Human Capital in New Firms

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Executive Summary

This dissertation is a collection of three stand-alone research papers on the composition of human capital in newly founded firms. The papers are all empirical but they are closely related to two theoretical approaches. The first approach is the jack-of-all-trades model by Lazear (2005) and the second the O-ring theory introduced by Kremer (1993) and applied to new firms by Fabel (2004a,b) and Fabel and Weber (2005). Besides contributing to the search of stylised facts about the effects of the composition of human capital in new firms, this dissertations aims at discovering to what extent the predictions of these theoretical approaches can be confirmed by the data. In the introduction (Chapter 1), it is motivated why there is interest in new firms. The three papers are included in Chapters 2 to 4.

In Chapter 2, it is analysed whether heterogeneity in the educational backgrounds of the founders matters for the success of academic spinoffs. Furthermore, it is examined whether team foundations are more successful than single entrepreneurs. These questions are analysed using a data set on academic spinoffs in Germany. Firm success is measured by employment growth. The results show that team foundations are more successful than single entrepreneurs. Team foundations of engineers perform better when they have a business scientist in the team. However, different subjects per se and homogeneity with respect to the academic origins of the founders do not play a significant role for the success of academic spinoffs.

In Chapter 3, it is investigated to what extent the predictions of the O-ring theory are supported by the data. The O-ring theory predicts that individuals sort between firms according to their level of ability and that a higher average ability level within firms is positively related to both the number of individuals in the firm and capital per head. For the analysis, a rich register data set is used, covering the whole population of firms founded in Denmark in 1998 as well as all individuals involved in these new firms in the start-up year and in the following three years. In order to analyse the extent of sorting of individuals between firms, statistical tests are

constructed, which compare the actual distribution of individuals among firms with the distribution resulting from random assignment of individuals to firms. The results show that, contrary to the prediction of the theory, individuals with different levels of ability tend to team up in new firms. Also contrary to the prediction of the theory, firm size and average level of ability of the involved individuals turn out to be negatively related. The only hypothesis that is confirmed by the data is the positive relationship between capital per head and the average level of ability in a firm.

In Chapter 4, the implications of the O-ring theory for the survival of new firms are considered. The theory assumes that (given team size) average ability in a team is positively and (given ability) team size is negatively related to firm survival. Moreover, it can be inferred that a higher level of homogeneity with respect to ability and a higher level of heterogeneity with respect to the field of education leads to higher survival chances of new firms. Using the same data as in Chapter 3, it turns out that both the average level of ability in a team and team size have positive effects on a firms' probability to survive. Most important is the fact that a firm is founded by a team at all. In contrast, homogeneity with respect to ability and heterogeneity with respect to educations do not affect the probability of firm survival. It can be concluded that the main reason why most of the hypotheses tested in Chapter 3 fail is that an additional person does not increase firm failure.

Zusammenfassung

Diese Dissertation ist eine Zusammenstellung von drei eigenständigen Forschungspapieren zur Zusammensetzung von Humankapital in neu gegründeten Unternehmen. Die Papiere sind alle empirisch, stehen aber in enger Beziehung zu zwei theoretischen Ansätzen. Der erste Ansatz ist das "Jack-of-all-Trades"-Modell von Lazear (2005) und der zweite die O-Ring-Theorie, die von Kremer (1993) vorgeschlagen und von Fabel (2004a,b) und Fabel and Weber (2005) auf neu gegründete Unternehmen angewendet wurde. Ziel dieser Disseratation ist zum einen, zur Suche von stilisierten Fakten über den Einfluss der Zusammensetzung des Humankapitals in neu gegründeten Unternehmen beizutragen, und zum anderen, herauszufinden, inwieweit die Vorhersagen der genannten theoretischen Modelle von den Daten bestätigt werden können. In der Einleitung (Kapitel 1) wird dargestellt, warum man sich für neue Unternehmen interessiert. Die drei Papiere bilden die Kapitel 2 bis 4.

In Kapitel 2 wird untersucht, ob ein heterogener Bildungshintergrund der Gründer relevant für den Erfolg von akademischen Spinoffs ist. Weiterhin wird untersucht, ob Teamgründungen erfolgreicher sind als Einzelgründer. Als Grundlage werden Daten zu akademischen Spinoffs in Deutschland verwendet. Der Unternehmenserfolg wird anhand des Beschäftigungswachstums gemessen. Die Ergebnisse zeigen, dass Teamgründungen erfolgreicher sind als Einzelgründer, und dass Teamgründungen von Ingenieuren besser abschneiden, wenn ein Wirtschaftswissenschaftler Mitglied des Teams ist. Unterschiedliche Studienfächer per se sowie die Heterogenität in der akademischen Herkunft der Gründer spielen keine Rolle für den Erfolg von akademischen Spinoffs.

In Kapitel 3 wird analysiert in welchem Ausmaß die Vorhersagen der O-Ring-Theorie von den Daten bestätigt werden können. Die O-Ring-Theorie sagt vorher, dass Individuen sich entsprechend ihrer Fähigkeiten zwischen Unternehmen sortieren, und dass ein höheres durchschnittliches Fähigkeitsniveau innerhalb eines Unternehmens positiv mit der Unternehmensgröße und dem Kapitaleinsatz pro

Kopf zusammenhängt. Für die Analyse wird ein umfangreicher Datensatz verwendet, der alle Unternehmensgründungen in Dänemark im Jahr 1998, sowie alle Individuen, die im Gründungsjahr und den nachfolgenden drei Jahren in den neuen Unternehmen involviert sind, umfasst. Um das Ausmaß der Sortierung der Individuen zwischen den Unternehmen zu bestimmen, werden statistische Tests konstruiert, die die tatsächliche Aufteilung der Individuen auf die Unternehmen mit der Aufteilung, die sich aus der zufälligen Zuweisung der Individuen auf die Unternehmen ergibt, vergleichen. Die Ergebnisse zeigen, dass entgegen der Vorhersage der Theorie sich eher Individuen mit verschiedenen Fähigkeitsniveaus in neuen Unternehmen zusammenfinden. Weiterhin zeigt sich, wiederum der Vorhersage der Theorie widersprechend, dass zwischen der Unternehmensgröße und dem durchschnittliche Fähigkeitsniveau ein negativer Zusammenhang besteht. Die einzige Beziehung, die bestätigt werden kann, ist der positive Zusammenhang zwischen Kapital pro Kopf und dem durchschnittlichen Fähigkeitsniveau der Individuen eines Unternehmens.

Im Kapitel 4 werden die Implikationen der O-Ring-Theorie hinsichtlich des Überlebens von neuen Unternehmen betrachtet. Die Theorie nimmt an, dass (gegeben die Teamgröße) die durchschnittliche Fähigkeit in einem Team positiv und (gegeben die Fähigkeit) die Teamgröße negativ mit dem Überleben des Unternehmens zusammenhängt. Weiterhin kann man aus der Theorie ableiten, dass ein höherer Grad an Homogenität hinsichtlich der Fähigkeiten und ein höherer Grad an Heterogenität hinsichtlich der Bildungsabschlüsse zu einer höheren Überlebenswahrscheinlichkeit der Unternehmen führt. Für die Analyse wird derselbe Datensatz wie in Kapitel 3 verwendet. Die Ergebnisse zeigen, dass das durchschnittliche Fähigkeitsniveau in einem Team und die Teamgröße einen positiven Einfluss auf die Überlebenswahrscheinlichkeit der Unternehmens haben. Am wichtigsten ist es, überhaupt im Team zu gründen. Homogenität hinischtlich der Fähigkeiten und Heterogenität hinsichtlich des Bildungsabschlusses haben dagegen keinen Einfluss auf das Fortbestehen der Unternehmen. Aus den Ergebnissen dieser Analyse kann gefolgert werden, dass die Hypothesen aus Kapitel 3 deswegen fast alle verworfen werden, weil ein zusätzliches Teammitglied die Überlebenswahrscheinlichkeit eines Unternehmens nicht senkt.

1 Introduction

This dissertation is a collection of three papers that focus empirically on the composition of human capital in new firms. In the last 30 years, small firms and entrepreneurship have received considerable attention both by politicians and in academia. Before that, small firms had not got much room in the thinking about the economy for a long period of time. Since the 1920s, the prevalent view was that economic growth is based on mass production in large firms. Small firms were regarded as a relict of past times and some authors actually predicted their demise when industries mature. For example, Galbraith wrote in 1956, "With many notable exceptions – [...] – the number of firms participating in a business is likely to be at its maximum within a few years or even a few months after the business is born. Thereafter there is, typically, a steady decline until a point of stability is reached with a handful of massive survivors and, usually, a fringe of smaller hangers-on." (Galbraith (1956), pp. 32-33). It came as a surprise when it became clear in the 1980s that small firms did not vanish, but seemed to play an even increasing role. For example, Brock and Evans (1989) notice that in 1986, 76 percent of the 17 million tax-paying firms in the United States give work only to their owners, that only approximately 10,000 firms had more than 500 employees, and that the number of new business incorporations increased by 87 percent between 1976 and 1986.

Compared to craft production, which is predominant in small firms, mass production is characterised by high fixed, but low variable costs. It receives its appeal via fixed cost degression, which is achieved by increasing labour productivity through a high degree of division of labour, the standardizing of the final product and the use of highly specialised machinery on a large scale. The downside of this form of production is that it comes along with a high degree of specialisation of capital and labour which makes the production process inflexible. For example, a machine that is aimed at producing moulding blanks for knives can only produce these blanks but nothing else. This requires that the market of the final product is not only large enough, but also sufficiently stable to recover the costs of expensive machines. Until the 1970s, governments and firms succeeded in both enlarging and stabilising markets. For example, one goal of the payment of five dollar per day by Henry Ford was to enable his workers to buy mass produced goods like his Model T. Variation in wages and product prices were confined by flexible resorting to workers outside the industry workforce and by stockkeeping of storable goods.

According to Piore and Sabel (1984), the attractiveness of mass production in its original form approached its limits when the mass markets began to saturate at the end of the 1960s. It furthermore lost much of its appeal due to the turbulences of the 1970s. Piore and Sabel (1984) identify a series of five events that upset the belief in mass production as the superior way of organising production. 1) The social disturbances at the end of the 1960s, 2) the termination of the Bretton Woods-Agreement on fixed exchange rates, 3) the first oil price shock, 4) the second oil price shock, and 5) the high interest rates and the worldwide recession at the beginning of the 1980s.

The social disturbances at the end of the 1960s not only expressed resentments against the war in Vietnam and the discrimination of some social groups, such as the black people in the United States, but also resulted in the inclusion of former marginal groups (farm workers, women, young persons, immigrants) in the working standards of the industrial workers (minimum wages, job security, unemployment insurance). As a consequence, it was no longer possible to stabilise wages by using the marginal groups as a flexible labour source for production. This made the industrialised countries more vulnerable to inflation caused by rising wages. The termination of the Bretton Woods-Agreement resulted in a system of floating exchange rates, which exposed the goods prices in international trade to changes in the demand for currencies. As currency demand is not only determined by transactions in the goods markets but also by the heavily fluctuating assessment of the rate of return in different countries by money investors, the import prices became much more volatile and the prediction of their development a challenging task. The two oil price shocks resulted not only in substantial inflation but also in increased scepticism about the long term availability of essential resources. As the most important sources of the oil price changes lay outside the sphere of influence of the industrialised countries, the planning reliability of the mass producers decreased.

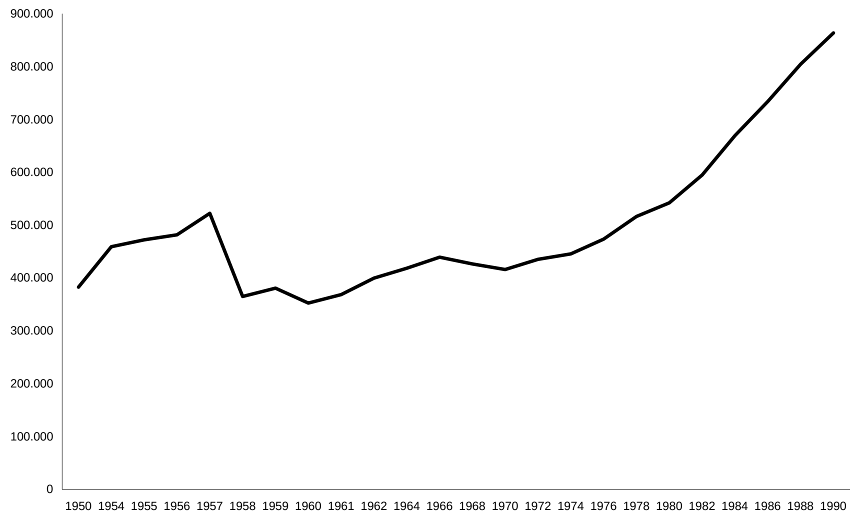
The lasting inflation after the second oil price shock led the American Federal Reserve Bank to raise the discount rate drastically, which triggered the first worldwide recession after the Second World War. In sum, together with the saturation of the mass markets these five events undermined the basis of mass production – large and stable markets – and led to a reassessment of the way economic activity should be organised.

This reassessment brought small firms into the focus for several reasons. First, the increased uncertainty in the economic environment made a more flexible way of production more attractive because it allows the firms to react more quickly to market changes. During the period of time when mass production was the dominant mode of production, flexible technologies survived in small firms. Second, the upcoming computerisation reduced the cost disadvantage of small scale production compared to large scale production. For example, in the metalworking industries computer numerically controlled machines were introduced. By allowing a quick and very precise movement of tools and easy adjustment to different workpieces, these machines substantially reduced the costs of producing small batches. Carlsson, Audretsch, and Acs (1994) find evidence for the hypothesis that the adoption of numerically controlled machine tools has reduced average firm size in US manufacturing and metalworking industries between 1979 and 1984. Third, the mass producers responded to the increased competition by major restructuring and corporate downsizing. They outsourced all the activities that can be better, cheaper or more flexibly provided by other firms. Most of these activities were services, which are typically offered by small firms. As can be seen from Figure 1.1 for the case of Germany, the number of firms providing business services rose considerably between 1970 and 1990.

