched samples. The results for the treatment effect show striking differences for the matched and unmatched samples. For HGFs the treatment effect is insignificant in the unmatched sample for begin size, and statistically significant and negative for end size. Using the matched samples, the effect of being an HFG is significant and positive for begin size, while it is insignificant for end size. This strongly suggests that the higher survival probability using the matched sample (approx. 1.5% higher after three years and around 3% after 6 and 9 years) for begin size is entirely due to the larger size acquired during the HGF period. We will call this effect the "effect of increased size" in order to distinguish it from the true treatment effect. Consistently with the stylised facts on firm survival (e.g Dosi 2007), firm age and firm size increase the likelihood of survival. Industry growth and industry size are not important determinants for survival in the matched HGF sample. A higher excess job reallocation rate (XJCR) decreases the likelihood of survival in the matched sample for τ =6, 9. This confirms the interpretation of

[8]Casual comparisons between marginal effects at the mean from a probit regression and the results from the LPM showed that there is no qualitative difference in the interpretation of the results. For the two-part model used to study growth we use a probit model.

the excess job reallocation rate (XJCR) as an(inverse) indicator of mobility costs. Survival is higher in industries with high sunk costs or mobility barriers.

For HIFs we observe that being an HIF increases the likelihood of survival for HIFs using both the unmatched and matched sample for begin size. For end size we only observe a statistically significant positive effect for $\tau = 6, 9$. The effect of increased size accounts for approximately 50% of the effect measured using begin size for $\tau = 9$. The effect of increased size is even larger for $\tau = 3, 6$. similarly to what we observe in the HGF regressions, firm age and firm size are important determinants affecting survival. Larger and older firms have a higher probability of survival. Industry growth only increases survival in the short term ($\tau = 3$). Industry size is not a significant influence. For the excess job creation rate (XJCR) we observe a statistically significant negative sign for $\tau = 6, 9$.

The comparison of intercepts clearly indicates that HIFs have a much higher survival baseline than HGFs. This is related to the fact that HIFs are on average larger and older than HGFs. The survival baseline declines with time.

6.2 Persistence

Let us next consider the persistence of being a HGF (HIF). We construct the dependent variable by recording whether a firm was an HGF (HIF) during the following $\tau = 3, 6, 9$ years. When we find that a firm has again been an HGF (HIF), we code this as 1 and 0 otherwise. Thus, our dependent variable is again binary and we use the same estimation method as before.

Table 6 presents the regression results. The difference to the non-matched regressions is much less striking than in the case of survival regressions. therefore, we only report the results for the matched samples. The results for HGFs show that the likelihood of repeating the high growth event 3, 6 or 9 years after having been an HGF cannot be explained by the effect of increased size alone. More than 50% of the increased likelihood of repeating the growth event is due to a pure HGF treatment effect for $\tau = 6, 9$. For $\tau = 3$, we find that being an HGF leads to a 5% higher probability of once again becoming an HGF, and that this is almost exclusively due to the HGF treatment effect. As expected from the firm growth literature (e.g. Coad and Hölzl 2010), firm age has a negative sign. Younger firms are more likely to repeat the high growth event. In contrast to the firm growth literature, the sign on firm age is not negative and significant. For $\tau = 9$ it is even positive and significant, implying that larger firms have a higher probability of being an HGF after 9 years. This is most likely due to the increased survival probability of larger firms. Industry growth has a positive effect on the likelihood of being an HGF after 3, 6 or 9 years. The excess job reallocation (XJCR) that proxies mobility and exit barriers only comes into play for $\tau = 9$ with the expected negative sign. Industry size does not affect the

