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Is success hereditary? Evidence on the performance of spawned ventures

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Abstract A common phenomenon in entrepreneurship is that employees turn away from employment to found their own businesses. Prior literature discusses the former employers' characteristics that influence the creation of entrepreneurial ventures. An investigation of whether these characteristics also affect the success of the spawned ventures is missing so far. This paper contributes to the literature by showing that entrepreneurial ventures spawned by well performing firms are financially more successful than ventures stemming from poorly performing firms. This suggests that spawned entrepreneurs are able to exploit valuable knowledge from their previous employers which impacts their ventures' performance positively. The analysis is based on a linked employee–employer data set for the Netherlands for the period 1999–2004.

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1 Introduction

The public image of entrepreneurship is shaped by talented individuals who lack education and work experience but still manage to found highly successful and world-renowned companies (Chatterji 2009). Famous examples include Bill Gates, Steve Jobs and Sir Richard Branson who have all become self-made billionaires (Miller and Kroll 2010). The more realistic view on entrepreneurship, however, is that entrepreneurs display significant employment histories (Cooper 1985; Chandler 1996). In fact, several academic studies argue that many entrepreneurs make use of business ideas encountered through previous employment (Klepper 2001; Agarwal et al. 2004; Klepper and Sleeper 2005; Cassiman and Ueda 2006; Hyytinen and Maliranta 2008).[1]

Accordingly, existing firms seem to be an important driving force of entrepreneurship as many new ventures are bred by their founders' previous employers. This

[1] This view has been confirmed in interviews with 100 founders of fast growing companies (Bhidé 1994). 71% of these founders admitted that they took advantage of a business idea they had come across at their previous employer.

process, by which former employees create new, independent ventures, is referred to as “entrepreneurial spawning”. Although entrepreneurial spawning appears to be a rather common and acknowledged phenomenon (Gompers et al. 2005; Klepper and Sleeper 2005; Garvin 1983; Cooper 1985), only a few studies analyze the characteristics of firms that spawn entrepreneurial ventures (Gompers et al. 2005; Hyytinen and Maliranta 2008; Elfenbein et al. 2010). Rather prominent themes within these studies deal with the impact of firm size and performance on the rate at which new ventures are spawned (Gompers et al. 2005; Hyytinen and Maliranta 2008; Franco and Filson 2006; Elfenbein et al. 2010). Especially large firms are often argued to have high spawning rates. An explanation could be that employees start new ventures because they become frustrated that the entrepreneurial opportunities they identify are constantly rejected by their employers (Gompers et al. 2005). Small firms, in contrast, are assumed to equip their employees with the necessary skills for founding new ventures which is reflected in increased spawning rates (Elfenbein et al. 2010). Regarding firm performance, two opposing views can be brought forward as well. Whereas less successful firms could spawn more new ventures because the opportunity costs for employees to leave the firm are low, well performing firms might have high spawning rates as employees become exposed to more entrepreneurial opportunities (Gompers et al. 2005).

A shortcoming in the current literature on entrepreneurial spawning, however, is that the link between the characteristics of the spawning firms (the former employers) and the success of the newly spawned ventures is insufficiently discussed (Gompers et al. 2005; Cassiman and Ueda 2006; Klepper and Thompson 2010). Of particular interest is the question whether successful firms also spawn successful ventures. It can be assumed that better performing firms provide an excellent learning environment for their employees, resulting in the creation of more successful ventures (Klepper 2007; Boschma and Wenting 2007). In this paper, we address this gap in the entrepreneurship literature and scrutinize if a positive relationship between venture performance and spawning firm performance exists. Information that helps predict the success or the default risk of young ventures is useful for banks, investors and credit suppliers. Especially young and small firms typically face financial constraints (Denis 2004), but also greater difficulties in accessing funds than their larger and older counterparts since it is more difficult for the lender or investor to assess the “quality” of these firms (Harhoff and Koerting 1998). If characteristics of the former employer help determine the success of new ventures this is of interest for potential external capital providers who can facilitate capital access for young and small ventures.

Our empirical analysis is based on the official employee–employer data sets of Statistics Netherlands for the years 1999–2005. The data set covers all manufacturing and service sectors. Since most previous studies on the determinants of entrepreneurial spawning focus on specific sectors (e.g. Agarwal et al. 2004; Klepper and Sleeper 2005; Franco and Filson 2006; Chatterji 2009) or on samples that are selected according to specific criteria (e.g. only publicly listed venture-capital backed spawned ventures, see Gompers et al. 2005; or only on spawned ventures created by entrepreneurs with a degree in science or engineering, see Elfenbein et al. 2010) we make use of the rich information we have and re-investigate the effect of firm size and performance on the rate at which new ventures are spawned in the Netherlands. Our results for a sample that covers the most important industries and various types of spawned ventures largely confirm the findings of a previous study for the United States (Gompers et al. 2005), as we show that large firms are the most active spawners. Furthermore, financially successful firms are found to spawn fewer ventures than unsuccessful firms. In the second step, we contribute to the literature by investigating a more novel research question, namely, whether the spawning firms’ characteristics have an effect on the ventures’ performance. We find that being spawned by successful firms has a positive impact on the financial performance of the new ventures. This suggests that venture founders who worked at well performing firms have gathered more valuable knowledge about founding and running new businesses successfully than founders previously employed by less successful companies.

Our analysis contributes to the literature on entrepreneurial spawning in the following ways. First, to our knowledge, we are the first to study the effect of the spawning firms’ characteristics on the ventures’ financial performance.[2] Second, our data set

[2] There are only two previous studies investigating the link between venture performance and the characteristics of the

encompasses a broad variety of spawning firms and newly spawned ventures. This means that our data is neither restricted to publicly listed spawning firms nor to newly spawned ventures that are venture capital backed (cf. Gompers et al. 2005). The data set further covers entrepreneurial spawning in all manufacturing and service industries so that our study is not limited to one specific industry sector as in Agarwal et al. (2004) or Klepper and Sleeper (2005).

The remainder of this paper is organized as follows. In the next section, the existing literature on entrepreneurial spawning is reviewed. Afterwards, we describe our data set and present the econometric results. The final section concludes.

2 Theory and research questions

Since entrepreneurial spawning has received increasing attention in the academic literature, scholars became interested in the characteristics of firms that breed new ventures. Two recurring characteristics within most studies are firm size and firm performance (Gompers et al. 2005; Hyytinen and Maliranta 2008; Elfenbein et al. 2010). Up until now, however, the empirical findings vary across different industry sectors and countries. Whereas some studies observe a negative relationship between firm size and spawning rate (Hyytinen and Maliranta 2008, for Finland's manufacturing and service industries; Elfenbein et al. 2010, for spawned ventures in the United States that are founded by entrepreneurs with a science or engineering degree), Gompers et al. (2005) report a positive relationship for venture capital backed spawned ventures in the United States. Ambiguous findings also exist for the implications of performance on the rate at which new ventures are spawned. Gompers et al. (2005) discover that less successful firms spawn more ventures whereas Franco and Filson (2006) find no significant result for the U.S. disk drive industry. Previous literature provides theoretical arguments for these different empirical results.