Interest in small firms also derives from interest in entrepreneurship. In general, entrepreneurship is a vague concept,[1] but most often it is understood to be the establishment and operation of small firms (OECD (1998), van Praag and Versloot (2007)). The interest in entrepreneurship arose as entrepreneurs are considered to be "agents of change" who could contribute to reduction in unemployment. One consequence of the economic crisis of the 1970s is high and persistent unemployment in the industrialised countries. In the 1950s and the 1960s, the average number of unemployed workers amounted to 10 million in the OECD countries. Between 1972

[1] See, for example the varying use of the term in OECD (1994, 1997, 2001a,b).

Figure 1.1: Number of firms in business services (West-Germany)



Source: Federal Statistical Office, Germany.

to 1982, this number rose to 30 million (OECD (1994)) and has remained at a high level until today. Politicians concluded that the main reason why there are not enough jobs in industrialised countries is that their product and labour markets were not able to adapt to change. Representative for this view is the OECD with its 1994 Jobs Study. In this study, the OECD also recommended a series of actions to increase its member countries' flexibility, among which the fostering of entrepreneurship is to be found.

On the part of policy, a series of hopes and expectations are linked to small and newly founded firms. They are supposed to react better to changing environments and to be more innovative thereby enhancing growth and creating jobs. They are expected to increase efficiency by rising the competitive pressure in an industry, provide consumers with a greater variety of products, foster structural change in the direction of more knowledge-intensive activity, and increase job satisfaction by allowing the entrepreneurs to fulfil themselves (European Comission (2003), OECD (1998)).

These hopes might be exaggerated but they are not fully unrealistic. In a review of the recent literature, van Praag and Versloot (2007) find that countries and regions within countries that have higher start-up rates experience higher employment rates immediately and in the long run. Young firms as a group have higher net employment growth rates than old firms[2] and small firms have higher number of innovations per employee and higher growth in value added and labour productivity than large firms.

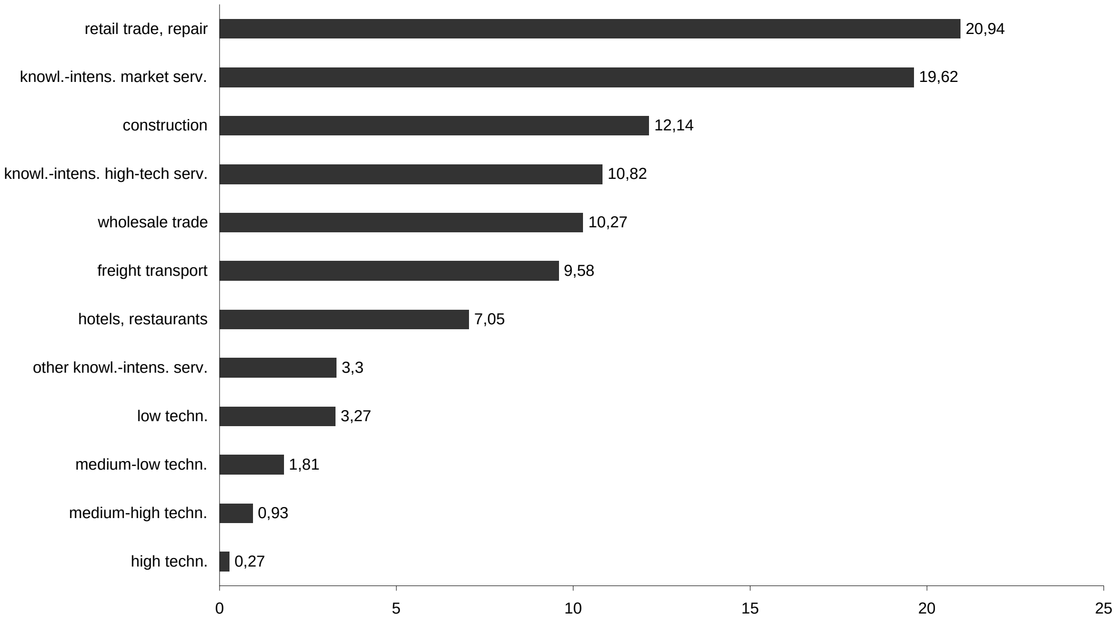
In order to provide indications how to foster entrepreneurship, research in the last decades has tried to identify success factors for new firms. One factor that turned out to be very important is human capital. Van der Sluis, van Praag, and Vijverberg (2008) find in a meta-analysis of almost one hundred studies since 1980 that the level of education is positively related to the performance of young firms. There are authors that claim that human capital is even more important than financial capital for young firms. For example, Cressy (1996) argues for the UK that "the influence of finance on performance is nil and the correlation between finance and survival vanishes once human capital is controlled for." (Cressy (1996), p. 1254). The papers in this dissertation are related to this strand of literature.

In addition to human capital as a success factor, there is a second perspective from which human capital in new firms is of interest. This is the perspective of the theory of the firm which centers around the question how economic activity is organised within firms. As can be seen from Figure 1.2 for the example of Denmark, the majority of new firms is founded in services, which are human-capital intensive sectors. Yet, human-capital intensive firms are characterised by different organisational patterns than firms that are built around physical assets.

In his seminal article, Coase (1937) notes that economic activity within firms is coordinated via power relationships and not via prices as it is the case in markets. Using power as a coordination device can be superior when the costs of using the price mechanism are high. According to Williamson (1975, 1985), this is particularly the case when parties must make relationship-specific investments and when the returns of these investments cannot be split up in advance due to the impossible of writing detailed long-term contracts. These constellations may give rise to opportunistic behaviour which then prevents transactions with gains from trade for all involved parties. Accomplishing transactions with the help of power rather than

[2]The net employment growth rate is defined as the difference between the job creation rate and the job destruction rate.

Figure 1.2: Distribution over industries of firms founded in Denmark in 1998



Source: Statistics Denmark, author's calculation.

prices can attenuate the adverse effects of opportunistic behaviour and make these transactions possible.

Power in a firm can stem from different sources. Economically probably the most relevant source is the ability to exercise residual rights of control over resources that are valuable for the production process (Grossman and Hart (1986), Hart and Moore (1990)). Residual rights of control include all rights for using a given asset except those specified in a contract. They confer power to its holder by e.g. providing her with the constant threat to withdraw the resource from the production process (if the withdrawal is not explicitly excluded by contract).

In physical-capital intensive firms, power can arise from ownership of the physical assets of the firm (Grossman and Hart (1986), Hart and Moore (1990)). However, in human-capital intensive firms, ownership does not provide a basis for power. The reason is that the human capital of individuals cannot be owned by someone else unless slavery is permitted. Rajan and Zingales (2000, 2001) therefore suggest that power in human-capital intensive firms is based on the existence of complementarities. Complementarities are said to exist if the output that individuals create together is higher than the sum of the output if each individual would produce on her own.

The papers in this dissertation consider both human capital as a success factor of new firms and human capital induced complementarities as an organisational aspect of these firms. In contrast to most of the existing literature, this dissertation concentrates on the composition instead of the level of human capital. The type of complementarities considered is complementarities between the abilities of the individuals involved in the new firms. The papers are all empirical, but they are closely related to two theoretical approaches. The first is the jack-of-all-trades model by Lazear (2005) and the second the O-ring theory introduced by Kremer (1993) and applied to new firms by Fabel (2004a,b) and Fabel and Weber (2005). Lazear (2005) puts forward that jacks-of-all-trades are more likely to become entrepreneurs as their primary job is coordinating different tasks, which requires knowledge in different areas. The O-ring theory is a theory about teams in which the necessary knowledge is provided by several individuals who are each a specialist in a particular task. These theories are the only ones that focus on the composition of human capital in new firms. The aims of this dissertation are, a) to contribute to the search of stylised facts about the effects of the composition of human capital in new firms and b) to discover to what extent the predictions of these theoretical approaches can be confirmed empirically.

In Chapter 2, it is analysed to what extent the employment growth of academic spinoffs is affected by the heterogeneity in the educational backgrounds of the founders. In Chapter 3, it is examined whether we can infer from the human capital composition and from the relationship between average ability, firm size and the amount of capital employed that new firms are characterised by complementarities between the abilities of the individuals involved in the new firms. In Chapter 4, the implications of complementarities in abilities for the survival of new firms are derived and the resulting hypotheses are tested. In summary, the three analyses yield the following results,

- Team foundations have higher employment growth and higher survival chances than firms founded by single entrepreneurs.
- If firms are founded by a team, individuals match more often with other individuals who have the same education than under random matching.

- If firms are founded by a team, individuals match more often with other individuals who have the same level of ability than when randomly matched. However, this holds only for the start-up year. When the firms mature, the degree of homogeneity decreases. And it decreases even more than it would be the case under random recruitment of new employees. Thus, diversification in ability turns out to be the recruitment strategy of young firms.
- The average level of ability in new firms is negatively correlated with firm size.
- The average level of ability in new firms is positively correlated with capital per head.
- The average level of ability in new firms increases the survival chances of new firms.
- Team size increases the survival chances of new firms.
- Team foundations of engineers experience higher employment growth when they have a business scientist in the team.
- The degree of heterogeneity in the educational background or the abilities per se of the individuals involved has no effect on the survival chances or the employment growth of new firms.

With these results, the following main insights can be gained from this dissertation. First, neither of the two conventional wisdoms "opposites complement each other" and "birds of a feather flock together" can be turned into a promising strategy for new firms with respect to the analysed dimensions, education and ability. It is consistently put forward in the literature that, as a broad range of skills is required, it is beneficial to have either a multiskilled person or an interdisciplinary team for setting up a new firm. This also corresponds to intuition. However, this conjecture cannot be supported. With respect to the subject studied, individuals of the same type tend to build teams and, apparently, it is not harmful for them. Firms founded by teams whose members have a degree in the same subject do not perform worse than interdisciplinary teams. Likewise, individuals who have studied only one subject have no less employment growth than individuals who studied several subjects. With respect to ability, individuals tend to build teams of their sort in the beginning, but they diversify their workforce in the years after founding. And this again is not harmful. Firms with a heterogeneous workforce with respect to ability do not have lower survival rates than firms with a homogeneous workforce. For policy, this means that there is no need to influence the composition of founding teams or interdisciplinary education of single entrepreneurs when taking actions to foster new firms. What is relevant, in contrast, is that firms are founded by at least two persons. Team foundations live longer and tend to grow with higher rates than firms founded by single entrepreneurs.

Second, it is not very likely that complementarities between individual abilities exist in new firms. The empirical analyses have been performed as closely as possible to the above mentioned theoretical models, especially in Chapter 3 and 4. However, the facts do not support the assumption that new firms are characterised by complementarities in abilities. The most important result that causes conflict with the existence of this type of complementarities is that firm size decreases in the average ability level of the individuals involved in the new firms. If there were complementarities, the opposite should be observed.

2 Does Interdisciplinarity Lead to Higher Employment Growth of Academic Spinoffs?

2.1 Introduction

A common assumption in the theoretical literature on entrepreneurship is that interdisciplinarity is important for successfully running a new firm. Lazear (2005) claims that single entrepreneurs must have knowledge in different areas, and Fabel (2004b) uses a model in which firm success depends on the knowledge and abilities of the different individuals in the team that performs the essential tasks of the firm. There is some evidence that interdisciplinarity increases the probability to become an entrepreneur. Lazear (2005) and Wagner (2006) find that individuals are the more likely to found a firm the more diverse their educational background is.

However, it is empirically still an open question whether interdisciplinarity is a success factor of new firms. So far, there is no evidence for firms founded by single entrepreneurs and for firms founded by teams, the results are mixed. Ensley, Carland, and Carland (1998) and Ensley and Amason (1999) find that heterogeneity in the subjects studied has a negative effect on the level of sales, but no effect on sales growth and profitability. Zimmerman (2008) finds a positive effect of the same variable on the amount of capital that the firms obtain at their initial public offering, and Amason, Shrader, and Tompson (2006) report no effect on sales growth, profitability and market performance (net return to shareholders in the 3-year period after initial public offering).

In this paper, I analyse whether interdisciplinarity of the founders of academic spinoffs is important for the employment growth of these firms. Academic spinoffs are spinoffs from universities and other research institutes. They are considered to be important for economic growth because they are a vehicle for spreading new ideas. Often, new ideas emerge by recombining existing knowledge, which could be encouraged by different knowledge backgrounds of the involved persons. Thus, for these firms interdisciplinarity might be especially important as it is not only relevant for running the firm but also as a basis for the business idea itself.

As theoretical basis for the derivation of the hypotheses, the models by Lazear (2005) and Fabel (2004b) mentioned above are used. To my knowledge, these are the only formal theories that consider the effects of the composition of human capital for new firms. Lazear focusses on single entrepreneurs whereas Fabel allows for the possibility that firms are founded by teams. These two models suggest to compare the following groups of firms with respect to employment growth: a) team foundations versus single entrepreneurs, b) single entrepreneurs who studied several subjects versus single entrepreneurs who studied only one subject, c) team foundations whose members studied different subjects versus team foundations whose members all studied the same subject, and d) team foundations whose members all have the same level of ability versus team foundations whose members have different levels of ability. The outcome of this analysis is relevant for developing guidelines to set up promising start-ups. But it also concerns education policy as it indicates whether universities should set up interdisciplinary curricula when aiming at fostering academic spinoffs.