Table 5: HGF and HIF survival after 3,6 and 9 years

	High growth firms (HGF)						High impact firms (HIF)					
tau	3 all	3 match	6 all	6 match	9 all	9 match	3 all	3 match	6 all	6 match	9 all	9 match
	a) firm size measured at the beginning of the period						a) firm size measured at the beginning of the period					
HGF	-0.0097	0.0159^b	-0.0148	0.0310^a	-0.0179	0.0324^b	0.0127^a	0.0228^a	0.0262^a	0.0449^a	0.0431^a	0.0638^a
	(0.006)	(0.006)	(0.009)	(0.010)	(0.014)	(0.014)	(0.004)	(0.004)	(0.006)	(0.006)	(0.009)	(0.009)
age	0.0016^a	0.0025^a	0.0019^a	0.0028^a	0.0022^a	0.0052^a	0.0017^a	0.0021^a	0.0020^a	0.0026^a	0.0024^a	0.0056^a
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
ln (E_{t-3})	0.0051^a	0.0159^a	0.0115^a	0.0116	0.0187^a	0.0190	0.0043^a	0.0155^a	0.0098^a	0.0266^a	0.0162^a	0.0363^a
	(0.001)	(0.004)	(0.001)	(0.007)	(0.002)	(0.010)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.004)
Ind. Growth	0.2924^a	0.0173	0.3048^a	-0.2827^b	0.4494^a	-0.0449	0.2880^a	0.1124^b	0.2932^a	-0.1132	0.4335^a	0.2218
	(0.024)	(0.083)	(0.045)	(0.144)	(0.065)	(0.208)	(0.024)	(0.055)	(0.045)	(0.100)	(0.065)	(0.146)
XJCR	0.0223	0.1531	-0.5479^a	-0.8383^a	-1.3082^a	-1.6926^a	0.0262	0.0383	-0.5411^a	-0.4218^a	-1.2938^a	-1.0107^a
	(0.030)	(0.110)	(0.060)	(0.211)	(0.100)	(0.358)	(0.030)	(0.070)	(0.060)	(0.131)	(0.100)	(0.213)
Ind. Size	0.0573^a	0.1328^b	0.0425	-0.0675	0.0844^b	0.0557	0.0570^a	0.0471	0.0411	0.0520	0.0780^b	0.1574^b
	(0.016)	(0.057)	(0.025)	(0.085)	(0.039)	(0.115)	(0.016)	(0.028)	(0.025)	(0.044)	(0.039)	(0.061)
Constant	0.8787^a	0.7993^a	0.8162^a	0.8003^a	0.7734^a	0.7352^a	0.8791^a	0.8174^a	0.8173^a	0.7116^a	0.7746^a	0.6020^a
	(0.004)	(0.018)	(0.008)	(0.030)	(0.012)	(0.045)	(0.004)	(0.010)	(0.008)	(0.017)	(0.012)	(0.025)
Obs.	102,254	9,254	79,196	6,871	54,114	4,092	102,254	17,437	79,196	13,490	54,114	8,608
r^2	0.003	0.008	0.005	0.009	0.008	0.0172	0.003	0.015	0.005	0.022	0.009	0.039
	b) firm size measured at the end of the period						b) firm size measured at the end of the period					
HGF	-0.0239^a	-0.0047	-0.0384^a	0.0072	-0.0482^a	0.0001	-0.0091^b	0.0024	-0.0070	0.0188^a	0.0034	0.0300^a
	(0.006)	(0.006)	(0.009)	(0.010)	(0.014)	(0.015)	(0.004)	(0.004)	(0.006)	(0.007)	(0.009)	(0.010)
age	0.0015^a	0.0025^a	0.0018^a	0.0022^a	0.0021^a	0.0055^a	0.0015^a	0.0021^a	0.0018^a	0.0024^a	0.0022^a	0.0059^a
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
ln (E_t)	0.0144^a	0.0190^a	0.0248^a	0.0160^b	0.0340^a	0.0402^a	0.0146^a	0.0212^a	0.0247^a	0.0340^a	0.0330^a	0.0492^a
	(0.001)	(0.004)	(0.001)	(0.007)	(0.002)	(0.011)	(0.001)	(0.003)	(0.001)	(0.004)	(0.002)	(0.006)
Ind. Growth	0.3087^a	0.0735	0.3154^a	-0.1614	0.4596^a	0.2075	0.3084^a	0.1779^a	0.3093^a	-0.0442	0.4499^a	0.2091
	(0.024)	(0.084)	(0.045)	(0.149)	(0.065)	(0.216)	(0.024)	(0.058)	(0.045)	(0.108)	(0.065)	(0.159)
XJCR	0.0271	0.1017	-0.5114^a	-0.7535^a	-1.2486^a	-1.5499^a	0.0276	0.0406	-0.5103^a	-0.2790^b	-1.2462^a	-0.8509^a
	(0.030)	(0.110)	(0.060)	(0.218)	(0.100)	(0.371)	(0.030)	(0.071)	(0.060)	(0.140)	(0.100)	(0.223)
Ind. Size	0.0217	0.0116	-0.0101	-0.0040	0.0084	0.0561	0.0225	0.0071	-0.0089	0.0363	0.0096	0.1123
	(0.016)	(0.057)	(0.025)	(0.086)	(0.039)	(0.119)	(0.016)	(0.028)	(0.025)	(0.046)	(0.039)	(0.063)
Constant	0.8535^a	0.8054^a	0.7772^a	0.7935^a	0.7274^a	0.6546^a	0.8521^a	0.8046^a	0.7760^a	0.6789^a	0.7274^a	0.5421^a
	(0.004)	(0.020)	(0.008)	(0.034)	(0.012)	(0.053)	(0.004)	(0.013)	(0.008)	(0.022)	(0.012)	(0.031)
Obs.	102,254	8,203	79,196	6,137	54,114	3,680	102,254	14,419	79,196	11,227	54,114	7,258
r^2	0.006	0.007	0.009	0.007	0.013	0.019	0.006	0.015	0.008	0.018	0.013	0.039

Notes: Standard errors in parentheses, ^{a}: $p < 0.001$, ^{b}: $p < 0.005$; all denotes all firms with more than 5 employees at t and $t-3$ in the sample. match denotes matched sample. HGFs are high growth firms (OECD-Eurostat). HIFs are high impact firms (Birch index).