Large and bureaucratic firms are often argued to feature high spawning rates for a variety of reasons. Gompers et al. (2005) summarize these reasons and refer to them as the "Xerox view"[3] of entrepreneurial spawning. First of all, unlike industry entrants, incumbent companies may be unable to adapt to radical technological change because their existing capabilities and routines are too inflexible (Tripsas and Gavetti 2000; Sull 1999; Tushman and Anderson 1986). Henderson (1993) shows in her study on the photolithographic industry that incumbent firms are less productive than industry entrants at introducing radical technologies because of their outdated organizational capabilities. Such circumstances can induce creative and entrepreneurial employees to leave the firm and start their own ventures, where they can freely implement new ideas. A second reason for high spawning rates within large companies is that managers are incapable of evaluating and implementing entrepreneurial opportunities—as identified by employees—that are not within the firms' core lines of business (Gompers et al. 2005; Klepper and Sleeper 2005, for the U.S. medical devises industry). Because managers lack the knowledge to make an informed decision about an unrelated entrepreneurial opportunity, they tend to dismiss it. Similarly, established companies could make a deliberate choice to leave out on entrepreneurial opportunities which are not in line with their core competencies. In this case, the decision to neglect employees' entrepreneurial opportunities is not driven by organizational inefficiencies but by the conviction that remaining a focused firm is more value enhancing than being a diversified firm (Berger and Ofek 1995). Accordingly, incumbents can act quite rigidly as they purposely forego profitable entrepreneurial opportunities for reasons of strategic commitment (Hellmann 2007). All arguments of the Xerox view suggest that employees start new ventures because they are frustrated that the entrepreneurial opportunities they identified are not capitalized on by their employers (Gompers et al. 2005; Hellmann 2007; Garvin 1983; Klepper 2001).

But not only large firms are considered as potential incubators for entrepreneurial ventures. Some studies

Footnote 2 continued
spawning companies (Franco and Filson 2006; Eriksson and Kuhn 2006). Both studies, however, employ a survival based performance measure, while we focus on the ventures' financial performance.

[3] Gompers et al. (2005) term this view the Xerox view because Xerox is exemplary for a large, incumbent firm that had to deal with the departure of several employees who founded their own ventures.

report a negative relationship between firm size and spawning rate (Dobrev and Barnett 2005; Elfenbein et al. 2010; Sørensen 2007). Small firms can be active spawners because employees benefit from essential information on how to found new businesses. Relative to employees of large firms employees of small firms are granted superior access to valuable outside networks with customers and suppliers (Elfenbein et al. 2010; Wagner 2004; Eriksson and Kuhn 2006). Such network ties can be particularly useful when starting entrepreneurial ventures. Employees of small firms are also not bound to specialize on a single task. Instead, they can develop skills in a vast range of business related activities (Dobrev and Barnett 2005; Elfenbein et al. 2010; Cooper 1985). Lazear (2004, 2005) argues that successful entrepreneurs need to be "jacks-of-all-trades" and possess a balanced set of skills. Hence, small firms seem to provide the perfect organizational environment for employees to develop such sets of diversified skills, leading to higher rates of entrepreneurial spawning (cf. Sørensen 2007; Elfenbein et al. 2010). The reasons presented above suggest that small firms shape their employees and provide them with the necessary skills, knowledge and contacts that could drive them into entrepreneurship eventually (Elfenbein et al. 2010).

It is also possible though that small firms breed new ventures because risk seeking individuals tend to self-select into such firms (Gompers et al. 2005; Sørensen 2007). Working for smaller firms is risky since, compared to large firms, wages are more variable (Parker 2006; Elfenbein et al. 2010) and the likelihood of firm exits in the first years is high (Wagner 1994). There is evidence that less risk averse people start working in small companies and do not hesitate to turn to entrepreneurship once they spot a valuable business opportunity (Elfenbein et al. 2010). Accordingly, individuals preferring to work for small firms might be those with a preference for becoming self-employed all along. A final reason is related to the salaries paid in small firms. Usually, employees in small firms receive lower salaries than individuals working for larger companies (see Elfenbein et al. 2010, and the references therein). Consequently, the opportunity costs for leaving the employer and founding a new venture are significantly lower.

Based on these two perspectives it becomes obvious that the theoretical literature as well as the empirical evidence lack a clear standpoint whether a positive or negative relationship between size and spawning rate exists. On the one hand, employees of large firms could start new ventures because they are frustrated that the entrepreneurial opportunities they would like to pursue are hardly implemented by their employers. On the other hand, employees of small firms could become entrepreneurs because they have gathered the necessary know-how from their previous employers. Hence, the following research question arises:

RQ1 What effect does firm size have on the rate at which new ventures are spawned?

In a similar vein, the theoretical arguments for the relationship between employer performance and spawning rate are ambiguous. Irrespective of the employer's size, the employee's opportunity costs for starting a new venture are also low if the performance of the employer is weak. Most empirical studies confirm that employees who work at an unsuccessful firm turn to entrepreneurship because the rents from remaining employed are small (Gompers et al. 2005; Hyytinen and Maliranta 2008). Eriksson and Kuhn (2006) characterize ventures emerging from unsuccessful firms to be "pushed" as they are a reaction to unfavorable conditions at the spawning firms.

Alternatively, a firm could spawn more entrepreneurial ventures if its performance is high. This argument is based on the fact that employees working at a financially viable firm are assumed to be exposed to more entrepreneurial opportunities (Gompers et al. 2005; Franco and Filson 2006), which they could pursue as self-employed individuals. Such ventures are "pulled" by the market as employees would only leave a profitable firm if the returns from the perceived entrepreneurial opportunity are high enough (Eriksson and Kuhn 2006).

Since existing research suggests that the relationship between firm performance and spawning rate could either be positive or negative, the second research question reads as follows:

RQ2 What effect does firm performance have on the rate at which new ventures are spawned?

As previous literature mainly focuses on the determinants of entrepreneurial spawning, Gompers et al. (2005) suggest examining whether the spawning firms' characteristics can affect the success of the new ventures. In particular, they probe the question if ventures of successful spawning companies turn out to be successful as well. This positive relationship could be based on the quality of knowledge that founders of newly spawned ventures have learnt from their previous employers. Previous research has shown that nascent entrepreneurs can acquire useful knowledge about technologies (Klepper and Sleeper 2005; Agarwal et al. 2004), markets (Jovanovic 1982; Agarwal et al. 2004) and organizational processes (Buenstorf 2009) during their employment phases. Since successful companies have accumulated a rich knowledge base (Klepper and Sleeper 2005; Klepper 2001), it can be assumed that ventures originating from such firms have superior initial knowledge endowments as compared to ventures of less successful spawning companies. In other words, depending on their origin, some ventures have a knowledge advantage at birth, which can have long-lasting effects on their performance (Agarwal et al. 2004; Chatterji 2009; Klepper and Sleeper 2005; Stinchcombe 1965). This implies that ventures which have been spawned by successful companies are likely to be successful themselves (cf. Klepper and Thompson 2010; Klepper 2001; Cassiman and Ueda 2006). In addition to the learning argument, ventures spawned by successful firms turn out to be successful because, as was described before, employees are only tempted to become entrepreneurs if the perceived entrepreneurial opportunity is of high quality and promises high returns (Eriksson and Kuhn 2006).

So far, the only empirical evidence on the relationship between the performance of former employers and spawned ventures is provided by Franco and Filson (2006) and Eriksson and Kuhn (2006). Using data from the disk drive industry, Franco and Filson (2006) conclude that ventures of successful spawning companies turn out to be successful as well. Instead of using financial measures, however, they rely on the ventures' life span to approximate performance. Eriksson and Kuhn (2006) conduct a similar analysis and find that ventures of firms which stopped their operations have lower survival probabilities than ventures of "healthy" firms. A drawback of survival measures is that they assume a strong correlation between economic performance and survival. This assumption is, in particular, questionable when firm exit includes acquisitions and IPOs. Gimeno et al. (1997) further argue that performance is not the sole determinant of survival. Firms' exit decision is the decision of the entrepreneur so that given the same level of (under-)performance some firms decide to exit while others do not. All previous studies dealing with the relationship between venture performance and spawning firm performance are subject to this limitation (Franco and Filson 2006; Eriksson and Kuhn 2006). This paper circumvents this limitation by employing financial performance measures to analyze if there is a positive relationship between spawning firm success and venture success. Therefore, the final research question reads as follows:

RQ3 Is there a positive relationship between the financial performance of the spawning firm and the financial performance of the venture?