One reason for the inconclusive results of the existing studies is that they rely on rather small data sets. The most extensive data set used has just 174 observations, which could lead to imprecise estimates. Furthermore, the existing results are presumably based on selected samples as the authors only observe surviving firms. As firm performance and survival are not independent (Dunne, Roberts, and Samuelson (1989)), estimates based only on surviving firms are potentially biased. In this paper, I use the ZEW spinoff survey, which contains educational information on the founders of roughly 3,000 academic spinoffs in Germany. Additionally, it is possible to use information on non-surviving firms founded in research and knowledge intensive sectors to correct for the bias arising from the fact that the effect of heterogeneity in educations can only be calculated for surviving firms.

The results of this paper show that employment growth of academic spinoffs is higher when the firm is founded by a team than when it is founded by a single entrepreneur. Team foundations of engineers have higher employment growth when they have a business scientist among them. However, heterogeneity with respect to the subjects studied per se and with respect to the institution of academic origin is irrelevant for the employment growth of academic spinoffs. Thus, it is only important that several persons are involved, but it is by and large negligible who matches with whom to set up the firm.

The paper is organized as follows: Section 2.2 presents the theoretical approaches by Lazear (2005) and Fabel (2004b) and develops the hypotheses for the empirical analysis. Section 2.3 describes the data set and the relevant variables. Section 2.4 presents the estimation method. Section 2.5 shows the results, and Section 2.6 concludes.

2.2 Theory and Hypotheses

In this section, the hypotheses for the empirical analysis are developed. They are based on the jack-of-all-trades model by Lazear (2005) and the partnership model of entrepreneurship by Fabel (2004b). These theories make statements about the probability to become an entrepreneur and about the equilibrium size of firms. The approaches are therefore extended in order to derive hypotheses about employment growth.

2.2.1 The "Jack-of-all-Trades" Model

Lazear (2005) views entrepreneurs as persons whose primary task is to bring together different factors of production for creating a new product or producing an old product at lower costs. They "must possess the ability to combine talents and manage those of others" (Lazear (2005), p. 650). In order to be able to fulfil such a task, entrepreneurs must have knowledge in different areas. Lazear (2005) therefore assumes that entrepreneurs need the full range of their skills and that income depends on the skill with which the entrepreneurs are least endowed. This is in contrast to employees who can exploit their best skill to generate income. As a consequence, individuals with a balanced skill profile (jack-of-all-trades) choose to become entrepreneurs and individuals with one outstanding skill choose to become employees.

If the jack-of-all-trades argument applies, individuals have different investment strategies in education depending on their skill profile. Individuals with a clear imbalanced skill profile invest in only one of their skills because they will use only one of their skills in future work. In contrast, individuals with a more balanced skill profile either do not invest, invest in the skill with which they are least endowed or invest in more than one skill. This depends on the investment costs in human capital they face. Thus, following Lazear, the two types of individuals can be distinguished empirically by the breadth of their investment in human capital.[1] In this paper, the breadth of investment in human capital is measured by the fact whether or not an individual has studied several subjects.

For analysing who will become an entrepreneur (which is the concern of Lazear), this reasoning straightforwardly transforms into the hypothesis that individuals with a broad human capital investment strategy are more likely to become entrepreneurs. Concerning employment growth, the case is a little bit more complicated as it is not clear who is observed when we look at an individual with only one subject studied given that she founded a firm: someone with an unbalanced skill profile who "wrongly" chose to become an entrepreneur or someone with a balanced skill profile whose investment costs in education are such that she only chose to study one subject. This leads to different hypotheses about the relationship between heterogeneity in educations and employment growth from the jack-of-all-trades model. One is

H1a: Given start-up size, firms founded by single entrepreneurs who studied only one subject have lower employment growth than firms founded by single entrepreneurs who studied more than one subject.

This hypothesis applies if individuals face some uncertainty about their skill profile which makes it necessary that they actually start a firm before they know whether their skill profile is sufficiently balanced. If the actual skill profile is only revealed

[1] A more direct strategy would be to use information on test scores from school. This information is neither available for the paper by Lazear nor for this paper.

incrementally, the unsuitable entrepreneur will not shut down overnight but may will first reduce employment in order to reduce costs.[2]

The contrasting hypothesis is

H1b: Given start-up size, firms founded by single entrepreneurs who studied only one subject have equal employment growth as firms founded by single entrepreneurs who studied more than one subject.

This hypothesis applies if the observed entrepreneurs all have a sufficiently balanced skill profile but for some, the investment costs are such that they can invest in more than one skill whereas for others, it is only beneficial to raise their weakest skill to the level of their other skills.

A drawback of the jack-of-all-trades model is that it allows predictions only about single entrepreneurs. In teams, it is possible that the weaknesses of one team member is compensated by the strengths of another. But this is implicitly ruled out in the jack-of-all-trades model. Alternatively, Fabel (2004b) presents an approach which also permits team foundations.

2.2.2 The Partnership Model of Entrepreneurship

In his model, Fabel (2004b) adopts the O-ring production function approach of Kremer (1993). According to this theory, the performance of each task in a project is essential.[3] If any member of the team that performs the essential tasks makes a considerable mistake, the project fails. The project success therefore depends crucially on the ability of the team members.

The O-ring theory implies that there is a unique optimal team size for each firm and that team foundations have more employees than single entrepreneurs in equilibrium.

[2]This reasoning is similar to Jovanovic (1982) who models the evolution of the size structure of an industry as a process of noisy selection. Firms do not know their efficiency at the outset but become acquainted with it through learning. Efficient firms grow, and inefficient firms decline. Almus (2004) finds empirically that exiting firms indeed shrink before they close down.

[3]The O-ring approach got its name from the accident of the space shuttle Challenger which exploded because of the malfunctioning of only one of its components: the O-rings of the booster. This event is used as a metaphor for production processes in which everything has to work sufficiently well for the project to be a success.

This approach therefore allows to formulate a hypothesis with respect to the question whether or not the relevant knowledge should be provided by different persons. If start-up size is equal for both single entrepreneurs and team foundations and if it is below optimal size, team foundations should have higher employment growth than single entrepreneurs. The second hypothesis is therefore

H2: Given start-up size, firms founded by teams experience higher employment growth than firms founded by single entrepreneurs.

Fabel (2004b) assumes that each task requires exactly one person. This is a rather strong assumption as it rules out the cases that one individual can perform several tasks and several individuals are assigned to one task. However, with this assumption it can be conjectured that teams whose members have acquired similar types of skills ("specialised teams" in the following) are more likely to split up on the way to equilibrium because the skills of their members are redundant. Teams whose members obtained different skills ("generalistic teams" in the following) can rely on a broader basis which could help them to better run and grow the business. Thus, assuming again that the start-up size of the firms is smaller than their optimal size, the third hypothesis is

H3: Given start-up size, firms founded by generalistic teams experience higher employment growth than firms founded by specialised teams.

A further implication of the O-ring theory is that in competitive labour markets, teams are homogeneous with respect to the ability of their members. The reason is that the abilities of the team members are complementary, i.e. the marginal productivity of the ability of one team member increases in the abilities of the other team members. This implies that a team consisting of individuals with the highest ability level in the population can benefit the most from an equally able team member for a further task and will therefore offer the highest wage. Firms with medium ability individuals cannot successfully compete for higher able individuals but are successful in attracting medium ability individuals compared to firms with lower average ability level. This leads to homogeneity in the ability levels of all individuals within firms.

This sorting mechanism requires that abilities are observable. If, however, abilities are not perfectly observable at the outset, it is possible that also heterogeneous firms are founded. These firms must fail on the way to equilibrium, because for the highest able individual in each team it is always appealing to join a team with equal (or even higher) ability and to leave the lower able individuals. The reason is that having a partner with at least equal ability reduces the probability of firm failure compared to being a member of a heterogeneous team with lower ability individuals. If abilities only become known gradually over time, the employment in firms with heterogenous teams might be reduced before the firm is closed completely. This leads to the fourth hypothesis.

H4: Given start-up size, firms founded by heterogeneous teams experience lower employment growth than firms founded by homogeneous teams.

2.3 Data and variables

2.3.1 Data

The data set used in this paper is the ZEW-spinoff survey 2001 (Egeln, Gottschalk, Rammer, and Spielkamp (2002, 2003)). This survey covers firm foundations in research and knowledge intensive sectors in Germany between 1996 and 2000. These sectors are

- high technology: sectors with high R&D intensity, e.g. the chemical and pharmaceutical industry, engineering, and the computer industry,
- technology oriented services: service sectors in which new technologies are particularly relevant for the business, e.g. software consulting, technical offices, and research services,
- knowledge intensive services: sectors in which the qualification of the employees or the use of knowledge is important, e.g. consulting, tax accountancy, and education.

The ZEW-spinoff survey is sampled from the Mannheim Foundation Panel (MFP) of the Centre for European Economic Research (ZEW), which contains almost all firms founded in Germany since 1989 (Almus, Engel, and Prantl (2000)). The information on the firms for this panel is made available to the ZEW by CREDITREFORM, the largest credit rating agency in Germany. In the MFP, only start-ups with at least one full-time job are included. Changes in legal form or addresses, foundations of investment companies, and part-time foundations do not count as firm foundations. For the spinoff survey, a random sample of almost 70,000 firms stratified by the sector groups defined above, foundation year, and region is drawn. The survey was conducted between October and December 2001 using computer-aided telephone interviews (CATI) and led to a total of 20,241 interviews.

Since the focus of this study is on academic spinoffs, all start-ups which are not academic spinoffs are discarded from the set of firms. A start-up is defined as an academic spinoff if at least one of the founders has studied or is currently studying at a university or a technical college and if academic skills, new scientific methods, or new scientific results are essential for the new firm.

By construction of the survey, only firms that survive until 2001 are interviewed. For the sampled firms that do not survive until 2001, the basic information that is provided by CREDITREFORM for all firms is available. This information can be used to correct for the selection bias that arises because employment growth is not independent of survival. In total, a market exit is observed for 10,498 firms. Since the information relevant for identifying spinoffs is collected during the telephone interviews, the set of non-surviving firms can only be restricted to firms which have at least one university graduate among the founders. In the end, there remain 2,906 surviving firms and 1,752 non-surviving firms for the analyses, which makes a total of 4,658 firms.

The data for the surviving firms cover the number of employees at start and the number of employees in 2001. This information can be used to calculate the average rate of employment from the year of start up to 2001. Additionally, the data include information on the subjects studied by the founders, the research institution the founders come from, and facts about the firms, such as the year of foundation, the size of the foundation team, contacts to the scientific world, and whether the firm received subsidies. The basic information provided by CREDITREFORM includes the number of employees at start, the year of foundation, the region in which the firm is located, information about real estate property and the educational degree of the founders.

2.3.2 Variables

In addition to the variables describing the general characteristics of the firms, a number of additional variables is generated that form the core input to the test of the hypotheses. Due to the character of the information available in the data set, these variables are all dummy variables.

Generalist: This variable captures whether or not a single entrepreneur has a broad investment strategy in human capital. It takes the value one if a single entrepreneur has chosen at least two subjects during her studies. This variable is relevant for H1a and H1b.

With this definition, a single entrepreneur is regarded to have a broad investment strategy if she studied at least two subject regardless of how much related these subject are. E.g., she is termed a generalist if she studied physics and chemistry. A less broad definition is to only consider someone having a broad investment strategy if she studied at least two different subjects from different disciplines, e.g. natural sciences and business sciences. Therefore, an additional dummy is constructed taking the value one if a single entrepreneur obtained skills from at least two different disciplines, which is used alternatively in the regressions. Table 2.6 in the appendix shows which subjects and disciplines are considered for the analysis.

Team: This variable takes the value one if the size of the foundation team amounts to at least two individuals. This variable is relevant for H2.

Generalistic team: This variable takes the value one if the members of a team have studied different subjects. It is zero if all team members have studied the same subject. This variable is relevant for H3.

As in the case of single entrepreneurs, a further dummy variable is generated which takes the value one only if the team is composed of individuals coming from different disciplines, e.g., if the team is composed of a physicist and a business scientist but not if it is composed of a physicist and a chemist.

Homogeneous teams: This variable takes the value one if the firm is founded by a team and all founders come from the same type of research institution. For the analyses in this paper, the founders can originate from three types of research institutions: universities, technical colleges, and non-university research institutes. The variable takes the value zero if at least two team members come from different research institutions. This variable relates to H4.

Defining the variable this way is only a crude approximation to the homogeneity in abilities of the O-ring model applied by Fabel (2004b). In this model, ability corresponds to the probability of performing a task sufficiently well. However, these probabilities are not observable. In this paper, I use the academic origin of the founders as a measure of their ability. This is motivated by the fact that in Germany technical colleges provide more practically oriented and universities more theoretically oriented education. The education or qualification one obtains is therefore likely to be differently demanding in different types of research institutions.

Although the data is quite extensive, it has some limitations. As Table 2.6 in the appendix shows, the information on the subjects is quite detailed but does not cover the whole variety of study courses in Germany. Especially, study courses which have a wide focus, such as business informatics (*Wirtschaftsinformatik*), cannot be identified. For the analyses, an individual who studied such subjects appears as someone with a narrow investment strategy although she receives a rather broad education.

A further drawback of the data is that it is unknown how many team members studied a given subject. E.g., for a team of three individuals, who studied physics and engineering, it is unknown whether there are two physicists and one engineer or one physicist and two engineers. Thus, for the analyses it can only be determined whether or not a team is generalistic. The Herfindahl- or Blau-Index, which is used as a measure for team heterogeneity in the literature, cannot be calculated.