Table 6: Persistence of HGFs and HIFs after 3, 6 and 9 years

τ	3	6	9	3	6	9
	matched sample E_{t-3}			matched sample E_t		
			a) HGFs			
HGF	0.0583^a	0.0235^a	0.0220^a	0.0534^a	0.0149^a	0.0191^a
	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)
age	-0.0020^a	-0.0003	-0.0013^a	-0.0021^a	-0.0006^b	-0.0011^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(E)	0.0014	0.0032	0.0091^a	-0.0011	-0.0008	0.0098^a
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Ind. growth	0.4948^a	0.4576^a	0.1887^a	0.6837^a	0.4833^a	0.1858^b
	(0.063)	(0.057)	(0.069)	(0.068)	(0.064)	(0.077)
XJCR	-0.1038	0.1238	-0.7286^a	-0.0611	0.1195	-0.6530^a
	(0.083)	(0.084)	(0.119)	(0.089)	(0.094)	(0.131)
Ind. size	-0.0014	0.0123	0.0721	0.0174	0.0095	0.0443
	(0.043)	(0.034)	(0.038)	(0.046)	(0.037)	(0.042)
Constant	0.0415^a	-0.0094	0.0551^a	0.0473^a	0.0135	0.0420^b
	(0.013)	(0.012)	(0.015)	(0.016)	(0.015)	(0.019)
Obs.	9,254	6,871	4,092	8,203	6,137	3,680
r^2	0.03	0.02	0.02	0.03	0.01	0.02
			b) HIFs			
HIF	0.1707^a	0.1191^a	0.1002^a	0.1242^a	0.0748^a	0.0601^a
	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)	(0.008)
age	-0.0028^a	-0.0009^b	-0.0016^a	-0.0032^a	-0.0012^b	-0.0015^b
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
ln(E)	0.0677^a	0.0587^a	0.0521^a	0.0931^a	0.0753^a	0.0708^a
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
Ind. growth	1.1461^a	1.1091^a	0.6323^a	1.3072^a	1.3580^a	0.6854^a
	(0.076)	(0.091)	(0.113)	(0.088)	(0.104)	(0.132)
XJCR	0.1440	0.2898^b	-0.6535^a	0.2473^b	0.2871^b	-0.6300^a
	(0.095)	(0.119)	(0.164)	(0.107)	(0.135)	(0.185)
Ind. size	-0.0227	-0.0353	-0.0399	-0.0692	-0.0719	-0.0868
	(0.039)	(0.040)	(0.047)	(0.042)	(0.045)	(0.052)
Constant	-0.1743^a	-0.1807^a	-0.0616^a	-0.2914^a	-0.2473^a	-0.1390^a
	(0.014)	(0.016)	(0.020)	(0.019)	(0.021)	(0.026)
Obs.	17,437	13,490	8,608	14,419	11,227	7,258
r^2	0.10	0.08	0.06	0.08	0.06	0.05

***Notes*:** Standard errors in parentheses, ^{a}: $p < 0.001$, ^{b}: $p < 0.005$. HGF are high growth firms (OECD-Eurostat). HIF are high impact firms (Birch index).

likelihood of becoming an HGF in the future.

Even if we find a genuine treatment effect for HGFs, this effect is small, and much smaller than the treatment effect for HIFs. Being an HIF increases the probability of being an HIF by approximately 12% (7.5%, 6%) for $t+3$ ($t+6$, $t+9$) for the matched sample using end size. For begin size the coefficients are higher. Up to 40% of the effect recorded for the begin size regression is due to the effect of increased size. For HIFs we find that firm age and size increase the likelihood of being an HIF: Younger and larger firms have a higher probability of being an HIF after τ years than do older and smaller firms. Industry growth positively affects the likelihood of being an HIF after τ years positively. Industry size does not have a statistically significant impact. The excess job reallocation rate (XJCR) carries a positive sign for $t+3$ and $t+6$, while it is negative for $t+9$.

The transition matrices in table 3 provide complementary evidence that the status of being a HGF is not persistent: In the short run, 43% of HGFs are able to repeat their HGF status. However this declines to 7,6% for a three-year period, a number that is slightly lower than the probability of exit. Being an HIF is more persistent. This is due to the low relative growth requirement of the modified Birch index for large firms. Approximately 62% of HIFs are able to repeat their HIF status one year later. For a three-year period the probability is 29% and substantially higher than the likelihood of exit (6.5%).

6.3 Growth

The econometric analysis of growth after the high growth event is complicated by the fact that we only observe growth rates for continuing firms and not for firms that have exited. For firms that have exited we observe a growth rate of -1. This raises the question of how the processes of exit and growth are related. If the decision to exit is the same as the decision to grow this would support the use of a Tobit model or a model that includes a growth rate of -1 for exited firms. If the two processes are independent, this would suggest modeling growth rates by using two equations - one for the exit decision and a second for the growth performance of firms that did not exit. If there is some dependence between exit and growth, then a sample selection model should be used. Appropriate tests suggested the use of a two-part model. Our use of the two-part model follows Oberhofer (2010) with the difference that we model survival instead of an non-zero growth rate in the first stage of the two-stage model.