3 Data

The empirical analysis relies on data sets provided by Statistics Netherlands. Statistics Netherlands offers a rich set of information as it stores a variety of administrative registers, like employment statistics, self-employment statistics, financial statements for large and small firms and detailed firm level information (including firm location and firm age) for all firms in the Netherlands. All of these data sets contain unique employer and employee identifiers so that they can be linked to each other.

In order to answer our three research questions we construct two data sets. By means of the first database, we investigate the firm attributes affecting spawning rates. Hence, this database constitutes a sample of spawning firms and a control group of non-spawning firms. The second database is required to analyze if the ventures' performance is influenced by the characteristics of their spawning firms. The unit of analysis is therefore the spawned venture. The next two subsections describe in detail how both databases were compiled.

3.1 Database 1: the spawner data set

Statistics Netherlands keeps track of the whole working population of the Netherlands. They not only observe individuals who are employed at companies but also hold information on self-employed individuals. The unit of observation in both data sources is the individual who can be linked to the company for which she works or, in case of self-employment, the venture she owns. Merging both data sets allows us to identify individuals who have been employed and then left their employers to start spawned ventures.[4] By means of this information on the level of the individual, we identify the aggregate number of ventures a particular employer has spawned per year.[5] We can then relate these annual spawning levels to a set of detailed firm level characteristics from the General Business Register and their financial statements provided by Statistics Netherlands.

We restrict our sample to spawning firms from manufacturing and service industries. Furthermore, we exclude firms from the construction sector as this industry displays an unusually high rate of newly spawned ventures. A likely explanation is that the Dutch construction sector is characterized by "bogus self-employment", which means that contractors disguise their workers' employment status as self-employed, as this exempts them from paying national work disability insurance contributions, which are relatively high in the construction sector (Vandenheuvel and Wooden 1997).

In total, we identify 19,895 spawning firms for which we have access to their financial performance that have spawned 26,010 ventures during the period 1999 to 2004.[6] Table 9 in Appendix 2 shows the spawning frequency per firm. The majority of the firms in our sample (85%) spawn only one venture in the period of interest while only a few firms spawn more than six ventures.

Since we want to scrutinize if certain firm characteristics (firm size and performance, in particular) increase the rates at which new ventures are spawned and the likelihood of spawning at the firm level, we drew a random sample of 10% of the non-spawning firms in our sample.[7] A random sample was chosen because we want to investigate the determinants of spawning and, hence, do not want to condition the control group on certain firm characteristics. This control group of non-spawning companies contains of 28,320 firms. In total, the data set contains 122,272 firm-year observations of Dutch manufacturing and service firms. A total of 43% (52,597) of these observations are spawning firms in the sense that they have spawned at least one venture in the period from 1999 to 2004. Table 10 in Appendix 2 shows the distribution of spawning and non-spawning firms across the different industries. The sectors with the highest spawning intensities are electricity, gas and water supply, manufacturing of chemicals and chemical products, manufacturing of pulp, paper and paper products and manufacturing of food products, beverages and tobacco. Table 11 in Appendix 2 shows the panel structure of the sample.

The following subsections describe the variables that are used for the empirical analysis and provide descriptive statistics for spawners and non-spawners.

3.1.1 Variables: the spawner data set

As indicated above, the dependent variable of our analysis is the annual number of ventures that an employer has spawned (*Spawning Rate*).

Our main independent variables are size and performance of spawners and, given our control group, non-spawners. As in Gompers et al. (2005), our measure of firm size is total assets.[8] Since the asset distribution is skewed across firms, we employ the logarithm of total assets (*Size*). Firm performance is measured by both annual growth in sales (*Sales Growth*) and return on assets (*ROA*). The latter performance variable is calculated as net income over total assets.

In addition, we use a number of control variables: we include the companies' total wage bill in our regression models. As it can be assumed that the

[4] We allow for a gap of one year between employment and self-employment. This accounts for the fact that the transition process from employment to self-employment is not always smooth. It seems improbable that an employee quits her job in 1 month and has her own venture in the same or the following month already. Furthermore, our database only contains of first-time entrepreneurs. Serial entrepreneurs have been eliminated, which is consistent with Gompers et al. (2005).

[5] We define a spawning company as the last employer an entrepreneur has worked for although she could have had multiple previous jobs. This definition is also consistent with Gompers et al. (2005).

[6] We can only analyze spawning rates in this time frame since the self-employment statistics and the employment statistics are unavailable before 1999.

[7] Firms in the control group did not engage in entrepreneurial spawning during the whole period of interest.

[8] Note that employment as an alternative measure was not available to us since the data sets only provide firm size classes.

"quality" of human capital is positively related to wage, we use this variable as a proxy for the skill composition of the spawning firms' labor force (Griliches 1969; Devine 1994; Arnold and Hussinger 2005). Since the total wage bill of a firm is typically highly correlated with its size, we normalize this variable by our firm size measure. This variable is labeled *Average Wage* in the remainder of the paper. Furthermore, some firms decide to remain undiversified regarding their business activities and refuse exploring unrelated business opportunities. As a result, entrepreneurial employees may decide to leave the firm and start their own ventures. To control for this, we introduce a dummy variable that takes the value one for firms that are active in only one industry segment and zero otherwise (*Focused*).

We also account for the age of spawners and non-spawners in our regression models (*Age*). Since several studies have reported that especially young firms have a tendency to spawn new ventures (Gompers et al. 2005; Dobrev and Barnett 2005; Wagner 2004), we add a dummy variable that equals one if a spawning firm is five years old or younger and zero otherwise (*Young*). Firm age is censored at 37 years in our database. The reason is that Statistics Netherlands only started its data collection process in 1967. Firms that already existed before this year are treated as if they were founded in 1967. To account for this data limitation in our empirical specifications, we create a dummy variable, which takes the value one if a firm is 37 years of age—according to the Statistics Netherlands information—and zero otherwise (*Old*).

Several studies find that certain regions are more likely to prompt entrepreneurship (Venkataraman 2004; Audretsch 2005, 2007a, b; Malecki 1994). This result is attributed to the fact that entrepreneurship capital, which forms the capacity for entrepreneurial activity, differs within regions. Entrepreneurship capital refers to a broad spectrum of legal, institutional and social factors (Audretsch 2007a). In order to account for the fact that different regions might have different levels of entrepreneurial capital, we add 12 region dummies corresponding to the 12 officially recognized regions that exist in the Netherlands (see Table 12 in Appendix 2). Finally, we create 34 industry dummies based on the 2-digit NACE industry classification (see Table 10 in Appendix 2) and include 6 year dummies that control for business cycle effects.

3.1.2 *Descriptive statistics: the spawner data set*

Table 1 shows descriptive statistics for our sample of spawning firms and the control group of non-spawning firms. All financial variables are measured in thousands of Euros.

The descriptive statistics reveal that, on average, a spawning firm breeds roughly 2.21 ventures over the analyzed period of 6 years. This corresponds to an average of 0.39 spawned ventures per year. Comparing spawners with non-spawners shows that the former are, on average, almost four years older than the latter. Spawning firms are also much larger than non-spawning firms. This is reflected in the significantly higher average asset level. However, non-spawning firms significantly outperform spawning firms in terms of ROA. There is no significant difference regarding the sales growth of spawning and non-spawning firms. Finally, spawning companies pay significantly higher average wages than non-spawning companies and are also less likely to be diversified.