Table 2.1 shows descriptive statistics for the variables used in the regressions. The majority of the firms in the data set are founded by teams (62 percent), but a considerable part is also founded by single entrepreneurs (38 percent). The average number of employees at start is higher for team foundations than for single entrepreneurs. This is partly due to the fact that the number of employees is given in full time

Table 2.1: Descriptive statistics

variable	**single entrepreneurs**		**team foundations**	
	mean	std.dev.	mean	std.dev.
fraction[1]	0.381		0.619	
employment growth	0.155	0.316	0.204	0.334
generalists (subjects)	0.053	0.224		
generalists (disciplines)	0.036	0.187		
generalistic teams (subjects)			0.449	0.498
generalistic teams (disciplines)			0.372	0.484
homogeneous teams[2]			0.794	0.404
number of employees at start[3]	3.311	5.211	5.339	6.882
firm age	3.094	1.373	2.807	1.369
min. labour market experience	8.453	8.986	5.753	7.480
number of contacts to science	1.304	1.648	1.818	1.829
continuous R&D	0.291	0.455	0.381	0.486
occasional R&D	0.131	0.338	0.150	0.357
public support	0.279	0.449	0.320	0.466
high technology	0.153	0.361	0.172	0.377
technology oriented services	0.423	0.494	0.427	0.495
knowledge intensive services	0.423	0.494	0.401	0.490
number of observations	883		1,618	

Notes: [1]based on 2,620 observations. [2]based on 1,508 observations. [3]full time equivalents including founders.
Source: ZEW-spinoff survey 2001, author's calculations.

equivalents including the founders. For the estimations, the founders are not separated from the employees as the relevant comparison is to contrast the employment growth of a team with the hypothetical situation that all team members started as single entrepreneurs. A separation would overestimate the effect of having a team. Furthermore, the new firms also provide employment for the founders. In this sense, the founders are also employees of the firms. On average, a firm founded by a team grows with a higher rate than a firm founded by a single entrepreneur.

Almost all of the single entrepreneurs in the sample (95 percent) have studied only one subject. This fraction becomes 96 percent if "generalist" is defined in terms of disciplines. Among the team foundations, 45 percent have partners with different backgrounds with respect to subjects studied. Considering disciplines, the fraction of generalistic teams is 37 percent. Regarding the homogeneity of the ability, 79 percent of the team foundations are set up by partners who originate from the same type of research institution.

2.4 Estimation Method

The econometric model for estimating employment growth is related to the framework used by Evans (1987b). It is assumed that the relationship between initial employment and employment in 2001 for firm i can be described as

$$E_{t_2,i} = [G(x_i'\beta)]^{t_2-t_{1,i}} E_{t_1,i}\epsilon_i, \tag{2.1}$$

where E denotes employment, $t_{1,i}$ the year of foundation of firm i, t_2 the year of the survey 2001 and ϵ a lognormally distributed error term. The vector x contains the variables which capture the effects of team foundation, generality and homogeneity as well as the control variables including a constant. After taking logs and rearranging the resulting regression equation is

$$\frac{ln(E_{t_2,i}) - ln(E_{t_1,i})}{t_2 - t_{1,i}} = ln[G(x_i'\beta)] + u_i, \tag{2.2}$$

where $u_i \sim N(0, \sigma_i^2)$ and independent of the observed explanatory variables X. As in Evans (1987b), age and initial employment enter the regression equation by the second order logarithmic expansion

$$ln(E_{t_1}) + ln(age) + ln(E_{t_1}) * ln(age) + (ln(E_{t_1}))^2 + (ln(age))^2. \tag{2.3}$$

As it is possible that the effects of the central variables are different in each sector, the key dummy variables defined above are interacted with the industry dummies. For example, for the hypothesis comparing team foundations with single entrepreneurs, the regression equation for the growth relationship is

$$\begin{aligned} Growth &= \beta_0 + \beta_1 team\ in\ high\ technology \\ &\quad + \beta_2 team\ in\ technology\ oriented\ services \\ &\quad + \beta_3 team\ in\ knowledge\ intensive\ services \\ &\quad + z_i'\gamma + u_i. \end{aligned} \tag{2.4}$$

The regression equations for the other hypotheses are built equivalently by replacing the variables in the first three rows by the respective dummies for the other hypotheses. The only exception is the estimation of the effect of generalistic single entrepreneurs. For this relationship, the dummy "generalist" is not interacted with the industry dummies since the number of generalists is too small to produce meaningful results at the sectoral level.

The central variables for the analysis in this paper are only available for firms which survive the whole period from their initiation until 2001. This could give rise for selection issues since growth is not independent of survival (Dunne et al. (1989)). Therefore, a sample selection model is estimated.

$$Growth = ln[G(x_i'\beta)] + u_i \quad (2.5)$$

$$Survival = \mathbb{1}[w_i\delta + \nu_i > 0], \quad (2.6)$$

where correlation between the error terms u_i and ν_i is permitted. The vector w_i contains variables which influence the survival probability of the firms. These variables are taken from the basic information provided by CREDITREFORM for all firms. The model is estimated by applying the two-step procedure proposed by Heckman (1976, 1979). As exclusion restrictions, the region in which the firms are located (the German federal states) and real estate property are used.

2.5 Results

The presentation of the results starts with the effects for the hypothesis comparing team foundations with single entrepreneurs (H2), because it uses the full sample and is thus the most encompassing. Then the results concerning the effects of the heterogeneity in educational backgrounds for single entrepreneurs and team foundations (H1, H3, and H4) are shown. In order to save space, the results for the growth regressions are presented in the main text. Table 2.7 in the appendix shows the results of the selection equation for the regression comparing team foundations with single entrepreneurs. The signs of the coefficients are plausible. Due to the different sample sizes considered, the coefficients in the selection equation differ between regressions, but yield similar results.

Teams vs. single entrepreneurs. The results of the regression for the hypothesis that team foundations have higher employment growth than single entrepreneurs

Table 2.2: Employment growth of team foundations in comparison to single entrepreneurs

dep. var.: *employment growth*: $\frac{ln(E_{t2,i})-ln(E_{t_1,i})}{t_2-t_{1i}}$		
	coeff.	std. error
team in high technology	0.082***	0.032
team in technology oriented services	0.070***	0.021
team in knowledge intensive services	0.077***	0.020
$ln(E_{t_1})$	-0.169***	0.024
$ln(age)$	-0.108*	0.056
$ln(E_{t_1}) * ln(age)$	0.055***	0.014
$(ln(E_{t_1}))^2$	0.015***	0.006
$(ln(age))^2$	-0.042*	0.024
minimum labour market experience	-0.003***	0.001
number of contacts to science	0.028***	0.004
continuous R&D	0.075***	0.015
occasional R&D	0.023	0.018
public support	0.047***	0.014
ref. cat. high technology		
technology-oriented services	-0.034	0.030
knowledge-intensive services	-0.013	0.031
constant	0.303***	0.038
λ	-0.077	0.048
$\chi^2_{(15)}$	315.93***	
number of observations: uncensored	2,620	
number of observations: censored	1,559	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively.
Source: ZEW-spinoff survey 2001, author's calculations.

are shown in Table 2.2. The key coefficients in this case are the ones relating to the dummies *team in high technology*, *team in technology oriented services* and *team in knowledge intensive services*.

Team foundations experience higher employment growth than single entrepreneurs. The coefficient of *team in industry j* is positive and highly significant. Regarding the magnitude of the effect, it turns out that it is not significantly different across industries. Running a regression without the sector differentiation yields that firms founded by a team experience a 7.5 percent higher employment growth than a firm founded by a single entrepreneur. Thus, H2 cannot be rejected.

Concerning the control variables, the results are consistent with what one would expect and what has previously been found in the literature. Employment growth is negatively related to both employment at start and age. The number of contacts to science, the conduction of R&D and the attainment of public support have all positive and highly significant effects. Somewhat unexpected is the negative sign of the coefficient for minimum job experience, which is defined as the difference between the year of foundation and the year in which the last founder left academia. A possible explanation is that the variable due to its definition also captures the effect of individuals' age. Older entrepreneurs probably do not tend to expand their firm because they cannot reap the benefits for a sufficiently long time. These two effects cannot be separated since there is no information about the age of the individuals in the data set.

Generalists vs. specialists. H1a and H1b contrast single entrepreneurs who studied several subjects (generalists) and single entrepreneurs who studied only one subject (specialists). The results of this comparison are shown in Table 2.3. The columns denoted with (1) show the results for the case that a single entrepreneur studied at least two subjects and the columns denoted with (2) for the case that she studied at least two different subjects that are from different disciplines. The crucial coefficient is the one in the first row.

It turns out that single entrepreneurs who studied several subjects do not have higher employment growth than single entrepreneurs who studied only one subject. The coefficient for *generalist* is insignificant. This result persists if generalists with respect to disciplines rather than subjects are considered. This is consistent with H1b but not with H1a.

With respect to the jack-of-all-trades model, there are several explanations for this result. First, individuals who are entrepreneurs are all jack-of-all-trades (have a balanced skill profile) but have different investment costs in education. For some it is worthwhile to invest in more than one skill and for others it is only reasonable to invest in one of their skills. If it is only relevant for the success of new firms that individuals are jack-of-all-trades, we should get no effect because all individuals

Table 2.3: Employment growth of generalists in comparison to specialists

sample: single entrepreneurs				
dep. var.: *employment growth*: $\frac{ln(E_{t2,i})-ln(E_{t_1,i})}{t_2-t_{1i}}$				
	coeff.	std. error	coeff.	std.error
	(1)		(2)	
generalist	0.007	0.045	0.017	0.054
$ln(E_{t_1})$	-0.133***	0.038	-0.133***	0.038
$ln(age)$	-0.102	0.106	-0.103	0.106
$ln(E_{t_1}) * ln(age)$	0.047**	0.022	0.048**	0.022
$(ln(E_{t_1})^2$	0.012	0.011	0.011	0.011
$(ln(age))^2$	-0.026	0.048	-0.026	0.048
minimum labour market experience	-0.004***	0.001	-0.004***	0.001
number of contacts to science	0.034***	0.007	0.034***	0.007
continuous R&D	0.055**	0.025	0.055**	0.025
occasional R&D	-0.011	0.032	-0.011	0.032
public support	0.049**	0.023	0.049**	0.023
ref. cat. high technology				
technology-oriented services	-0.043	0.033	-0.043	0.033
knowledge-intensive services	-0.016	0.034	-0.016	0.034
constant	0.246***	0.048	0.246***	0.048
λ	0.093*	0.054	0.094*	0.054
$\chi^2_{(13)}$	92.31***		92.40***	
number of observations: uncensored	886		886	
number of observations: censored	1,559		1,559	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Columns denoted with (1): single entrepreneur studied at least two subjects. Columns denoted with (2): single entrepreneur studied at least two subjects that are from different *disciplines*.
Source: ZEW-spinoff survey 2001, author's calculations.

are in fact equal in the crucial dimension, although we cannot observe it. This is the explanation based on H1b. Second, it is possible that also individuals with an imbalanced skill profile are among the founders but they are able to compensate their disadvantage by, say, a high motivation for being an entrepreneur or having a broad social network they can rely on. Finally, it cannot be ruled out that the jack-of-all-trades theory is wrong and that a balanced skill is not important for successfully running a new firm. In order to determine whether the jack-of-all-trades theory is not only reasonable for the probability to become an entrepreneur but also for the success of new firms founded by single entrepreneurs, more detailed information on the skill profile of the individuals would be necessary.

Generalistic vs. specialised teams. There is also no support for the hypothesis that teams whose members all studied different subjects experience higher employment growth than teams in which all members have studied the same subject (H3, Table 2.4). The crucial coefficient is insignificant in all sectors both when subjects (columns denoted with (1)) and disciplines (columns denoted with (2)) are considered. Presumably, this is the result of what is called the double-edged sword of heterogeneity in the literature (Hambrick, Cho, and Chen (1996), Ensley and Amason (1999)): Different subjects also represent different ways of interpreting the business environment which could lead to misunderstandings and even to conflict among the team members. This could offset the advantage of having a broader skill basis due to different educational backgrounds.

Homogeneous vs. heterogeneous teams. The fourth hypothesis contrasts homogeneous teams with respect to ability with heterogenous teams. The results of the regression are shown in rows four to six in Table 2.4. It turns out that the coefficient for homogeneous teams with respect to ability is insignificant in each industry. Thus, it is irrelevant whether team members are graduates from only one type of research institution or whether there is a mix of graduates from different research institutions. This result allows two different conclusions concerning the partnership model of entrepreneurship. Either, there is a measurement problem. It is possible that the sort of qualification one gets in the different research institution does not measure ability differences adequately. Or, the theory is false. In this case, tasks are not as essential as assumed in the partnership model of entrepreneurship so that it is better to have a mixed team with respect to ability. The latter is the case if some tasks can be assigned to rather low ability individuals since these individuals are cheaper. In Müller (2009), I use lifetime wages as a measure of ability in a regression on the determinants of the survival probability of young firms. There is again no effect of the degree of homogeneity with respect to ability detectable. Thus, the evidence suggests that the the second conclusion mentioned above must be drawn.