The first part of the two-part model describes the binary choice of survival versus non-survival for a particular firm i in period t:

$$y^*_{it+\tau} = \begin{cases} 0 & \text{for } g_{it+\tau} = -1 \\ 1 & \text{for } g_{it+\tau} \neq -1 \end{cases} \tag{4}$$

Table 7: Growth rates of HGFs (HIFs): Second stage of the two-part model

τ	3	6	9	3	6	9
VARIABLES	matched sample E_{t-3}			matched sample E_t		
			a) HGFs			
HGF	0.0250^a	0.0175^a	0.0173^a	0.0201^a	0.0148^a	0.0150^a
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)
age	-0.0011^a	-0.0006^b	-0.0011^a	-0.0012^a	-0.0008^a	-0.0012^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(E)	-0.0027	-0.0010	0.0007	-0.0026	0.0029	0.0027
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Ind. growth	0.1998^a	0.1472^b	0.1845^b	0.3121^a	0.2319^a	0.2814^a
	(0.069)	(0.071)	(0.075)	(0.082)	(0.077)	(0.079)
XJCR	-0.3587^a	-0.2350^a	-0.3633^a	-0.3801^a	-0.2345^a	-0.3594^a
	(0.101)	(0.079)	(0.102)	(0.108)	(0.078)	(0.100)
Ind. size	-0.0576	-0.0408	-0.0291	-0.0524	-0.0276	-0.0199
	(0.043)	(0.036)	(0.045)	(0.048)	(0.036)	(0.045)
Constant	0.0392^a	0.0160	0.0271	0.0468^a	0.0066	0.0206
	(0.014)	(0.012)	(0.015)	(0.016)	(0.013)	(0.015)
Obs.	7,145	4,814	2,374	6,454	4,417	2,215
r^2	0.016	0.013	0.031	0.019	0.016	0.035
			b) HIFs			
HIF	0.0287^a	0.0222^a	0.0202^a	0.0286^a	0.0228^a	0.0196^a
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
age	-0.0007^a	-0.0004^b	-0.0007^a	-0.0006^a	-0.0006^a	-0.0008^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ln(E)	-0.0047^a	-0.0047^a	-0.0042^a	-0.0070^a	-0.0051^a	-0.0053^a
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Ind. growth	0.2899^a	0.2351^a	0.1764^a	0.3197^a	0.3347^a	0.2468^a
	(0.049)	(0.047)	(0.055)	(0.058)	(0.054)	(0.064)
XJCR	-0.2958^a	-0.3067^a	-0.4624^a	-0.2954^a	-0.3900^a	-0.4803^a
	(0.056)	(0.051)	(0.057)	(0.059)	(0.055)	(0.060)
Ind. size	-0.0122	-0.0141	-0.0007	-0.0197	-0.0210	-0.0041
	(0.016)	(0.016)	(0.017)	(0.017)	(0.016)	(0.017)
Constant	0.0315^a	0.0302^a	0.0444^a	0.0434^a	0.0433^a	0.0545^a
	(0.008)	(0.007)	(0.008)	(0.010)	(0.009)	(0.010)
Obs.	13,639	9,671	5,197	11,371	8,189	4,507
r^2	0.025	0.028	0.041	0.026	0.036	0.045

***Notes*:** Standard errors in parentheses, ^{a}: $p < 0.001$, ^{b}: $p < 0.005$. HGF are high growth firms (OECD-Eurostat). HIF are high impact firms (Birch index).

where $g_{it+\tau}$ is the growth rate between t and $t+\tau$.

Based on equation (4) we parameterize the probability of $y^*_{it+\tau}$=1 such that:

$$P(y^*_{it+\tau}=1 \mid X) = P(g_{it+\tau} \neq 0 \mid X) = \Phi(X'\gamma)$$

where Φ is the Cumulative Distribution Function of the standard normal distribution, X is the set of regressors and γ is the vector of estimation coefficients. Thus the first stage is a probit regression that is equivalent (in terms of marginal effects at the mean) to the survival regressions in table 5.

In the second stage we only consider the growth rates of surviving firms. The actual growth rates for surviving firm is modeled under the linearity assumption:

$$E(y_{it+\tau} \mid X, y^*_{it+\tau}=1) = X\beta$$

where β is another vector of parameters to be estimated with ordinary least squares (OLS) and X represents the set of covariates.