3.2 Database 2: the venture data set

Creating a database that allows us to scrutinize if venture performance is affected by the characteristics of their spawning companies involves three steps. First, we need to link financial information to our identified set of spawned ventures. Statistics Netherlands provides financial information for a stratified sample of firms which are obliged to pay corporate taxes. About 80% of the total population of these firms is sampled by Statistics Netherlands. Since most of the spawned ventures are one-person businesses and exempted from corporate taxation, financial information is not available for them.[9] As a result, our sample contains 438 ventures that are subject to corporate taxes. The 438 ventures correspond to 637 venture-year observations, which define our final venture sample.

In a second step, non-financial information is linked to these ventures. By means of this information, we are able to assess the ventures' age as well as their regional and industry affiliations. The final step is to link our subset of ventures back to their spawning companies.

[9] Examples of such ventures that are not subject to corporate taxation are one-man consulting businesses and independent sales agents.

Table 1 Descriptive statistics: spawner data set

Variables	Spawner ($N = 52{,}597$)		Non-spawner ($N = 69{,}675$)		Mean difference	t
	Mean	SD	Mean	SD		
Total spawning	2.21	11.85	–	–	–	–
Spawning Rate	0.39	2.26	–	–	–	–
Size	7.51	1.91	6.29	1.42	1.22	130.00***
ROA	0.04	0.19	0.05	0.22	−0.01	−3.81***
Sales Growth	0.02	0.35	0.02	0.39	0.00	−0.89
Age	18.53	11.63	14.75	11.25	3.78	57.26***
Young	0.16	0.002	0.27	0.002	−0.11	−46.45***
Old	0.03	0.18	0.02	0.14	0.01	16.05***
Average Wage	0.49	0.41	0.41	0.37	0.08	38.19***
Focused	0.36	0.48	0.21	0.41	0.15	57.77***

Note: Industry dummies, year dummies and region dummies are omitted; *** (**, *) indicate a significance level of 1% (5%, 10%), respectively

This reveals that the 438 ventures have been spawned by 413 firms during the period 2000–2005.[10] Since our ventures stem from spawning firms in manufacturing or services, most ventures start operating in these sectors as well. Only 10% become active in non-manufacturing or non-service industries.[11]

In the next subsection, the variables that are used for the empirical analysis are described.

3.2.1 Variables: the venture data set

We examine the ventures' performance by considering two different performance measures. The first one is the ventures' returns on assets (*V_ROA*). This measure has been frequently used in studies on the performance of young and small ventures (e.g. Murphy et al. 1996; Robinson 1999). Since ROA could be influenced by differences in capital structure or dividend policies across firms, we also use operating returns on assets (*V_OROA*) as a second performance measure. OROA is calculated as the ratio of earnings before interest and taxes (EBIT) to total assets and is a widely accepted performance measure (cf. Bennedsen et al. 2007; Hvide 2010). The fact that our sample is highly unbalanced (most of the ventures are only observed once) does not allow us to use growth measures as dependent variables since we would lose most of our observations.[12]

The same firm characteristics that have been used for our spawning companies are also used for the ventures. We control for the size of the ventures by taking the logarithm of total assets (*V_Size*). The quality of the ventures' labor force is accounted for by the average wage (*V_Average Wage*). We also control for the age of the ventures (*V_Age*). Since some ventures are founded by more than one entrepreneur, we incorporate a dummy variable that takes the value one if ventures have been established by founding teams and zero otherwise (*Founding Team*).[13] Furthermore, ventures that are active in the same industry as their spawning companies might be more successful than others as they are more familiar with the industry conditions. To control for this possibility,

[10] The time frame of the analysis for the spawner database is the period 1999–2004. We loose the year 2005 since we allow for a 1 year gap when defining our spawned ventures. For the venture database, we focus on the period 2000–2005. We lose the first year for this data set as it is not possible to observe the previous employment situation of entrepreneurs who founded new ventures in 1999.

[11] An alternative set up would be to compare spawned ventures with a control group of ventures that have been established by entrepreneurs without any employment histories. Given our short observation period of 5 years, we decided to not follow this approach as we cannot determine whether the founders of the ventures within our potential control group have not been employed by a company prior to the designated time period.

[12] Note that our 5-years sample does not allow us to conduct a meaningful survival analysis. Only 16 ventures exit in the period 2000–2005.

[13] It is important to note that all members of the founding team must have been employed prior to the foundation of the new ventures if the variable takes the value one.

Table 2 Descriptive statistics: venture data set

Variables	$N = 637$			
	Mean	SD	Min	Max
V_ROA	0.003	0.22	−1	0.58
V_OROA	0.04	0.20	−0.93	0.62
V_Size	5.53	1.42	0.69	9.49
V_Age	2.58	1.74	0	5
V_Average Wage	0.32	0.36	0	1.97
V_Founding Team	0.02	0.14	0	1
Size	8.79	3.23	1.39	17.43
ROA	0.01	0.17	−0.29	1
Sales Growth[a]	−0.016	0.21	−0.56	0.94
Age	15.11	10.57	1	37
Young	0.23	0.42	0	1
Old	0.022	0.15	0	1
Average Wage	0.41	0.40	0	1.97
Focused	0.94	0.23	0	1
Same Industry	0.26	0.44	0	1

Note: Industry dummies, year dummies and region dummies are omitted for both ventures and spawners

[a] Since we lose 1 year in creating the sales growth variable, we only end up with 426 observations

we add a dummy variable that takes the value one if ventures and spawners are in the same industry and zero otherwise (*Same Industry*). Lastly, we include six industry and four region dummies for both spawned ventures and spawning companies.[14]

Besides these venture characteristics, the data set allows us to control for the attributes of the spawning firms. These spawning firm attributes have been described in Sect. 3.1.1. The performance of spawning companies—measured by *ROA* and *Sales Growth*—is most important for our empirical analysis as we want to analyze if successful firms also spawn successful ventures.

3.2.2 Descriptive statistics: the venture data set

Our final sample consists of 637 ventures observations and their respective spawning companies. Table 2 shows descriptive statistics of this sample.[15] As before, all financial variables are measured in thousands of Euros.

The results show that the average ROA (*V_ROA*) of spawned ventures is considerably lower than the average OROA (*V_OROA*). This shows that tax and interest payments account for a large share of the ventures' returns. The average age of the ventures in the sample is 2.5 years. It can also be seen that most ventures were founded by individual entrepreneurs. Only 2% were created by founding teams. Furthermore, 26% of the ventures remain in the same industry as their parent companies.

If one compares the spawning firms in the venture database with the spawning companies of the previous database containing all spawning firms in the Netherlands in our period of interest, several differences can be observed. First of all, the spawning companies in this data set, i.e. those that spawn ventures which are subject to corporate taxation, are, on average, larger and younger. In terms of performance, the spawning firms' average ROA and average sales growth have decreased. This should be kept in mind for the interpretation of the results. If it would be the case that we have a positive selection of ventures that are spawned by more successful parents we would underestimate the effect of the former employer's success on the venture success.

4 Econometric results

In the following subsections, we present the empirical results for our three research questions. We start in Sect. 4.1 by analyzing the effect of, inter alia, firm size and performance on the rate at which new ventures are spawned. Section 4.2 in turn is concerned with the relationship between spawning firm characteristics (the spawning firms' performance in particular) and venture performance.

4.1 Which firm characteristics influence the *Spawning Rate*?

As mentioned above, we consider the annual number of newly spawned ventures as the dependent variable

[14] Note that for the venture sample we use more aggregated regions and industries, based on the 2-digit NACE level, than for the spawner sample because of the smaller sample size.