Table 2.4: Employment growth of generalistic (homogeneous) teams in comparison to specialised (heterogeneous) teams

sample: team foundations				
dep. var.: *employment growth*: $\frac{ln(E_{t2,i})-ln(E_{t_1,i})}{t_2-t_{1i}}$				
	coeff.	std. error	coeff.	std. error
	(1)		(2)	
generalistic team in high technology	-0.029	0.039	-0.039	0.040
generalistic team in technology oriented services	0.015	0.025	0.010	0.025
generalistic team in knowledge intensive services	-0.005	0.026	-0.004	0.026
homogeneous team in high technology	0.036	0.049	0.038	0.049
homogeneous team in technology oriented services	0.020	0.031	0.021	0.031
homogeneous team in knowledge intensive services	0.024	0.031	0.023	0.030
$ln(E_{t_1})$	-0.267***	0.037	-0.266***	0.037
$ln(age)$	-0.128*	0.073	-0.129*	0.073
$ln(E_{t_1}) * ln(age)$	0.081***	0.021	0.081***	0.021
$(ln(E_{t_1})^2$	0.034***	0.010	0.033***	0.010
$(ln(age))^2$	-0.060**	0.031	-0.059**	0.031
minimum labour market experience	-0.004***	0.001	-0.004***	0.001
number of contacts to science	0.026***	0.005	0.026***	0.005
continuous R&D	0.079***	0.019	0.079***	0.019
occasional R&D	0.039*	0.024	0.039*	0.024
public support	0.044***	0.018	0.044***	0.018
ref. cat. high technology				
technology-oriented services	-0.051	0.059	-0.046	0.056
knowledge-intensive services	0.000	0.060	0.000	0.057
constant	0.478***	0.067	0.477***	0.065
λ	0.033	0.044	0.034	0.044
$\chi^2_{(18)}$	228.20***		228.40***	
number of observations: uncensored	1,504		1,504	
number of observations: censored	1,559		1,559	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Columns denoted with (1): at least two team members studied different subjects. Columns denoted with (2): at least two team members studied different subjects that from different *disciplines*.
Source: ZEW-spinoff survey 2001, author's calculations.

Table 2.5: Employment growth of teams with technical and business skills in comparison to teams with technical but without business skills

sample: team foundations				
dep. var.: *employment growth*: $\frac{ln(E_{t2,i})-ln(E_{t_1,i})}{t_2-t_{1i}}$				
	coeff.	std. error	coeff.	std. error
	(1)		(2)	
team foundations with natural and business scientists	0.039	0.033		
team foundations with engineers and business scientists			0.082***	0.032
$ln(E_{t_1})$	-0.319***	0.068	-0.194***	0.048
$ln(age)$	-0.203*	0.115	-0.218*	0.115
$ln(E_{t_1}) * ln(age)$	0.101***	0.035	0.046*	0.027
$(ln(E_{t_1}))^2$	0.030*	0.018	0.027**	0.012
$(ln(age))^2$	-0.034	0.052	0.005	0.049
minimum labour market experience	-0.004*	0.002	-0.003**	0.001
number of contacts to science	0.026***	0.008	0.017***	0.007
continuous R&D	0.107**	0.034	0.039	0.028
occasional R&D	0.058	0.042	0.005	0.034
public support	0.095***	0.030	0.064***	0.026
ref. cat. high technology				
technology-oriented services	-0.047	0.037	-0.060*	0.032
knowledge-intensive services	-0.003	0.046	-0.060	0.039
constant	0.578***	0.080	0.438***	0.068
λ	-0.018	0.051	0.083*	0.051
$\chi^2_{(15)}$	120.55***		80.94***	
number of observations: uncensored	637		614	
number of observations: censored	1,559		1,559	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively.
Source: ZEW-spinoff survey 2001, author's calculations.

Natural scientists and engineers with business scientists. A conjecture often put forward in discussions is that teams whose members attained technical skills perform better if they form a team with someone with commercial skills. Table 2.5 shows the results for the comparison between teams of natural scientists and engineers with and without business scientists, respectively. For natural scientists, it does not seem to make any difference whether or not they have a business scientist among them, but for engineers it does. Teams of engineers with business scientists experience a 9 percent higher employment growth than teams of engineers without business scientists.

2.6 Conclusions

In this paper, I analyse how employment growth of academic spin-offs is affected by the degree of heterogeneity in the educational backgrounds of the founders and the size of the founding team. As theoretical basis, the approaches by Lazear (2005) and Fabel (2004b) are used. The results show that it is relevant that a firm is founded by a team. Additionally, there is evidence that engineers should choose business scientists as partners for setting up a successful firm. However, different subjects per se do not play a role, neither for single entrepreneurs nor for team foundations. For team foundations, it is also irrelevant whether or not all founders come from the same type of research institution.

For the design of academic curricula, the results suggest that the success of academic spinoffs cannot be fostered by organising curricula interdisciplinary. It is only important that several persons meet each other. This can happen in different ways and does not depend on the concrete design of curricula. University-wide social events or even events outside the university would also serve the purpose.

With respect to the jack-of-all-trades model (Lazear (2005)) and the partnership model of entrepreneurship (Fabel (2004b)), the empirical results seem to cast some doubts on the validity of these approaches. But it is possible that the rejection of most of the hypotheses is due to measurement problems. The crucial variables of the models – the skill profile in the jack-of-all-trades model and the ability of the individuals in the partnership model of entrepreneurship – are both not directly observed in the data. It could be the case that the measures used in this paper do not proxy these variables sufficiently well. Definite conclusions can only be drawn if the results of this paper are replicated with other measures of these variables.

Appendix

Table 2.6: Subjects and disciplines

subjects	disciplines
biology	natural sciences
chemistry	
computer sciences	
math	
physics	
other natural sciences	
medicine	
mechanical engineering	engineering
electrical engineering	
construction engineering	
other engineering	
business sciences	business sciences
social sciences	social sciences
law/humanities/languages	
other	other

Source: ZEW-spinoff survey 2001.

Table 2.7: Selection equation

	coeff.	std.err.
E_{t1}	0.103***	0.008
$(E_{t1})^2$	-0.001***	0.000
ref. cat. age: 1 year		
age: 2 years	-1.894***	0.191
age: 3 years	-2.129***	0.190
age: 4 years	-2.256***	0.190
age: 5 years	-2.458***	0.190
ref. cat. thuringia		
schleswig-holstein	-0.628****	0.195
hamburg	0.117	0.190
lower saxony/bremen	-0.307**	0.156
north-rhine westphalia	-0.432***	0.145
hesse	-0.503***	0.156
rhineland-palatinate/saarland	-0.351**	0.167
baden-wurttemberg	-0.252*	0.149
bavaria	-0.443***	0.147
berlin	-0.343**	0.163
brandenburg	-0.308*	0.181
mecklenburg-western pomerania	0.225	0.256
saxony	-0.184	0.166
saxony-anhalt	-0.256	0.191
professor or doctor (PhD) among founders	0.104*	0.055
real estate property	0.046	0.088
real estate property belonging to firm	0.090	0.270
real estate property missing	-0.265	0.166
equity holding by other firm	-0.154**	0.066
ref. cat. high technology		
technology oriented services	-0.178***	0.071
knowledge intensive services	-0.396***	0.070
constant	2.702***	0.239
number of observations	1,559	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Values refer to the regression comparing teams with single entrepreneurs.

Source: ZEW-spinoff survey 2001, author's calculations.

3 Complementarities in Ability in the Workforce of Start-Ups

3.1 Introduction

Individual abilities are an important factor for the success of young firms (van der Sluis, van Praag, and Vijverberg (2008)). In the literature, it is often claimed that a range of different skills is needed for running a new firm successfully.[1] This requirement might give rise to a particular sort of risk: If the different skills are provided by individuals who are each a specialist in one particular skill, a specific task cannot be taken over by another individual in case one individual makes a mistake. Consequently, if the performance of an individual assigned to an essential task is below a critical level, the whole project may fail. For example, a firm with an excellent business idea might fail because the idea is not marketed appropriately to potential costumers. In technical terms, it is reasonable to assume that new firms are characterised by complementarities in the abilities of the individuals involved. Roughly speaking, complementarities in ability mean that the output of a worker depends positively not only on her own abilities, but also on the abilities of her coworkers.

Fabel (2004a,b) and Fabel and Weber (2005) argue that complementarities between individual abilities are a characteristic of new firms and formulate a theory of entrepreneurship that is based on such complementarities. They apply the O-ring production approach by Kremer (1993), which is a particular example of these type

[1] Roure and Madique (1986), Roure and Keeley (1990), Ensley et al. (1998), Ensley and Amason (1999), Lazear (2005), Amason et al. (2006), Beckman, Burton, and O'Reilly (2007), and Zimmerman (2008).

of complementarities.[2] In this paper, I analyse to what extent the predictions of this theory are supported by the data.

The O-ring theory conceptualises the production process as a set of tasks, each of which must be fulfilled at a certain minimum level of quality for the output to have positive market value. Individual abilities are positively linked to the probability of reaching this quality level. The testable predictions of this theory are, 1) firms have a homogeneous workforce with respect to the level of ability, 2) the higher the average ability level of the workforce, the larger the firm, and 3) the higher the average ability level of the workforce, the more capital per head is employed. In order to determine whether specialists in different areas match for setting up a firm, it is additionally examined whether the individuals in a given firm have different educations.

As data base, I use register data covering the whole population of firms founded in Denmark in 1998 as well as all individuals involved in these firms. In total, more than 14,000 firms in all sectors of the economy are considered. The data provide rich information on the individual side allowing to determine the characteristics of the persons who match for setting up a new firm. Among this information are the hourly wages starting from the year of labour market entry which permits to use average hourly wage over the working life as a measure of ability. The firms are followed until 2001, so that the development of the employment composition of firms in their first three years of existence can be analysed.

The results of this paper suggest that neither the workforce of young firms is composed of specialists in different areas nor is the production technology characterised by complementarities in abilities. Individuals choose more often partners with an equal educational background than in a situation where they are randomly matched. Concerning ability, there is evidence against the hypothesis that individuals match with other individuals of the same ability level. Although teams are more homogeneous than under random matching in the start-up year, the degree of homogeneity decreases when the firms mature. Thus, building homogeneous workforces does not seem to be the recruitment strategy of new firms. Furthermore, firm size and aver-

[2] The O-ring approach got its name from the accident of the space shuttle Challenger, which exploded in 1986 because of the malfunctioning of only one of its components: the O-rings of the booster.

age ability of the workforce in a firm turn out to be negatively related. The only relationship that holds as predicted by the theory is the positive relation between capital per head and average ability. The conclusions do not change when industries are considered separately or when the analysis is restricted to firms with university graduates. Due to the high number of observations and since a whole cohort of new firms can be observed, this paper contributes to the search of stylised facts about new firms. The results provide a list of facts that can serve as a benchmark for further theory building.

There is one other paper that uses the O-ring theory explicitly to derive empirically testable hypotheses. Yu and Orazem (2008) apply the O-ring theory to hog farms and find that skills leading to higher wages are also positively correlated with output level and technological complexity. However, in contrast to this paper, they do not know which individuals work together in firms.

The paper is structured as follows: In Section 3.2, the empirical implications of the O-ring theory are worked out in detail and the hypotheses are derived. Section 3.3 describes the data. In Section 3.4, the empirical methods applied and the results are presented. Section 3.5 concludes.

3.2 Theoretical Background and Hypotheses

The O-ring theory applies to production processes which consist of a series of tasks each of which must be performed at a certain minimum level of quality for the output to have positive market value. Individual ability corresponds to the probability that an individual performs her task sufficiently well. The project as a whole only has a positive outcome if all team members perform their tasks at a certain minimum level of quality. Otherwise output is zero. For new firms, this seems to be an appropriate description of their situation since the whole project can fail if only one task is not performed carefully. Formally, the situation is modelled by including individual abilities multiplicatively in the production function

$$Y = F(k, n) \left[\prod_{i=1}^{n} q_i \right] n, \tag{3.1}$$

where k refers to physical capital, n to the number of tasks and $q_i \in (0,1)$ to the probability that the individual assigned to task i performs her task sufficiently well, which is her ability.

New firms can be assumed to maximise surplus per team member (Fabel (2004b)), so that their objective function can be written as

$$\max_{\{q_i\},k,n} \frac{pF(k,n)\left[\prod_{i=1}^{n} q_i\right] n - rk}{n}, \tag{3.2}$$

where p refers to the output price and r to the interest rate. In the literature, it is usually assumed that each task requires only one worker for reasons of simplicity, i.e. n is also interpreted as the number of individuals.[3] This assumption is debatable since it might be worthwhile to back up critical tasks by several persons or to have one person to perform several tasks. Additionally, if taken literally, this would imply that there is only one task to be accomplished in the firm if we observe a single entrepreneur. This is obviously nonsense. In the following, the assumption is maintained, but it is tried to conjecture from the data whether task allocation is accomplished in the assumed way.[4] The reasoning is the following: If individuals have different educations they acquire different knowledge which makes them better suited for certain tasks than for others. Thus, when several persons are involved in a start-up, it can be expected to be observed that all individuals have different educations.[5] Therefore, the first hypothesis of this paper is

H1: If the firm is founded by a team, team members match systematically so that different team members have different educations.

The O-ring production function exhibits the property that the marginal product of the ability level of the individual assigned to task i, q_i is positively related to the average ability level of the individuals assigned to the other tasks

$$\frac{d^2Y}{dq_i d\left(\prod_{j\neq i} q_j\right)} = F(k,n)n > 0. \tag{3.3}$$

[3] In his seminal paper, Kremer (1993) explicitly mentions that n indicates the number of tasks, and not necessarily the number of employees. But his exposition of the theory uses the assumption of one person per task and e.g. Fabel (2004b) follows him in this respect.

[4] Assignment of individuals to tasks is not reported in the data.

[5] Firms set up with more than one person are referred to as team foundations in the following.

This also holds for the output per team member Y/n and means that abilities are complementary.[6] It implies that firms which have started to employ individuals with the highest ability in the population can attract other individuals of the highest ability level since they can pay the highest wage. Firms with medium ability individuals in the first $n-1$ tasks cannot successfully compete for higher quality individuals but are successful in attracting medium ability individuals compared to firms with lower average ability level. If (and only if) labour markets are competitive, this leads to the result that individuals within a firm are homogeneous with respect to their ability.[7] (Formally, this means that $[\prod_{i=1}^{n} q_i]$ can be replaced by q^n). Accordingly, the second hypothesis is

H2: If the firm is founded by a team, team members match systematically so that the different team members have the same level of ability.