The conditional mean of the two-part model is given by:

$$\begin{aligned} E(y_{it+\tau} \mid X) &= P(y^*_{it+\tau}=1 \mid X)E(y_{it+\tau} \mid X, y^*_{it+\tau}=1) + \\ &\quad +P(y^*_{it+\tau}=0 \mid X)E(y_{it+\tau} \mid X, y^*_{it+\tau}=0). \end{aligned}$$

As $E(y_{it+\tau} \mid X, y^*_{it+\tau}=0) = -1$ the conditional mean function can be written as

$$E(y_{it+\tau} \mid X) = P(y^*_{it+\tau}=1 \mid X)E(y_{it+\tau} \mid X, y^*_{it+\tau}=1) - P(y^*_{it+\tau}=0 \mid X). \quad (5)$$

This allows us to calculate conditional means for different sets of firms. The results for the conditional means are quite similar to the results from a Heckman sample selection model, as the LR-test of independence of the two-stage equations could not be rejected across the specifications.

Table 7 presents the results from the growth regressions for surviving firms. This is the second stage of the two-part model. The coefficients on the treatment indicator show that, on average HGFs have a higher growth rate than non-HGFs. This effect decreases slightly over time, e.g. from 2.5% for the 3 year period to 1.7% for the 9-year period for HGFx at begin size. The results for end size show a small decline from 2.0% to 1.5% and highlight that the result is not primarily due to the acquired size during the HGF-period of the firm. The results show that younger firms grow faster, that size has no statistically significant effect, and that industry firm growth affects the growth rate positively. XJCR display a negative sign, indicating that exit and mobility costs positively affect the growth rate.

Table 8: Conditional growth rates predicted from the two-part model

			T=1			T=0			Difference		
			(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
3	begin	HGF	0.90	0.03	-0.07	0.88	0.00	-0.12	0.02	0.03	0.04
6	begin	HGF	0.80	0.01	-0.19	0.77	-0.01	-0.24	0.03	0.02	0.05
9	begin	HGF	0.72	0.01	-0.28	0.68	-0.01	-0.33	0.04	0.02	0.05
3	end	HGF	0.90	0.03	-0.07	0.90	0.01	-0.09	0.00	0.02	0.02
6	end	HGF	0.81	0.01	-0.18	0.79	0.00	-0.21	0.01	0.02	0.03
9	end	HGF	0.72	0.01	-0.27	0.71	-0.01	-0.30	0.02	0.02	0.03
3	begin	HIF	0.93	0.02	-0.05	0.90	-0.01	-0.11	0.03	0.03	0.05
6	begin	HIF	0.85	0.01	-0.14	0.80	-0.01	-0.21	0.05	0.02	0.07
9	begin	HIF	0.79	0.00	-0.21	0.72	-0.02	-0.30	0.07	0.02	0.09
3	end	HIF	0.93	0.02	-0.05	0.92	-0.01	-0.09	0.01	0.03	0.03
6	end	HIF	0.85	0.01	-0.14	0.82	-0.01	-0.19	0.03	0.02	0.04
9	end	HIF	0.79	0.00	-0.20	0.74	-0.02	-0.27	0.05	0.02	0.06

***Notes*:** Columns (1) reports the conditional probability of survival, columns (2) present the conditional mean growth rate for surviving firms. Columns (3) report the overall conditional mean growth rates. HGF are high growth firms (OECD-Eurostat). HIF are high impact firms (Birch index).

The results for HIFs are similar in magnitude. However, for HIFs size has a clear negative effect, average industry growth affects the average growth rate positively and firm age and XJCR display a negative sign. Although effects of being an HGF and a HIF are statistically significant and the magnitude of the effect on the growth rate is not small, ranging from 1.5% to approximately 3%, the results are not spectacular. Table 8 presents the conditional means from the estimated two-part model for HGFs and HIFs ($T = 1$) and non-HGFs and non-HIFs ($T = 0$).

Columns (1) and (2) report conditional probabilities for survival, and the conditional mean growth rates for surviving firms, respectively. Column (3) show the conditional mean growth rates for all firms in the respective firm groups. The conditional means in Table 8 show that the survival probability (column (1)) decreases for both the HGF and HIF samples with τ. The average survival probabilities and the conditional means of the growth rate after the high growth event (column (2)) for the treated groups ($T = 1$) are, as expected, quite similar for the begin and end size specifications. The treatment groups cover the same set of firms. Differences are stronger for the non-treatment control groups (T=0). Here the comparison groups at the end of the period have higher survival probabilities. This also shows up in the difference between the conditional means of the treated and the non-treated group. The difference is higher for the begin specification, reflecting the existence of a substantial effect of increased size for both HGFs and HIFs.