[15] All variables starting with a "V" are venture characteristics. The same variables without the "V" account for spawning firms' characteristics.

(*Spawning Rate*). Since this variable only contains positive integers and zeros, count data models are applied. Two types of count data models are estimated, namely, Poisson models and negative binomial models. Likelihood ratio tests for the null hypothesis of equidispersion show, however, that Poisson models are always rejected. As a result, only negative binomial models are presented.[16] Since firms do not spawn new ventures every year and since our sample also includes a control group of non-spawning firms, the dependent variable consists of many zero counts (74.5%). We account for this by also estimating zero-inflated negative binomial models. In order to test if the zero-inflated negative binomial models outperform the standard negative binomial models, Vuong tests are performed for all model specifications. All Vuong test statistics reveal that the zero inflated models fit the data better than the standard models.[17] Nevertheless, we always report both zero-inflated negative binomial models and standard negative binomial models. Standard errors are clustered on the firm level since some of the ventures are observed more often than once.[18] The results are presented in Table 3. Table 4 shows the marginal effects for the main variables.

The first two columns of Table 3 (Models 1 and 2) provide estimation results for the full sample of spawning firms and the control group of non-spawning firms. Both the zero inflated negative binomial model and the regular negative binomial model provide similar results. First of all, it can be seen that large companies have high spawning rates. It makes sense that large firms spawn more given that there are more people and technologies that could spark the ideas for new ventures. The positive size effect remains robust if we estimate Tobit models (Models 6 and 7) in which the dependent variable is the annual number of spawned ventures normalized by total assets.[19] Our first research question formulates a relationship between firm size and spawning rates. Based on the described result, it can now be concluded that large firms spawn more frequently than smaller firms, providing support for the Xerox view as suggested by Gompers et al. (2005). The size of the effects is significant. If the assets of a firm increase by 1% the firms spawns 0.04 additional new ventures (Model 1). In other words, if an average spawning firm's assets (7.51) increase by one standard deviation (1.91), i.e. by 25%, the firm spawns one more venture. The coefficient estimates of the two performance variables (*Sales Growth* and *ROA*) in Models 1 and 2 are significantly negative. By referring back to our second research question, this implies that financially unsuccessful firms spawn more ventures than successful firms (cf. Gompers et al. 2005; Eriksson and Kuhn 2006; Hyytinen and Maliranta 2008). One could explain this finding by arguing that the opportunity costs for staying at bad performing firms are high, leading employees to found their own entrepreneurial ventures. Table 4 shows that the economic effect of performance is rather small. If a firm's return on assets increases by one unit it will spawn 0.03 ventures less. The marginal effect for sales growth is rather small as well. This suggests that the effect of firm size is more important than the effect of firm success.

Regarding the control variables, the results reveal that firms have a tendency to spawn new ventures when they are young, as indicated by the significantly negative coefficient of the *Age* variable. This result is consistent with studies by Dobrev and Barnett (2005) and Gompers et al. (2005). A likely explanation is that young firms are usually characterized by higher uncertainty and informational asymmetries (Gompers and Lerner 2001; Bates 2005). Hence, employees working for such firms might found their own ventures to forestall layoffs. Another possible explanation for our finding could be that aging firms are likely to shift their strategic focus from product innovations to process innovations. Such a strategic change could cause the character of the firms' knowledge to become embodied in physical rather than human capital,

[16] The Poisson estimates revealed the same results as the negative binomial models and are available from the authors upon request.

[17] Vuong test statistics are reported at the bottom of Table 3.

[18] The results are robust if we cluster the standard errors on the industry or regional level.

[19] We run Tobit regressions because the dependent variable does not consist of integer values anymore and is truncated at zero. Not only does the firm size coefficient display a similar magnitude and direction as in the count data estimations, also the other main results remain comparable. The marginal effects

Footnote 19 continued
for age, size, ROA, and sales growth vary by not more than 0.01 across the different models. The marginal effect for the average wage shows the highest variation across the different models with 0.04.

Table 3 Count data results and Tobit results on the annual *Spawning Rate* for the full sample and the high tech subsample

Parameter	Dependent variable: *Spawning Rate*				Dependent variable: *Spawning Rate*/total assets	
	ZI negative binomial[a]	Negative binomial	ZI negative binomial[a]	Negative binomial	Tobit model	
Sample	Full sample		High tech sample		Full sample	High tech sample
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Size	0.52***	0.52***	0.55***	0.55***	0.02***	0.01**
	(0.01)	(0.01)	(0.02)	(0.03)	(0.06)	(0.006)
ROA	−0.43***	−0.43***	−0.46***	−0.54***	−0.03***	−0.02**
	(0.07)	(0.06)	(0.12)	(0.12)	(0.07)	(0.09)
Sales Growth	−0.16***	−0.14***	−0.02	−0.01	−0.06***	0.001
	(0.04)	(0.03)	(0.08)	(0.08)	(0.02)	(0.003)
Age	−0.01***	−0.01***	−0.01**	−0.01**	−0.001**	−0.001*
	(0.001)	(0.01)	(0.004)	(0.004)	(0.0001)	(0.0001)
Young	−0.05	−0.03	−0.05	−0.08	0.000	−0.004
	(0.04)	(0.04)	(0.08)	(0.09)	(0.02)	(0.003)
Old	0.16	0.19**	−0.06	−0.04	0.07	−0.002
	(0.10)	(0.09)	(0.38)	(0.37)	(0.05)	(0.01)
Average Wage	0.91***	1.13***	1.11***	1.12***	0.06***	0.03**
	(0.06)	(0.04)	(0.07)	(0.07)	(0.02)	(0.01)
Focused	−0.02	0.01	−0.01	−0.003	0.006**	0.003
	(0.03)	(0.03)	(0.07)	(0.08)	(0.02)	(0.003)
Intercept	−8.04***	−8.39***	−8.69***	−8.64***	−0.44***	−0.27**
	(0.13)	(0.09)	(0.32)	(0.34)	(0.13)	(0.11)
Joint significance of year dummies, $\chi^2(4)$	1055.71***	1925.29***	252.71***	251.31***	3.61***	1.78
Joint significance of industry dummies, $\chi^2(33)$	388.67***	434.55***	18.32**[,b]	17.61**[,b]	0.6	0.69[b]
Joint significance of region dummies, $\chi^2(11)$	123.32***	145.83***	19.59*	19.16*	1.13	0.44
Log-likelihood	−41250.03	−41472.61	−3819.47	−3828.25	−8387.29	−127.91
Vuong test statistic	10.39***	–	3.15***	–	–	–
Observations	122272	122272	11553	11553	122272	11553

Notes: Clustered standard errors at the firm level are in parentheses; *** (**, *) indicate a significance level of 1% (5%, 10%), respectively

[a] The inflation equation includes the same variables as the logit equation (coefficient estimates are not reported)

[b] Test of joint significance of industry dummies, $\chi^2(8)$

making it harder for employees to access the firms' key knowledge and found entrepreneurial ventures (Klepper and Sleeper 2005; Garvin 1983).

Another interesting result is that firms paying high average wages also have high spawning rates (*Average Wage*). Since our wage variable is taken as a proxy for the skill composition of a firm's labor force it can be concluded that qualified employees are more likely to generate more good ideas, which some may decide to exploit without their current employer. Finally, year dummies, industry dummies and region dummies are jointly significant throughout all two regression models, as Wald tests at the bottom of Table 3 show.