For the following, a specific functional form for $F(k,n)$ is needed. Specifying $F(k,n)$ as $k^{\alpha}n^{(1-\alpha)}$ as in Fabel (2004b), normalising output price p to one, and replacing $[\prod_{i=1}^{n} q_i]$ by q^n, the first order conditions of the optimisation problem given in equation (3.2) with respect to n and k are

$$(1-\alpha)k^{\alpha}n^{-\alpha}q^{n} + k^{\alpha}n^{(1-\alpha)}q^{n}log(q) + \frac{rk}{n^2} = 0 \tag{3.4}$$

and

$$\alpha k^{(\alpha-1)}n^{(1-\alpha)}q^{n} - \frac{r}{n} = 0 \tag{3.5}$$

Solving for n and k/n yields the optimal values for the number of employees n^* and for capital per head k^*/n^*

$$\frac{1}{n^*} = -log(q) \tag{3.6}$$

and

$$\frac{k^*}{n^*} = \left(\frac{\alpha q^{n^*}}{r}\right)^{\frac{1}{1-\alpha}} (n^*)^{\frac{1}{1-\alpha}} \tag{3.7}$$

From equation (3.6), we get

H3: Given that each tasks requires one person, team size and the (average) ability level in the team are positively correlated.

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[6] This is the same concept of complementarity as e.g. in Milgrom and Roberts (1990, 1995).

[7] Prat (2002) shows that complementarity is a sufficient condition for firms having a homogeneous workforce is optimal.

Note that by inserting numbers of the (0,1)-interval into equation (3.6), this equation implies that a firm is founded by a team only when the average ability level is at least 0.607. Dependent on the distribution of ability in the population, the probability to actually observe team foundations might therefore be rather low. For example, assuming that q is distributed uniformly, as in Fabel (2004b), the ability level for a team foundation has to be above average.

The fourth hypothesis is based on equation (3.7).

H4: The higher the ability level in a team, the more capital per head is deployed.

Intuitively, more able workers have a lower probability of failing, which means that the risk that they destroy valuable capital goods is rather low.

One of the challenges of the empirical analysis is to find an appropriate measure for ability, since the probability to fail while performing a task is usually not reported in data sets. However, the O-ring theory suggests to use wages as a representation of ability. To see this, consider a firm that maximises expected profit

$$\max_{q,k,n} \pi(q,k,n) = F(k,n)q^n - w(q) - rk \tag{3.8}$$

Here, the implied sorting of individuals is already exploited and $[\prod_{i=1}^n q_i]$ replaced by q^n. This firm will not want to change the ability level of its employees anymore if

$$F(k,n)q^{(n-1)}n = \frac{dw(q)}{dq}, \tag{3.9}$$

i.e. if marginal revenue of changing the ability level equals marginal costs. Integration and insertion of k^* yields

$$w^*(q) = (1-\alpha)\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} (n^*)^{\frac{1}{1-\alpha}} q^{\frac{n*}{1-\alpha}}. \tag{3.10}$$

Thus, the optimal wage is a monotonously increasing function of ability. In the empirical analysis, wages are therefore used as a measure of ability. This relates the analysis of this paper also to the literature on the distribution of workers across firms in the context of the development of the wage dispersion[8] as well as on the relationship between wages, ability and firm size.[9] However, the results of this

[8]e.g. Davis and Haltiwanger (1991), Dunne, Foster, Haltiwanger, and Troske (2004), Iranzo, Schivardi, and Tosetti (2008), Kramarz, Lollivier, and Pelè (1996) and Kremer and Maskin (1996).

[9]e.g. Mellow (1982), Oi (1983), Brown and Medoff (1989), Troske (1999) and Abowd, Kramarz, and Margolis (1999).

literature cannot be ascribed to the O-ring theory as all studies are conducted on rather large firms, for which it is not reasonable to assume that each task is critical in the sense of the O-ring theory.

3.3 Data

The data used in this paper are provided by Statistics Denmark, Denmark's federal statistical office. These are register data, which cover the whole population of firms set up in Denmark in 1998 and that were still in operation at the end of that year.[10] The total number of new firms started in this year amounts to 16,063. On an annual basis, the firms were observed until 2001 or until they shut down.[11] In the start-up year industry of business, legal form and location of the firm are registered. Additionally, the current number of employees and the current amount of exports, purchases, and sales are recorded in the start-up year and at the end of each year during the follow-up period.

By a combination of a firm and a personal identification number (ID) it is possible to link the firm-level information to information on individuals which is stored in the Integrated Database for Labour Market Research (IDA). The IDA database covers a wide range of variables on the total Danish population from 1980 onwards, especially the whole education and employment history. Additionally, it is possible to identify those who join the firms in the years right after foundation and therefore to look at the development of the workforce characteristics over time. The individual information exploited in the analyses comprises the highest level of education attained, wages, labour market experience, unemployment spells, prior self-employment experience, and leadership experience. Due to missing information about the employees for some firms, 14,171 firms of the original 16,063 firms can be used for the subsequent analysis.

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[10]Firms that started in 1998 and shut down within the same year are not contained in the data set.

[11]The same procedure has been applied to all firms founded in 1994. However, for these firms, it is only possible to merge individual information for the person who registered the firm with the authorities for the start-up year. Since it is essential for determining the degree of homogeneity between team members to either have information on all individuals or to have at least a representative sample of the individuals, the analysis is restricted to the 1998 cohort.

A drawback of the data is that it is not possible to identify the persons who perform the essential tasks in the firm. However, as the great majority of the new firms are small entities, each person can be considered to be important.[12] In the following, firms with at least two persons involved are referred to as "team foundations".

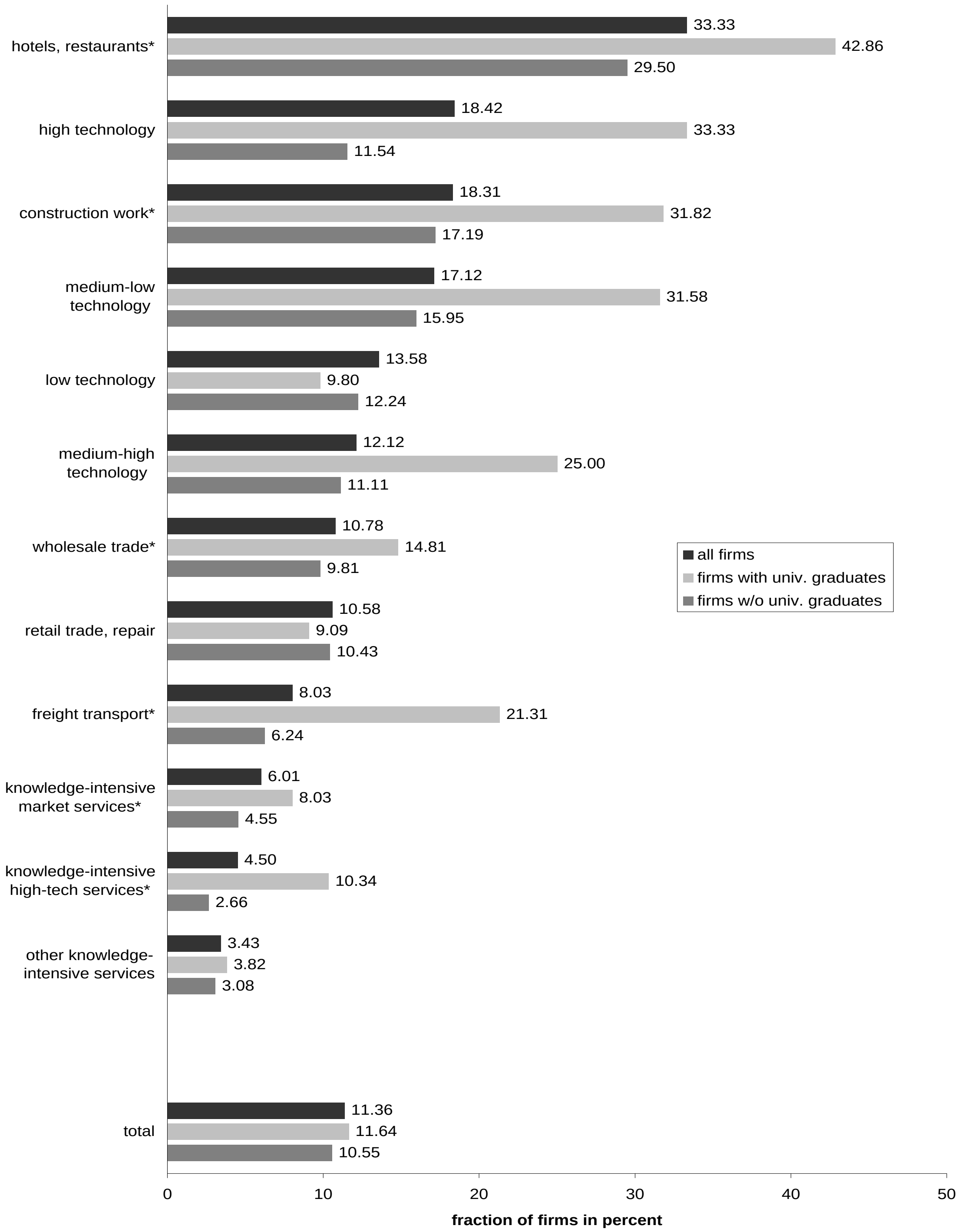
The O-ring theory is formulated for production environments in which tasks are complementary. Presumably, this applies for some industries to a greater extent than for others. Since it is not clear in advance for which industries the O-ring production function is most appropriate, all sectors are considered and the sample is split up into twelve industries for which the results are separately presented. Likewise, it might be the case that firms founded with university graduates are better described by the O-ring theory than firms founded without university graduates. The reason is that these firms are more likely to deal with innovative products (Koellinger (2008)) and therefore with more complex technologies which require specialists in different fields. Good matching might therefore be especially important for these type of firms.

The analyses concerning the degree of homogeneity with respect to education and ability (H1 and H2) is only relevant for firms which are founded by teams. Figure 3.1 shows the proportion of firms that are founded with at least two persons by industry.[13] It turns out that 11 percent of all firms have more than one employee at the end of the start-up year. Overall, firms founded with university graduates are not significantly more often set up by teams than firms founded without university graduates. Considering the sectors separately, firms with university graduates are more often set up by teams in hotels, restaurants, construction work, wholesale trade, freight transport, knowledge-intensive market services, and knowledge-intensive high-tech services.

[12]The average firm size over the whole period of consideration is 1.7 individuals, see also Table 3.3 in the appendix.

[13]For a detailed description of the combined industries, see Table 3.8 in the appendix.

Figure 3.1: Fraction of firms founded by a team



Reading aid: 42.86 percent of the firms in the sector hotels, restaurants founded with university graduates are set up with at least two persons.

Notes: Total number of firms: 14,171. Number of firms with university graduates: 2,543. Number of firms without university graduates: 11,095. The difference in the sum of the firms with university graduates and without university graduates is due to missing values in the education variable.

A * at the sector names indicates whether firms with university graduates differ significantly from firms without university graduates at the 5% level.

Source: Statistics Denmark, author's calculations.

3.4 Methods and Results

The presentation of results follows the order of the hypotheses derived in Section 3.2. Section 3.4.1 to 3.4.4 refer to the situation in the start-up year. In Section 3.4.5, the performed robustness checks are described. In Section 3.4.6, the development over time of the heterogeneity of educations, the degree of homogeneity with respect to ability as well as of the relation between ability and firm size is examined. The methods applied are described in the course of the presentation of the results.

3.4.1 Heterogeneity of educations

H1 states that each person of a founding team has attained a different education. In order to determine the degree of heterogeneity in this dimension, the Herfindahl-Index of the highest education attained is calculated for each team foundation. The Herfindahl-Index is a measure of concentration. For the present case it is computed as the sum of the squared shares of the different educations in each firm

$$H = \sum_{i=1}^{n} s_i^2, \tag{3.11}$$

where s_i denotes the share of education i.

The underlying education variable can take on more than 1,000 values, i.e. provides highly detailed information on the educational background of the individuals. Since the discipline of the highest educational attainment is only a crude measure for the task actually fulfilled in the firm – it is both possible that one education enables for several tasks and that one and the same task can be conducted by persons with different educational background – no obvious level of aggregation for this variable exists. Therefore, the variable is not aggregated in any respect for calculating the Herfindahl-Index.[14] Besides, if it turns out that even with such a high number of possible values, the Herfindahl-Index does not take the lowest possible value for all firms, the results are of highly informative value.

[14]Thus, "education" refers to a combination of years of education and field. These two components are not separated since it is reasonable to assume that, e.g. someone with a vocational training in a technical field is assigned a different task than an engineer.

There are two important points to note. First, the range of the values of the Herfindahl-Index depends on the number of individuals in the team. For example: If there are two persons, the Herfindahl-Index can take on the values 1 and $\frac{1}{2}$, in the case of three persons 1, $\frac{5}{9}$ and $\frac{1}{3}$ etc. This entails the question of how to compare Herfindahl-Indices of teams of different size. One possibility is to only consider the number of different educations within a firm. In this case, a team consisting of two persons who have different educations is regarded as diverse as a team consisting of four persons in which two at a time have the same education. Comparing teams of different size this way is just to take the Herfindahl-Index as defined in equation (3.11). A second possibility is to treat teams as equally diverse if all individuals have different educations regardless of team size. This can be achieved by transforming the Herfindahl-Index in the following way

$$H^{tr} = \left(H - \frac{1}{n}\right)\frac{n}{n-1} \quad \in [0,1]. \tag{3.12}$$

As a result, the Herfindahl-Index takes the value one if all individuals have the same education and becomes zero if each individual attained a different education. For the following analysis, I opted for the transformed index. However, the transformation is not necessary for the following analyses. It is just a matter of defining what is meant by "equally diverse". Referring to H1, the value of the Herfindahl-Index in equation (3.12) is expected to be zero for all firms, i.e. the individuals within a firm differ from each other with regard to their educations.