The fact that exit is associated with a growth rate of -1 and the conditional mean growth rates of surviving firms are quite small explains that the conditional mean growth rates for all firms are negative, ranging from -0.05 (end size HIF sample for

Table 9: Conditional mean growth rates: predictions from the two-part model for firm groups

			young		old		small		large	
τ			T=1	T=0	T=1	T=0	T=1	T=0	T=1	T=0
3	begin	HGF	-0.082	-0.127	-0.063	-0.104	-0.077	-0.121	-0.048	-0.087
6	begin	HGF	-0.208	-0.259	-0.161	-0.207	-0.191	-0.241	-0.170	-0.216
9	begin	HGF	-0.312	-0.365	-0.231	-0.278	-0.280	-0.330	-0.245	-0.277
3	end	HGF	-0.080	-0.096	-0.064	-0.081	-0.083	-0.097	-0.049	-0.067
6	end	HGF	-0.198	-0.225	-0.162	-0.186	-0.195	-0.221	-0.139	-0.163
9	end	HGF	-0.305	-0.335	-0.224	-0.248	-0.292	-0.320	-0.187	-0.202
3	begin	HIF	-0.068	-0.129	-0.043	-0.091	-0.063	-0.120	-0.039	-0.084
6	begin	HIF	-0.184	-0.261	-0.115	-0.177	-0.171	-0.244	-0.097	-0.151
9	begin	HIF	-0.279	-0.383	-0.159	-0.239	-0.252	-0.347	-0.131	-0.202
3	end	HIF	-0.072	-0.107	-0.042	-0.073	-0.073	-0.105	-0.038	-0.069
6	end	HIF	-0.182	-0.233	-0.119	-0.159	-0.184	-0.230	-0.100	-0.135
9	end	HIF	-0.283	-0.361	-0.157	-0.213	-0.273	-0.344	-0.130	-0.177

***Notes*:** Columns report the overall conditional mean growth rates. Young firms havee age $leq3$ at time $t-3$, old firms are older than 10 years at time $t-3$, small firms have more than 9 employees and less than 50 employees at time $t-3$ and large firms have more than 249 employees at time $t-3$. Time t refers to end of the three year period used to determine high growth firms.

HIFs after three years) to -0.33 (begin size HGF sample for non-HGFs after 9 years). Thus, the overall contribution to job creation after the high growth event is likely to be negative due to the non-survival of many firms in the sample. This also holds for HGFs and HIFs, even if both the probability of survival and the conditional growth rates of surviving firms are higher for the treated group than for the non-treated group. Table 9 provides a more detailed analysis for small, large, younger and older HGFs (HIFs) and non-HGFs (non-HIFs). The table reports the conditional mean growth rates for all firms calculated according to equation (5). The results highlight that, as a group, HGFs and HIFs (T=1) have higher (less negative) conditional mean growth rates. The differences between treated and non-treated firms are in general highest for young firms (younger than 6 years) and lowest for large firms (larger than 249 employees) among both HGFs and HIFs. In addition, the difference is generally higher for HIFs than for HGFs, which is consistent with the results obtained earlier.

As the r^2 of our regressions is quite low, we also provide descriptive statistics on the observed growth rates of surviving firms. Table 10 provides the average, non-annualized growth rates for HGFs (HIFs) and non-HGFs (non-HIFs). While the growth rates during their high growth period (denoted as $t-3/t$) are substantial - around 85 % for HIFs and 140 % for HGFs, the growth rates following the high growth event are modest. On average, the three-year growth rate following an HGF event is aboutss 1.5% for HGFs and even smaller for HIFs. In line with our econometric results, the average growth performance of non-HGFs and non-HIFs is even more disappointing (generally negative).

Table 10: Observed average growth rates in the matched samples

time period	matched sample E_{t-3}		matched sample E_t	
	HGF	non-HGF	HGF	non-HGF
$t-3/t$	141.20%	0.36%	135.08%	14.46%
$t/t+3$	1.43%	-1.06%	1.53%	-0.55%
$t/t+6$	0.60%	-1.06%	0.78%	-0.75%
$t/t+9$	0.82%	-1.04%	0.80%	-0.72%
	HIF	non-HIF	HIF	non-HIF
$t-3/t$	89.70%	-3.58%	88.03%	2.72%
$t/t+3$	0.94%	-1.93%	0.93%	-1.89%
$t/t+6$	0.31%	-1.75%	0.37%	-1.79%
$t/t+9$	0.14%	-1.63%	0.12%	-1.68%

7 Summary and Discussion

This paper has studied high growth in an extensive sample of the Austrian private sector by using two different definitions of high growth, in order to provide evidence of its temporal structure. We use the Eurostat-OECD definition to identify high growth firms (HIF) and a modified Birch Index to identify high impact firms (HIF). We bring the definitions to the data. The descriptive statistics clearly show that:

1. Different definitions of high growth firms select a different set of firms. The OECD-Eurostat definition (HGFs) selects young and small firms because of its stringent relative growth requirement, which is more likely to be fulfilled by smaller firms. For larger firms the modified Birch index (HIFs) is approximately equal to an absolute growth requirement. This implies that larger firms have a much lower relative growth requirement, and, thus larger firms are preferably selected as HIFs.
2. Firm size and age matter for high growth. HGFs and HIFs are younger than their non-HIF and non-HGF counterparts. HGFs are generally smaller while HIFs are generally larger than non-HGFs (non-HIFs).