As many studies on the transition process from employment to self employment focus on firms from high tech industries (Klepper and Sleeper 2005;

Table 4 Marginal effects for Table 3

Variables	ZI negative Binomial[a]	Negative binomial	ZI negative binomial[a]	Negative binomial	Tobit model	
	Full sample		High tech		Full sample	High tech
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Age	−0.0009***	−0.0006***	−0.0006**	−0.0006**	−0.0003 **	−0.0002*
Size	0.04***	0.03***	0.03***	0.03***	0.02***	0.01**
ROA	−0.03***	−0.03***	−0.03***	−0.03***	−0.02***	−0.02**
Sales Growth	−0.01***	−0.01***	−0.0006	−0.0006	−0.01***	0.002
Average Wage	0.07***	0.07***	0.07***	0.07***	0.06***	0.03**

*** (**, *) indicate a significance level of 1% (5%, 10%), respectively

[a] The inflation equation includes the same variables as the logit equation (Coefficient estimates are not reported)

Agarwal et al. 2004; Chatterji 2009), we re-run our regression models for a subset of firms from high tech sectors (Models 3 and 4).[20] This reduces the sample to 11,553 observations. The results are similar to the findings for the full sample. Young firms as well as large firms actively engage in entrepreneurial spawning. Moreover, successful firms spawn fewer ventures. The only difference to the full sample models is that just one performance variable has a significantly negative coefficient (*ROA*). *Sales Growth* turns insignificant. High tech firms that pay higher average wages also have higher spawning rates.

In a second robustness check we drop the control group of non-spawning firms and re-run the regressions for the subsample of spawning firms. All results remain robust. We also re-run the regressions for the subsample of 413 firms that spawn taxable ventures. It was mentioned before that these firms have spawned the 438 ventures we consider in the next part of our empirical analysis. The results are still robust: large and less successful firms have higher spawning rates.[21] As a last robustness check, we estimate probit models for the likelihood of being a spawning firm. The results are in line with previous findings and can be found in Appendix 1.

Furthermore, we re-run the regressions for the spawning rate in $t + 1$ and $t + 2$. While the results for $t + 1$ are very similar to the findings for the contemporaneous regressions the estimated coefficients for the firm characteristics in the regression $t + 2$ are much lower and some regressors turn insignificant. This is not surprising since one would expect that employees react on recent developments within the firm when deciding to leave for entrepreneurship. The results are available from the authors upon request.

4.1.1 Panel models

The cross sectional regression results have shown that large firms as well as firms with unfavorable sales growth and ROA have higher spawning rates than successful firms. Since cross-sectional results do not take into account that unobserved firm heterogeneity (due to differences in management skills, entrepreneurial climate within the firm, etc.) could drive spawning rates as well, we also estimate panel models with firm fixed effects. More specifically, we estimate fixed effects Poisson models as introduced by Hausman et al. (1984). Gourieroux et al. (1984) have shown that the Poisson estimator is consistent for panel data even if the dependent variable does not truly follow a Poisson-distribution as long as the mean specification is correct. In addition, previous research has shown that a significant portion of the overdispersion is accounted for if one allows for random or fixed disturbances (Hausman et al. 1984). The fixed effects in our Poisson model then control for some of the overdispersion in the data. If fully robust standard errors are calculated, the fixed effects Poisson models even provide protection against any residual overdispersion. Hence, we prefer Poisson estimators over negative binomial models for our panel data models. Compared to the negative binomial panel models, this

[20] We use the official Eurostat classification to identify high tech industries (Felix 2006).

[21] The regression results are available from the authors on request.

ensures that no assumption regarding the functional form of the variance term is necessary since one would have to cope with inconsistent estimates if this assumption fails.

Model 7 in Table 5 reports the estimates of the fixed effects quasi maximum likelihood Poisson model for our full sample. As before, large firms have high rates of entrepreneurial spawning, which is unsurprising given that more people work there. To this end, we confirm this finding by estimating panel Tobit models in which the dependent variable is normalized by total assets. The results in Model 9 reveal that large firms still have high spawning rates. Although the count data results show that spawning is unrelated to sales growth, a highly significant and negative effect is found for ROA. Hence, it can be concluded that employees do not leave firms that are well performing, but instead when firm performance (in terms of ROA) is low. Most employees decide to create their own ventures and pursue entrepreneurial opportunities outside the firm when the opportunity costs for remaining employed are diminished (also see Gompers et al. 2005; Hyytinen and Maliranta 2008; Eriksson and Kuhn 2006). The final result of Model 7 shows that firms paying high average wages also have higher spawning levels.

Running the fixed effects quasi-maximum likelihood Poisson regressions (Model 8) as well as the Tobit models (Model 10) for a subset of high tech firms, reveals similar results. Note that the predicted marginal effects decrease if firm-specific unobservable effects are taken into account (Table 6).

In summary, it can be said that controlling for unobserved firm heterogeneity does not change the answers to our two research questions regarding the effect of firm size and performance on spawning rates.[22]

4.2 Providing a link between venture performance and spawner characteristics

The entrepreneurship literature remains quiet when it comes to scrutinizing if the performance of spawned ventures is affected by their origin. To shed some light on this question, we run OLS regressions with the performance of the spawned ventures as the dependent variable (in terms of *V_ROA* and *V_OROA*) and venture and spawner characteristics as independent variables. Models 11 and 13 in Table 7 only regress the dependent variables on venture characteristics. In Models 12 and 14, we add the characteristics of the ventures' former employers.[23]

The results of Model 12 reveal that venture size has a positive impact on performance. Surprisingly, all other venture characteristics are insignificant. Regarding the spawning firms' characteristics, it can be seen that the better the performance of the spawning companies (in terms of *ROA*), the better the performance of the ventures (cf. Franco and Filson 2006, and the references within Klepper 2007). This result supports our third research question claiming that the financial success of the parent firms influences the financial success of the spawned ventures. One interpretation of this finding could be that venture founders who worked at such firms were able to access and exploit more valuable knowledge, possibly resulting in increased venture performance. An alternative explanation is provided by Klepper (2007) and Chatterji (2009). They argue that better firms have better employees who are more likely to start new ventures, which also perform better. Chatterji (2009) calls this the "good people work for good firms" explanation. We try to control for this objection by including average wage as a proxy for the skill level of the spawning firms' employees in our regressions.

Running the same regressions for our second performance variable (*V_OROA*) yields similar results. Size is the only venture characteristic that has a significant and positive effect on performance. Most importantly, however, it can still be shown that ventures of successful spawning firms (in terms of ROA) turn out to be successful as well, lending support to our third research question.[24]

Given that successful firms spawn few (as was discussed in the previous subsection) but profitable ventures, it can be concluded that employees of such

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[22] In addition we ran cross-sectional OLS and fixed effects models. The results are similar to what we find for the count data and Tobit models. Results are available from the authors upon request.

[23] Note that we lose some observations for these regressions (Models 12–14) as we add the sales growth of the spawning firms, which costs us one year by definition of the measure. The regression results for Models 11–13 are robust if the reduced sample of Models 12–14 is used.

[24] The result remains robust when we use OROA instead of ROA as a measure for the financial success of the spawning firm. Results are available from the authors upon request.