The second point to note is that the values of the Herfindahl-Index per se do not provide a means to test H1. The reason is that there is no natural reference level providing a basis to decide whether the heterogeneity in educations is low, high or on an average level. To make such a judgement possible, a statistical test is constructed with the help of which the values of the Herfindahl-Index actually observed are compared with the values of the Herfindahl-Index received in a situation where individuals match randomly. The null hypothesis of this test is

$H1_0$: *The composition of the actual observed teams with respect to educations equals a random selection of individuals.*

To perform the test, mean and variance of the Herfindahl-Index under random assignment (H^{tr}_{random}) have to be determined. However, both values can only be derived analytically for a given team size. Therefore, the distribution of H^{tr}_{random} is simulated. The procedure is as follows: All individuals of a given sector are selected and randomly assigned to firms, maintaining the actually observed size distribution of firms. After that, the Herfindahl-Index per firm is calculated and averaged on the industry level. The resulting value is then stored. The procedure is carried out 1,000 times in total. From the resulting distribution, the lower and upper 0.5, 2.5 and 5 percentiles are determined and then chosen as critical values for the decision whether H^{tr}_{actual} and H^{tr}_{random} differ significantly at the 1%, 5% and 10% level.[15]

Table 3.1 shows the actual average Herfindahl-Index by industry for all firms (column (1)) as well as for firms with university graduates (column (3)) and firms without university graduates (column (5)), respectively. The mean value of the distribution of the average Herfindahl-Index with random assignment of individuals to firms is given in columns (2), (4), and (6). In most cases, the actual Herfindahl-Index is rather close to zero but not exactly zero. And, in almost all industries, the value of the average Herfindahl-Index with random assignment of individuals to firms is even smaller than the actual average Herfindahl-Index. Additionally, the difference between the two values is significant in many cases.[16] Thus, it can be concluded that individuals apparently look systematically for their teammates, but tend to choose partners with similar educations. H1 is therefore rejected.

A possible explanation for the results is that individuals simply do not know persons from other fields. An engineer is much more likely to know other engineers than, say, a person with a business education because they usually have a closer contact especially during their studies. Personal contacts are probably the most common way how individuals come together for a firm foundation. Formal job advertisements ("Wanted: Partner for establishing a firm") are usually not observed.

[15]Procedures of random reference points are also used by Ellison and Glaeser (1997) and Armenter and Koren (2008).

[16]Table 3.9 in the appendix shows the 95%- confidence intervals for the average Herfindahl-Indices. The distributions are not symmetric. Therefore, the mean values in Table 3.1 do not lie in the middle of the interval.

Table 3.1: Heterogeneity of educations in start-up year

industry	**all firms**		**firms with univ. graduates**		**firms w/o univ.graduates**	
	observed	with random assignm.	observed	with random assignm.	observed	with random assignm.
	(1)	(2)	(3)	(4)	(5)	(6)
total (firms with $n > 1$)	0.131***	0.049	0.084***	0.023	0.145***	0.057
manufacturing						
low-technology	0.143***	0.077	0.103**	0.054	0.164***	0.082
medium-low technology	0.088*	0.047	0.065*	0.033	0.092	0.051
medium-high technology	0.086	0.039	0.033	0.025	0.098	0.046
high technology	0.099	0.055	0.063	0.040	0.148	0.064
construction work	0.223***	0.061	0.199***	0.031	0.228***	0.064
services						
wholesale trade	0.125***	0.033	0.027	0.015	0.150***	0.038
retail trade, repair	0.107***	0.049	0.045**	0.024	0.116***	0.052
hotels, restaurants	0.103***	0.060	0.039	0.034	0.110***	0.064
freight transport	0.082**	0.046	0.044	0.026	0.090**	0.050
knowl.-intens. high-tech serv.	0.112***	0.032	0.068***	0.018	0.169**	0.063
knowl.-intens. market serv.	0.128***	0.028	0.120***	0.018	0.137***	0.047
other knowl.-intens. serv.	0.033	0.021	0.000	0.013	0.050	0.026

Notes: The diversity of educations is measured by the Herfindahl-Index of highest educational attainment. Columns (1), (3) and (5) show the average Herfindahl-Index by industry based on the actual sorting of individuals to firms. Columns (2), (4) and (6) depict the mean value of the distribution of the average Herfindahl-Index by industry generated with random assignment of individuals to firms.
**, **, * indicate whether the values in column (1), (3) and (5) are significantly different from the values in column (2), (4) and (6) at the 1%, 5% and 10% level respectively.
Source: Statistics Denmark, author's calculations.

3.4.2 Degree of homogeneity with respect to abilities

As formulated in H2, the O-ring theory implies that individuals working in the same firm have the same level of ability. The O-ring framework also implies that wages can be used to measure abilities empirically. The degree of homogeneity with respect to abilities between individuals in a firm is therefore determined by calculating the standard deviation of individual wages. Statistics Denmark provides the average hourly wage once a year for each year the individual was wage employed. For this paper, these wages are corrected for inflation, disciplines and industry effects. Correcting the wages that way aims at excluding all components which do not represent ability.[17] Then, the average lifetime hourly wage of an individual starting from the year of labour market entry until 2001 is calculated.

As in Section 3.4.1, where a reference for the Herfindahl-Index had to be found, a reference value for the standard deviation of wages has to be chosen. From the theoretical perspective, the standard deviation must be zero since all individuals within a firm have the same ability and therefore the same wages. Zero, however, cannot be used to formulate the null hypothesis of a statistical test since this hypothesis would be rejected with probability one.[18] In order to get a reference point of how well the observed standard deviation meets the theoretical value of zero, the same procedure as in Section 3.4.1 is applied: The actual standard deviation is compared with the standard deviation in a situation where individuals match randomly. Then it is tested whether these two values differ significantly. The null hypothesis in this case is

$H2_0$: *The composition of the actual observed teams with respect to abilities equals a random selection of individuals.*

The results are presented in Table 3.2. Columns (1), (3), and (5) show the actual standard deviation for all firms, firms with university graduates and firms without university graduates respectively. Columns (2), (4), and (6) show the mean value of the distribution of the average standard deviation which results from randomly assigning individuals to firms. Considering all firms and firms without university graduates, the actual standard deviation of the wages lies below the one resulting from randomly assigning individuals to firms. The difference between the two values is significant in more than half of the cases.[19] That is, more often than it could

[17]The effects of disciplines and industries were corrected in order to take out demand effects. If, for example, engineers are in short supply, their wages go up due to the working of the market forces and not predominantly due to an increase in their abilities.

[18]The distribution of the standard deviation of wages is a one point mass distribution under the null hypothesis since the standard deviation cannot take on values below zero and standard deviations greater than zero are impossible to be observed under this null hypothesis.

[19]The 95%-confidence intervals of the standard deviation of log wages are given in Table 3.10 in the appendix. Again, the distributions are not symmetric. Thus, the mean values given in Table 3.2 do not lie in the middle of the intervals.

Table 3.2: Homogeneity of abilities in start-up year

industry	**all firms**		**firms with univ. graduates**		**firms w/o univ.graduates**	
	observed	with random assignm.	observed	with random assignm.	observed	with random assignm.
	(1)	(2)	(3)	(4)	(5)	(6)
total (firms with $n > 1$)	0.276***	0.308	0.300**	0.315	0.266***	0.306
manufacturing						
low-technology	0.292*	0.319	0.260***	0.330	0.304	0.316
medium-low technology	0.261**	0.305	0.284	0.321	0.255*	0.301
medium-high technology	0.236**	0.298	0.260	0.291	0.230*	0.301
high technology	0.438	0.442	0.534	0.453	0.309	0.436
construction work	0.236***	0.277	0.253	0.276	0.232***	0.278
services						
wholesale trade	0.319	0.321	0.340	0.322	0.312	0.320
retail trade, repair	0.262***	0.290	0.275	0.294	0.258***	0.290
hotels, restaurants	0.291***	0.328	0.338	0.334	0.279***	0.327
freight transport	0.291***	0.343	0.343	0.363	0.264***	0.339
knowl.-intens. high-tech serv.	0.283	0.300	0.279	0.293	0.287	0.316
knowl.-intens. market serv.	0.288***	0.318	0.292**	0.322	0.283	0.311
other knowl.-intens. serv.	0.305	0.334	0.351	0.338	0.282	0.332

Notes: Ability is measured by the average lifetime wage (in logs) of an individual corrected for inflation, disciplines and industry. Columns (1), (3) and (5) show the average standard deviation of ability by industry based on the actual sorting of individuals to firms. Columns (2), (4) and (6) depict the mean value of the distribution of the average standard deviation by industry generated with random assignment of individuals to firms.
**, **, * indicate whether the values in column (1), (3) and (5) are significantly different from the values in column (2), (4) and (6) at the 1%, 5% and 10% level respectively.
Source: Statistics Denmark, author's calculations.

be expected in a situation of random matching, individuals tend to match according to their abilities. H2 cannot be rejected for these firms. However, the situation is different for firms founded with university graduates. Firms of this subgroup in high-technology, wholesale trade and other knowledge-intensive services exhibit a higher actual standard deviation of wages than under random assignment. The difference is not significant, though. Thus, firms with university graduates do not systematically look for partners with the same level of ability and H2 can be rejected for this subgroup in most of the industries.

3.4.3 Relationship between ability and start-up size

The low fraction of team foundations observed (Figure 3.1) is not necessarily evidence against the O-ring theory, as explained in Section 3.2. It could be the case that the ability of the individuals is below the critical value necessary for a team foundation. Evidence against the theory can be established if H3 can be rejected, i.e. if start-up size and ability are either not correlated at all or negatively correlated.

In order to test H3, the equations of the O-ring model are used. Remember that the equilibrium equation for the relationship between team size n^* and ability q is

$$\frac{1}{n^*} = -log(q) \Leftrightarrow n^*log(q) = -1. \tag{3.13}$$

Since ability q is not observed, this equation cannot directly be employed. But $log(q)$ can be expressed in terms of wages. Take the equilibrium wage function of the O-ring model

$$w^*(q) = (1-\alpha)\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}}(n^*)^{\frac{1}{1-\alpha}}q^{\frac{n^*}{1-\alpha}}, \tag{3.14}$$

take logs, and solve for $n^*log(q)$

$$n^*log(q) = (1-\alpha)log(w^*(q)) - (1-\alpha)log(1-\alpha) - \alpha log\left(\frac{\alpha}{r}\right) - log(n^*). \tag{3.15}$$

Inserting this expression into equation (3.13) gives after rearranging

$$log(n^*) = 1 - (1-\alpha)log(1-\alpha) - \alpha log\left(\frac{\alpha}{r}\right) + (1-\alpha)log(w^*(q)). \tag{3.16}$$

This equation can be estimated by regressing the log of the number of employees on the log of wages and identifying $1-(1-\alpha)log(1-\alpha)-\alpha log(\alpha/r)$ with the regression constant.

The O-ring theory predicts that the regression coefficient of $log(w^*(q))$ lies in the interval (0,1) since $(1-\alpha)$ is the value share for labour. This can be seen if equation (3.14) is multiplied by n^*

$$n^*w^*(q) = (1-\alpha)(k^*)^{\alpha}(n^*)^{1-\alpha}q^{n^*}n^* = (1-\alpha)Y. \tag{3.17}$$

Table 3.3 shows the results of this regression. The upper part gives the regression coefficient while not differentiating between industries, whereas the lower part shows the coefficient for each sector. With the exception of the coefficients in medium-high

Table 3.3: Relationship between ability and team size

dep. var.: log(employment)						
	all firms		**firms with univ. graduates**		**firms w/o univ.graduates**	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
average ability	-0.081***	0.009	-0.070***	0.023	-0.068***	0.009
average ability in . . .						
low-technology	-0.307***	0.087	-0.136	0.160	-0.236***	0.080
medium-low technology	-0.137	0.102	-0.674	1.154	-0.185**	0.092
medium-high technology	0.056	0.097	0.466	0.297	0.003	0.106
high-technology	-0.390	0.267	-2.590*	1.444	-0.263	0.185
construction work	-0.136***	0.037	-0.430*	0.232	-0.117***	0.036
wholesale trade	-0.031	0.021	0.026	0.057	-0.032	0.020
retail trade, repair	-0.054***	0.018	-0.063	0.051	-0.058***	0.019
hotels, restaurants	-0.393***	0.072	-0.315	0.337	-0.314***	0.067
freight transport	-0.057**	0.028	-0.373	0.540	-0.003	0.018
knowl.-intens. high-tech serv.	0.006	0.013	0.013	0.056	0.002	0.009
knowl.-intens. market serv.	-0.043***	0.013	-0.058**	0.024	-0.029***	0.012
other knowl.-intens. serv.	-0.003	0.019	-0.007	0.039	-0.001	0.021
constant	1.371***	0.340	0.686	0.628	1.067***	0.318
industry dummies	YES		YES		YES	
R^2	0.065		0.097		0.058	
number of observations	13,467		2,481		10,815	

Notes: ***, **, * depict significance at the 1%, 5%, and 10% level respectively.
Source: Statistics Denmark, author's calculations.

technology and knowledge-intensive high-tech services – which are both not significantly different from zero – all coefficients are negative and significantly different from zero in most cases. More able individuals tend to found smaller firms instead of larger firms. (E.g. in low-technology, a 1% higher average ability leads to a 0.307% lower team size.) This holds for firms founded with university graduates as well as for firms founded without university graduates. Thus, the estimated coefficients do not represent value shares for labour and H3 can be rejected. A possible explanation is that more able persons are in a better position to adopt several tasks so that it is not necessary to resort to the knowledge of other persons.