We use matching as nonparametric preprocessing to estimate survival, persistence and growth regression on balanced datasets that control for confounding age and size effects. The most important results from the econometric analysis are:

1. Being a HGF does not increase the likelihood of survival in future periods compared to being an non-HGF. The size effect induced by the growth during the HGF selection period is important. For HIFs we are observe a distinctive positive treatment effect on the likelihood of survival (3% higher after 9 years).
2. High growth rates are not persistent. Even if we are able to observe a distinctive treatment effect for HGFs (OECD-Eurostat definition), being an HGF appears

to be a temporary event in the life of a few firms. Being an HGF is a rare event and most HGFs are not able to replicate the high growth event. Most HGFs are one-hit-wonders and being an HGF is likely associated with an onetime, large expansion project. When we use the modified Birch index to select HIFs we observe substantially higher persistence. This is clearly related to the fact that the modified Birch index has very low relative growth requirements for larger firms. However, we also observe a genuine HIF effect (between 12% and 6%, 3 and 9 years after the high growth event).

3. For post-HGF (post-HIF) growth we find genuine treatment effects for both HGFs and HIFs. HGFs and HIFs have a higher growth rate over 3, 6 and 9 years after being identified as high growth firm.
4. We do not observe a curse of high growth. On aberage, being a high growth firm leads to improved survival and growth performance compared to firms in the respective control groups.
5. However, while most of the effects are statistically significant and provide a clear indication that HGFs and HIFs are indeed different from non-HGFs and non-HIFs of comparable size and age, the magnitude of the effects is generally quite small for HGFs. For example, an HGF has the same probability of survival, a 2% higher likelihood of being an HGF again after 6 and 9 years and a 2% to 1.5% higher cumulative growth rate compared to a non-HGF of similar age and size. For HIFs we observe stronger treatment effects.
6. The market environment modulates the persistence and magnitude of growth after the high growth event. Mobility barriers and sunk costs, as well as industry growth, improve the probability of being a HGF or a HIF. Thus we conjecture that there should be a relationship between the economic characteristics of an industry (e.g. demand development, mobility barriers) and its share of HGFs or HIFs.

From a policy perspective our results suggest that policies to target HGF with specific programs are not likely to be useful, and they provide a serious challenge the view that dedicated government support programmes can be designed in such a way as to target "potential successful high growth firms". The actual number of these potential high growth firms is very small. Policy measures concentrating on market and system failures that amplify barriers to firm growth, for example in the financial system, innovation system, education system or through regulation, are likely to be much more rewarding for potential high growth firms.

We think that our results also have implications for the use of the "share of innovative high growth firms" as headline indicator for monitoring the progress of the EU 2020 strategy. The fact that most HGFs only grow once in their lifetime casts doubt on this indicator as a means of measuring sustainable microeconomic growth dynamics of countries, as it could capture more economic turbulence than economic dynamics. As not much is known about the responsiveness of the HGF indicator to different sets of policy measures, a more systematic analysis and assessment of high growth definitions and their usefulness in a policy context is needed.

Further research is clearly required. On the one hand, not much is known about internal and external barriers to growth. On the other hand, the evidence presented in this paper is restricted to the Austrian case. Even if the available stylized facts on firm growth and high growth firms suggest that similar results should be expected for other countries, this needs to be explicitly investigated. Based on the evidence on post-entry growth (Bartelsman, Scarpetta, and Schivardi, 2005), high growth firms (Hoffmann and Junge, 2006; Hölzl, 2011) and the growth rate distribution (Bravo-Biosca, 2010), we conjecture that the strongest deviation from our result should be found for the USA. In addition, our dataset has not allowed us to delve very deeply into the analysis of the HGF and HIF treatment effects. Richer data would make it possible to pin down the differences more accurately.

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A Appendix

A.1 Derivation of formulas underlying figure 1

As an indicator of relative growth we use the annualized arithmetic growth rate between time t and $t+3$:

$$g = (\frac{E_t}{E_{t-3}})^{\frac{1}{3}} - 1,$$

absolute growth is $c = E_t - E_{t-3}$.

For the OECD-Eurostat definition (excluding the threshold requirement of $size_{t-3} \geq 10$), the HGF-limit in annualized relative arithmetic growth is $g = 0.2$. For the absolute growth requirement we obtain

$$c = ((1.2)^3 - 1) * E_{t-3}.$$

For the derivation of the relative growth requirement of HIFs we use the definition $E_t = (1+g)E_{t-3}$ and the growth requirement 2. As a solution from the resulting quadratic equation we obtain:

$$g = \left(-0.5 + \left(0.5^2 + \frac{25.15968}{E_{t-3}}\right)^{\frac{1}{2}}\right)^{\frac{1}{3}} - 1.$$

For the absolute growth requirement we use $E_t = c + E_{t-3}$ and obtain $c^2 + cE_{t-3} - 25.15968B = 0$. Solving this equation leads to

$$c = -\frac{E_{t-3}}{2} + \left(\frac{E_{t-3}}{2}^2 + 25.15968E_{t-3}\right)^{\frac{1}{2}}.$$