Table 5 Panel models on the annual *Spawning Rate* for the full sample and the high tech subsample

Parameter	Dependent variable: *Spawning Rate*		Dependent variable: *Spawning Rate*/total assets	
	QML panel Poisson		Panel Tobit	
Sample	Full sample	High tech sample	Full sample	High tech sample
Variables	Model 7	Model 8	Model 9	Model 10
Size * (1000)	0.34***	0.41***	0.02**	5.01***
	(0.04)	(0.13)	(0.01)	(0.72)
ROA * (100)	−0.49***	−0.96***	−0.16***	−1.91***
	(0.10)	(0.23)	(0.01)	(0.59)
Sales Growth * (100)	0.03	0.12	−0.14**	0.52
	(0.04)	(0.11)	(0.01)	(0.37)
Age * (1000)	−0.004	0.004	−0.04***	0.12
	(0.005)	(0.03)	(0.002)	(0.12)
Average Wage * (100)	0.82***	0.86***	0.13***	0.94***
	(0.11)	(0.27)	(0.005)	(0.33)
Intercept * (100)	–	–	−0.31***	−13.9***
	–	–	(0.01)	(0.88)
Test of joint significance of year dummies, $\chi^2(4)$	2146.41***	217.33***	2024.81***	141.17***
Log-likelihood	−13638.57	−1115.84	23442.82	322.12
Observations	33768	2923	33768	2923

Table 6 Marginal effects for Table 5

Variables	QML panel Poisson	QML panel Poisson	Panel Tobit	
	Full sample Model 7	High Tech Model 8	Full sample Model 9	High Tech Model 10
Age * (1000)	−0.004	−0.0004	−0.00004***	0.0001
Size * (1000)	0.34***	0.41***	0.00002**	0.005***
ROA * (100)	−0.49***	−0.96***	−0.002***	−0.02***
Sales Growth * (100)	0.03	0.12	−0.0001**	0.005
Average Wage * (100)	0.82***	0.86***	0.001***	0.009***

*** (**, *) indicate a significance level of 1% (5%, 10%), respectively

firms are more reluctant to quit and create new ventures than employees of struggling companies. Working for a successful firm increases the opportunity costs of leaving so that employees only opt for the pursuit of entrepreneurial opportunities if the expected returns are high enough. For this reason, Eriksson and Kuhn (2006) describe ventures that have been spawned by profitable firms to be pulled by the market. This argument is in line with the superior performance of ventures spawned by successful firms as was just described.

5 Conclusion

The employment history of entrepreneurs has attracted the interest of academic scholars in recent years. Several studies argue that entrepreneurs became inspired by business ideas they came across at their previous employers (Klepper 2001; Agarwal et al. 2004; Klepper and Sleeper 2005; Cassiman and Ueda 2006; Hyytinen and Maliranta 2008). This process, by which former employees become entrepreneurs and found new ventures, is known as entrepreneurial

Table 7 OLS results on the ventures' performance for the full sample

Variables	Dependent variable: *V_ROA*		Dependent variable: *V_OROA*	
	Model 11	Model 12	Model 13	Model 14
V_Size	0.02**	0.03**	0.02**	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
V_Age * (100)	0.02	−0.42	−0.31	−0.83
	(0.71)	(1.33)	(0.72)	(1.21)
V_Average Wage * (100)[a]	−0.04	0.01	0.02	0.04
	(0.03)	(0.04)	(3.12)	(0.04)
V_Founding Team	−0.11*	−0.07	−0.07	−0.07
	(0.05)	(0.08)	(0.05)	(0.07)
Size * (100)	–	0.07	–	0.04
	–	(0.42)	–	(0.43)
ROA	–	0.19**	–	0.16**
	–	(0.09)	–	(0.08)
Sales Growth	–	−0.04	–	−0.06
	–	(0.06)	–	(0.05)
Age * (100)	–	0.03	–	0.005
	–	(0.21)	–	(0.11)
Young	–	0.02	–	0.02
	–	(0.04)	–	(0.03)
Old	–	−0.04	–	0.04
	–	(0.12)	–	(0.07)
Average Wage * (10)	–	−0.02	–	0.02
	–	(0.45)	–	(0.39)
Focused	–	0.02	–	0.02
	–	(0.06)	–	(0.06)
Same Industry	–	0.03	–	0.03
	–	(0.03)	–	(0.03)
Intercept	−0.11	−0.16	−0.06	−0.12
	(0.07)	(0.12)	(0.06)	(0.11)
R^2	0.04	0.11	0.03	0.12
Test of joint significance of the venture foundation year dummies, $\chi^2(5)$	1.23	1.45	1.28	1.27
Test of joint significance of the venture industry dummies, $\chi^2(5)$	0.51	0.77	0.51	0.97
Test of joint significance of the venture region dummies, $\chi^2(3)$	0.67	0.26	0.49	0.11
Test of joint significance of the year dummies, $\chi^2(5)$	–	1.12	–	1.05
Test of joint significance of the spawner industry dummies, $\chi^2(5)$	–	1.83	–	1.81
Test of joint significance of the spawner region dummies, $\chi^2(3)$	–	1.01	–	1.05
Observations	637	426	637	426

Notes: Clustered standard errors at the firm lever are in parentheses; *** (**, *) indicate a significance level of 1% (5%, 10%), respectively

[a] Only the coefficient and standard error of *V_Average Wage* in Model 12 have been multiplied by 100

spawning. Previous literature has already identified firm size and performance as important characteristics influencing the rate at which new ventures are spawned. The question if these spawning firm characteristics can also influence the financial success of new ventures, however, remains unanswered by existing studies. This paper provides a first empirical investigation of this research gap. In particular, we are interested in the question if successful firms spawn financially successful ventures.

Our analysis is based on the official employee–employer data sets of Statistics Netherlands. These data sets allow us to identify all spawning firms along with the newly created ventures. Based on this information we investigate three related questions. First, we follow previous studies and determine the effect of firm size and performance on the rate at which new ventures are spawned. As an answer to our first two research questions, the results show that large firms as well as firms lacking a good financial performance are the most active spawners. The former finding is in accordance with an earlier study by Gompers et al. (2005). Employees seem to create new ventures because they are frustrated that the large firms for which they work are unable or unwilling to fund their entrepreneurial ideas. Our second finding that there is a negative relationship between firm performance and spawning rate is a consistent finding throughout most studies (cf. Eriksson and Kuhn 2006; Hyytinen and Maliranta 2008; Wagner 2004). Employees found their own ventures if the performance of their employers drop and the rents from staying at the firm are reduced (cf. Eriksson and Kuhn 2006; Hyytinen and Maliranta 2008; Wagner 2004). This suggests that most new ventures are rather "pushed" by crises at the spawning firms (e.g. bad performances) and not "pulled" by the market or the wish to follow a business idea independently (Eriksson and Kuhn 2006).

The second part of our analysis answers the research question if the financial performance of entrepreneurial ventures is affected by the characteristics of their spawning companies. Specifically, we are interested in examining the relationship between the ventures' performance and the spawning firms' performance. We find, in accordance with our research question, that firms exhibiting a good performance also spawn successful ventures. A possible explanation for this finding is that well performing companies possess valuable and distinct knowledge, which their employees are able to exploit for founding and running successful ventures (Klepper 2009; Agarwal et al. 2004; Franco and Filson 2006; Eriksson and Kuhn 2006). In fact, founders of pulled ventures not only learned important knowledge about technologies (Klepper and Sleeper 2005; Agarwal et al. 2004), markets (Jovanovic 1982; Agarwal et al. 2004) and organizational processes (Buenstorf 2009) from their previous employers, but also established important contacts with suppliers and customers, which they can now take advantage of (Helfat and Lieberman 2002).

Finally, our analysis suggests that well performing firms spawn few but successful ventures. It seems that employees of such firms are more reluctant to quit and create new ventures than employees of struggling companies. In the former case, the opportunity costs of leaving are higher so that employees are only deciding to pursue entrepreneurial opportunities if the expected returns are high enough. This result is consistent with the superior performance of ventures spawned by successful firms as depicted before.

Our findings have important implications. In particular, they suggest that large firms, which have high spawning rates, might want to encourage the internal pursuit of entrepreneurial ideas if employees should be persuaded to stay. One way to do so would be the creation of corporate ventures (CVs) in which employees' entrepreneurial ideas are implemented. Corporate ventures are autonomous or semi-autonomous firms that reside within the organizational domains of their founding companies. An advantage of corporate ventures is that they can operate rather independently but still rely on the resources of their corporate sponsors (Hill and Rothaermel 2003; Sharma and Chrisman 1999). Recent research has shown that these specific characteristics make corporate ventures do well at generating radically new innovations (Czarnitzki et al. 2010). Cassiman and Ueda (2006) argue, however, that firms have a limited capacity for corporate venturing. This means that not all entrepreneurial ideas can be capitalized on. Firms have to consider the returns from an employee's innovation against both cannibalization effects and the option value of waiting for better projects in the future. Hence, corporate venturing is only feasible to a certain extent.

Our study is not free of limitations. First of all, we are not able to measure directly if venture founders have learned something from their previous employers. We can only conclude indirectly that employees of better performing firms must have learned valuable knowledge that facilitates the creation of successful ventures. Previous studies could state more specifically if employees have inherited knowledge from their previous employers (Agarwal et al. 2004; Franco and Filson 2006). In fact, both studies were able to distinguish between different knowledge types. The reason is that the authors can make use of specific knowledge measures that are only applicable to the disk drive industry. Agarwal et al. (2004), for instance, use these industry specific knowledge measures to approximate technical knowledge and marketing knowledge. Also Chatterji (2009) accounts for technical knowledge in his empirical analysis on the medical device industry and confirms the importance of marketing knowledge by conducting interviews with venture founders. Such detailed information, however, come at a cost as the data samples of these studies are restricted to a certain industry. While lacking some of the detailed information used in prior research, our study has the advantage that it is based on samples that cover the whole Dutch manufacturing and service industries.

Second, our analysis relies on an unbalanced sample of spawned ventures so that we cannot use growth measures to further test the robustness of our results. Information on the exit dates of the ventures is also missing since our panel is too short to observe many firm exits. Accordingly, a survival analysis cannot be performed either. Third, we lack information on the innovativeness of the last employers and the spawned ventures. Since we have only access to anonymized data sets at Statistics Netherlands and cannot observe firm names, we are not able to link publicly available patent records to our ventures and spawning firms.

A possible venue for future research would be to assess if the performance of the spawning companies worsens after their entrepreneurial employees leave to found new ventures. In this context, it would be interesting to obtain more information on the employment history of the spawned employees. What kind of positions did they hold at their previous employers? Is venture performance dependent on how long they worked for the spawning companies?

Appendix 1

Whereas Sect. 4.1 shed light on the effect of, inter alia, firm size and performance on a firm's rate of entrepreneurial spawning, we now analyze the attributes that determine whether firms spawn at all. A dummy variable, equaling one if a firm spawns at least one venture and zero otherwise (*Spawner*), was created to address this question.

Overall, the probit regressions in Table 8 largely support the key results from Sect. 4.1 in the sense that those firms displaying a high spawning rate are also

Table 8 Probit regression results on being a spawner for the full sample and the high tech subsample

Variables	Dependent variable: *Spawner* (1/0)	
	Model 15	Model 16
Size	0.33**	0.38***
	(0.005)	(0.02)
ROA	−0.18***	−0.26***
	(0.03)	(0.07)
Sales Growth	−0.19***	−0.16***
	(0.01)	(0.04)
Age	−0.004***	−0.01**
	(0.001)	(0.003)
Young	−0.19***	−0.19***
	(0.02)	(0.05)
Old	0.14***	0.21**
	(0.22)	(0.08)
Average Wage	0.79***	0.71***
	(0.02)	(0.05)
Focused	0.08***	0.04
	(0.02)	(0.05)
Intercept	−3.14***	−3.51***
	(0.05)	(0.47)
Test of joint significance of year dummies, $\chi^2(4)$	429.23***	36.94***
Test of joint significance of industry dummies, $\chi^2(33)$	535.84***	17.78**,[a]
Test of joint significance of region dummies, $\chi^2(11)$	86.30***	25.89***
Log-likelihood	−71238.73	−6538.89
Observations	122272	11553

Notes: Clustered standard errors are at the firm level are in parentheses; *** (**, *) indicate a significance level of 1% (5%, 10%), respectively

[a] Test of joint significance of industry dummies, $\chi^2(8)$

the ones that are most likely to spawn at least one entrepreneurial venture. Large firms, young firms and firms with an inferior performance have both a high spawning rate and a high likelihood of spawning at least one new venture. The results remain robust if one only considers the subsample of high tech firms (Model 16). The main difference to the results from Sect. 4.1 lies in the fact that focused firms (*Focused*), extremely young firms (*Young*) and old companies (*Old*) are more likely to spawn new ventures, although these characteristics had no impact on spawning rates.

Appendix 2

See Tables 9, 10, 11 and 12.

Table 9 Spawning percentage of firms

Number of spawned ventures	Percentage
1	84.89
2	7.76
3	3.82
4	1.02
5	0.53
6	0.41
>6	1.57
Total	100

Table 10 Classification of industry dummies

Industry	Description	Spawning firms per industry[a]	Non-spawning firms per industry[b]
1	Manufacture of food products, beverages and tobacco	452	292
2	Manufacture of textiles	127	103
3	Manufacture of wearing apparel; dressing and dyeing of fur	56	57
4	Manufacture of leather and leather products	26	22
5	Manufacture of wood and wood products	181	158
6	Manufacture of pulp, paper and paper products	99	63
7	Publishing, printing and reproduction of recorded media	582	661
8	Manufacture of chemicals and chemical products	212	102
9	Manufacture of rubber and plastic products	217	179
10	Manufacture of other non-metallic mineral products	176	116
11	Manufacture of basic metals	50	38
12	Manufacture of fabricated metal products, except machinery and equipment	885	787
13	Manufacture of machinery and equipment n.e.c.	665	522
14	Manufacture of electrical and optical equipment	366	386
15	Manufacture of motor vehicles, trailers and semi-trailers	118	77
16	Manufacture of other transport equipment	151	113
17	Manufacture of furniture; manufacturing n.e.c.	401	294
18	Recycling	31	28
19	Electricity, gas and water supply	43	19
20	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of automotive fuel	1105	1406
21	Wholesale trade and commission trade, except of motor vehicles and motorcycles	4509	6356

Table 10 continued

Industry	Description	Spawning firms per industry[a]	Non-spawning firms per industry[b]
22	Retail trade, except of motor vehicles and motorcycles; repair of personal and household goods	2451	2993
23	Hotels and restaurants	1265	1129
24	Land transport; transport via pipelines	936	908
25	Water transport	92	118
26	Air transport	33	19
27	Supporting and auxiliary transport activities; activities of travel agencies	405	629
28	Post and telecommunications	156	130
29	Financial intermediation	386	918
30	Real estate activities	146	244
31	Renting of machinery and equipment without operator and of personal and household goods	221	277
32	Computer and related activities	1115	1663
33	Research and development	93	127
34	Other business activities	5338	9078

[a] The number of spawning firms does not add up to 19,895 since spawning firms can also be active in more than one industry class

[b] The number of non-spawning firms does not add up to 28,320 since non-spawning firms can also be active in more than one industry class

Table 11 Structure of the unbalanced panel (1999–2004)

Number of yearly observations	Frequency	Percentage
1	3003	15.09
2	3209	16.13
3	3058	15.37
4	2582	12.98
5	2461	12.37
6	5582	28.06
Total	19895	100

Table 12 Classification of region dummies

Region	Description
1	Groningen
2	Friesland
3	Drenthe
4	Overijssel
5	Flevoland
6	Gelderland
7	Utrecht
8	North Holland
9	South Holland
10	Zeeland
11	North Brabant
12	Limburg

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