A.2 Bias reduction

Table 11: Bias reduction through matching

year	match E_t	variable	mean treat	mean control	bias in %	t-val	p-val	mean treat	mean control	bias in %	% bias reduct.	t-val	p-val
							a) HGF						
1988	begin	size	3,07	3,17	12	-1,74	0,08	3,04	3,05	1	92	0,15	0,88
1988	begin	age	7,22	11,06	90	-19,02	0,00	7,67	8,61	2	98	-0,20	0,84
1991	begin	size	3,11	2,79	34	6,48	0,00	3,08	3,03	4	88	0,84	0,40
1991	begin	age	8,32	12,55	76	-18,35	0,00	8,50	9,47	5	94	-0,70	0,49
1994	begin	size	3,09	3,17	8	-1,46	0,14	3,08	3,05	1	83	0,24	0,81
1994	begin	age	9,05	14,31	78	-16,89	0,00	9,25	10,05	4	95	-0,47	0,64
1997	begin	size	3,07	2,79	31	5,67	0,00	3,05	3,01	5	85	0,87	0,38
1997	begin	age	8,55	15,11	85	-18,00	0,00	8,66	9,42	1	98	-0,20	0,84
2000	begin	size	3,20	3,14	7	1,76	0,08	3,16	3,13	5	39	1,02	0,31
2000	begin	age	9,71	17,04	84	-21,65	0,00	9,73	11,02	0	100	-0,04	0,97
1988	end	size	3,88	3,15	80	12,07	0,00	3,81	3,72	11	86	1,76	0,08
1988	end	age	7,22	11,06	90	-19,02	0,00	8,05	8,86	2	98	-0,17	0,87
1991	end	size	3,95	2,83	119	22,71	0,00	3,89	3,71	11	91	2,14	0,03
1991	end	age	8,32	12,55	76	-18,35	0,00	8,58	9,77	2	97	-0,31	0,75
1994	end	size	3,93	3,11	87	15,85	0,00	3,86	3,74	8	91	1,49	0,14
1994	end	age	9,05	14,31	78	-16,89	0,00	9,26	10,24	3	97	-0,35	0,73
1997	end	size	3,92	2,78	122	23,02	0,00	3,82	3,67	10	92	1,84	0,07
1997	end	age	8,55	15,11	85	-18,00	0,00	8,75	10,15	1	98	-0,19	0,85
2000	end	size	4,09	3,11	101	24,23	0,00	3,96	3,84	8	92	1,93	0,05
2000	end	age	9,71	17,04	84	-21,65	0,00	9,86	11,62	0	99	-0,08	0,94
							b) HIF						
1988	begin	size	4,55	3,09	127	42,52	0,00	4,37	4,00	7	95	1,23	0,22
1988	begin	age	9,84	11,06	31	-9,90	0,00	10,18	10,23	2	94	-0,33	0,74
1991	begin	size	4,20	2,72	122	52,45	0,00	4,01	3,58	7	95	1,52	0,13
1991	begin	age	10,62	12,58	35	-14,04	0,00	10,92	10,85	1	99	-0,12	0,91
1994	begin	size	4,23	3,11	98	33,56	0,00	4,09	3,79	6	93	1,31	0,19
1994	begin	age	12,08	14,30	33	-10,49	0,00	12,34	12,41	2	94	-0,40	0,69
1997	begin	size	3,97	2,74	99	38,43	0,00	3,71	3,44	5	95	1,03	0,31
1997	begin	age	11,32	15,16	48	-16,09	0,00	11,31	11,57	2	97	-0,31	0,75
2000	begin	size	4,22	3,05	103	44,93	0,00	4,02	3,68	7	93	1,81	0,07
2000	begin	age	13,67	17,04	37	-14,20	0,00	13,63	13,79	0	99	0,08	0,94
1988	end	size	4,99	3,07	190	56,89	0,00	4,78	4,38	12	93	2,49	0,01
1988	end	age	9,84	11,06	31	-9,90	0,00	10,32	10,35	2	94	-0,31	0,76
1991	end	size	4,75	2,74	193	74,21	0,00	4,54	4,11	12	94	1,93	0,05
1991	end	age	10,62	12,58	35	-14,04	0,00	11,18	11,30	1	96	-0,29	0,77
1994	end	size	4,77	3,05	171	52,51	0,00	4,58	4,25	12	93	2,67	0,01
1994	end	age	12,08	14,30	33	-10,49	0,00	12,43	12,65	3	91	-0,57	0,57
1997	end	size	4,59	2,72	176	61,00	0,00	4,29	4,01	11	94	2,65	0,01
1997	end	age	11,32	15,16	48	-16,09	0,00	11,45	12,22	1	98	-0,21	0,83
2000	end	size	4,80	3,01	181	70,19	0,00	4,57	4,18	15	92	2.66	0,01
2000	end	age	13,67	17,04	37	-14,20	0,00	13,81	14,64	1	98	-0,15	0,88