3.4.4 Relationship between ability and capital per head

A similar procedure as in the case of the relationship between ability and team size can be applied for the test of H4, which states that ability and capital per head are positively related. Remember that the equation for capital employment per head in equilibrium is

$$\frac{k^*}{n^*} = \left(\frac{\alpha q^{n^*}}{r}\right)^{\frac{1}{1-\alpha}} (n^*)^{\frac{1}{1-\alpha}} \tag{3.18}$$

Taking logs and inserting equation (3.15) for $n^* log(q)$ yields after some rearrangements

$$log\left(\frac{k^*}{n^*}\right) = log\left(\frac{\alpha}{r(1-\alpha)}\right) + log(w^*(q)). \tag{3.19}$$

According to the theory, the coefficient of $log(w(q))$ has to be one. In the estimations of equation (3.19), the balance sum is used as a measure of capital k^*. Regressing the balance sum per head on average wages on the firm level, identifying $log\left(\frac{\alpha}{r(1-\alpha)}\right)$ with the regression constant, gives the results shown in Table 3.4. Note that the t-test performed on the coefficients has the null hypothesis that the respective coefficient equals *one*. Overall, the hypothesis that the estimated coefficient is one is rejected as can be seen from the upper part of the Table. However, in half of the sectors the rejection is not possible at the 5% level. This is the case in low-, medium-low, medium-high technology, and in the knowledge-intensive services.[20] Thus, there is some evidence that the relationship between ability and capital input per head is predicted correctly by the O-ring theory.

[20]The relationship appears to be more pronounced for firms with university graduates than for firms without university graduates. For firms with university graduates, in 10 out of 12 sectors the hypothesis that the estimated coefficient is equal to one cannot be rejected at the 5% level, compared to 6 out of 12 sectors for firms without university graduates. However, this result is mainly due to larger standard deviations because of fewer observations.

Table 3.4: Relationship between ability and capital per head

dep. var.: log(balance sum per head)						
	all firms		**firms with univ. graduates**		**firms w/o univ.graduates**	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
average ability	-0.081***	0.009	-0.070***	0.023	-0.068***	0.009
average ability in . . .						
low-technology	0.610	0.275	0.393	0.616	0.764	0.299
medium-low technology	0.776	0.322	-0.416	0.990	0.803	0.332
medium-high technology	0.729	0.617	5.620*	2.643	0.710	0.628
high-technology	-0.402***	0.545	-1.607**	1.114	-0.192*	0.628
construction work	0.133***	0.124	0.621	0.696	0.106***	0.127
wholesale trade	0.177***	0.137	0.532*	0.252	0.135***	0.151
retail trade, repair	-0.061***	0.102	-0.031***	0.277	-0.074***	0.110
hotels, restaurants	0.190***	0.116	0.295	0.480	0.193***	0.125
knowl.-intens. high-tech serv.	1.100	0.139	1.274	0.319	1.062	0.155
knowl.-intens. market serv.	0.832*	0.087	0.980	0.146	0.724***	0.108
other knowl.-intens. serv.	0.881	0.344	0.993	0.574	0.805	0.390
freight transport	0.427***	0.135	-0.650*	0.901	0.446***	0.139
constant	7.753***	1.021	8.326***	2.269	7.190***	1.112
industry dummies	YES		YES		YES	
R^2	0.066		0.110		0.064	
number of observations	11,052		1,960		8,929	

Notes: ***, * depict whether the respective coefficient is significantly different from 1 at the 1% and 10% level respectively.
Source: Statistics Denmark, author's calculations.

3.4.5 Robustness checks

Up to now, the results are mixed concerning the O-ring theory as an appropriate description for the situation of young firms. Individuals tend to choose partners with the same instead of different educational background and higher able individuals found smaller instead of larger firms. At the same time, there is some evidence that individuals match according to their level of ability and that the average ability level is positively correlated to capital input per head.

One reason for these inconclusive results might be that the variables and measures are not defined appropriately. Concerning the Herfindahl-Index, the aggregation of disciplines as well as the decision whether to use the transformed or untransformed index is arbitrary. Therefore, I also conducted the analysis with the untransformed Herfindahl-Index and a different level of aggregation. Basically, the results remained the same. Only level effects were detectable.

Concerns might also be raised with respect to the construction of the ability measure. The approach in this paper is to use wages corrected for all factors that do not represent ability components. These factors are defined to be disciplines and industry effects. It can be argued, however, that disciplines and industries also contain ability aspects, for example due to selectivity: High ability persons might pick high wage industries and disciplines which are highly rewarded. However, the fraction of demand effects in these factors is probably higher than the fraction of ability effects, so that the former are corrected for here.

The situation is different for other factors whose effect could be corrected for, such as gender, having children or place of residence (rural area or city). For each of these factors, it is possible to find reasons why they represent aspects of ability. For example: Women may be equally intelligent as men, but might lack bargaining strength and assertiveness, which results in lower wages. But bargaining strength and assertiveness are aspects of ability that are useful and important when establishing a new firm. Concerning the place of residence, high ability individuals might tend to live in cities because employers demanding able persons tend to have their offices and production halls there.

The correction of wages is also arbitrary to some degree. In order to check whether the results depend on the correction of wages, I also performed the analysis with raw wages (only corrected for inflation) and with wages corrected for gender, children and place of residence in addition to disciplines and industries. Again, only level effects were detectable. Qualitatively the results remained the same.

The final remark concerns the considered time span for calculating the average lifetime wage. Running from the year of labour market entry until 2001, the considered time span also covers the period an individual is involved in a new firm. This is done since no wage information is available for the time before 1998 for a considerable fraction of individuals, resulting in the impossibility to determine the degree of homogeneity for a number of firms. In order to test whether this procedure has an impact on the results, I restricted the sample to firms for which wage information of their employees is available for the time before 1998. Again, the results were not affected qualitatively. Thus, the construction of the variable does not seem to influence the results.

A second explanation for the inconclusive results in Sections 3.4.1 to 3.4.4 is that the hypotheses derived in Section 3.2 are based on equations which describe the situation in equilibrium. Regarding reality however, it can be assumed that adaption processes are necessary to reach an equilibrium, and individuals first have to figure out what the optimal behaviour is. This line of argumentation is pursuit in the next Section.

3.4.6 Development over time

If the O-ring theory provides reasonable explanations, it can be expected that the observed facts approach the predicted facts over time even when the observed facts do not correspond very well with the predicted facts in the start-up year. In detail, the following developments are expected to be observed

- The diversity of disciplines goes up (the Herfindahl-Index of the highest educational attainment goes down).
- The degree of homogeneity with respect to ability goes up (the standard deviation of log(wages) goes down).[21]
- The correlation between ability and team size becomes positive.

For the following analysis, the situations before and after new individuals (hereafter called: newcomers) join the firm are compared. The considered time span is 1998 to 2001. Since there is no obvious reason that the actual point of entry time is

[21] The development of homogeneity with respect to ability is included since for many cases, especially for firms with university graduates, it cannot be excluded that the matching occurs completely randomly.

relevant, all firms are treated as a pooled sample and the cases (firms and years) where newcomers joined the firm are selected.[22]

Figure 3.2 shows the fraction of firms which get newcomers in the period 1999 to 2001. In total, 20 percent of all firms have newcomers whereby the fraction of firms which take on new persons is significantly higher among firms without university graduates than among firms with university graduates (20 percent compared to 16 percent). What can also be observed is that the ranking of the sectors concerning the fraction of firms with new team members is similar to that concerning the fraction of firms founded with more than one person. The sector hotels, restaurants ranks first followed by the manufacturing sectors. The knowledge-intensive service sectors are again on the lower end.[23] The only sector in which firms with university graduates differ significantly from firms without university graduates is the sector knowledge-intensive high-tech services. In this sector the fraction of firms with university graduates hiring newcomers is significantly higher than the fraction of firms without university graduates.

3.4.6.1 Heterogeneity of qualifications

As shown in Section 3.4.1, individuals match in such a way that they choose partners with an educational background from the same field leading to the rejection of H1. In order to analyse whether this also holds for the recruitment of new employees, the difference between the Herfindahl before and after newcomers join the firm is calculated and compared with the same kind of difference but under random assignment of newcomers to firms. As before, a test is constructed to determine whether the outcomes of these two situations differ significantly. In this case, the null hypothesis is

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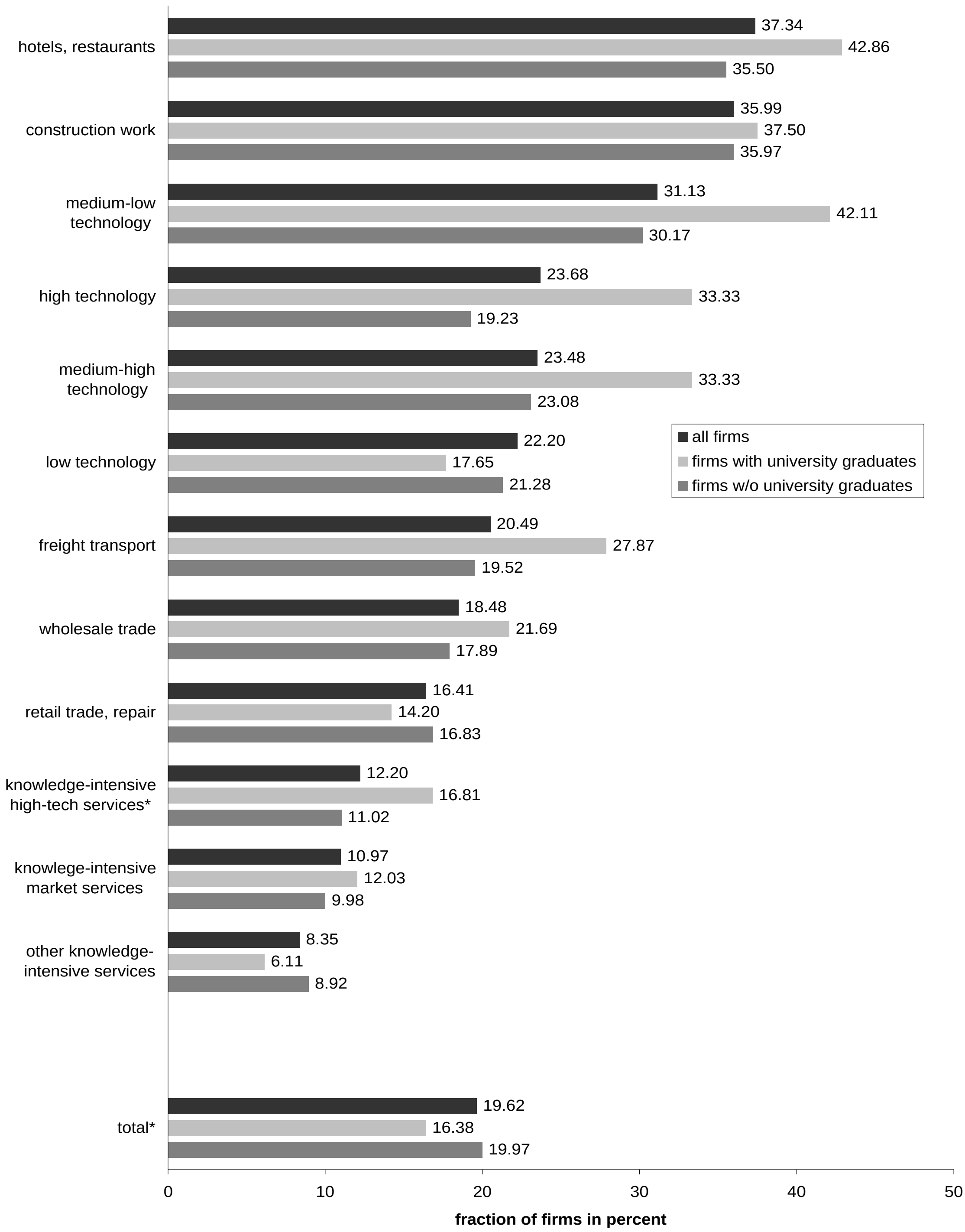
[22]For example, if a firm takes on a newcomer in 1999, then the situation in 1998 is stored in the variable X_before and the situation in 1999 is stored in the variable X_after. If a firm gets a newcomer in 2000, the situation in 1999 is the situation which is considered for the "before"-variable and the situation in 2000 is collected in the "after"-variable. If a firm gets newcomers both in 1999 and 2000, the situation in 1999 is considered once as the "after"-situation (with respect to 1998) and once as the "before"-situation (with respect to 2000).

[23]A simple probit estimation also reveals that firms founded by teams are more likely to get newcomers than single entrepreneurs.

Figure 3.2: Fraction of firms with newcomers in the period 1999 to 2001



Reading aid: 33.33 percent of the firms founded without university graduates in high technology take on new persons in the period 1999 to 2001.

Notes: Total number of firms: 14,171. Number of firms with university graduates: 2,543. Number of firms without university graduates: 11,095.

A * at the sector names indicates whether firms with university graduates differ significantly from firms without university graduates at the 5% level.

Source: Statistics Denmark, author's calculations.

$H1a_0^{dev}$: *The development of the actual observed composition of teams with respect to educations equals a random process.*

The difference between the value of the Herfindahl-Index before and after newcomers join the firm in case individuals are randomly assigned to firms serves as test statistic (ΔH^{tr}_{random}, where Δ = Herfindahl_after - Herfindahl_before). The distribution of ΔH^{tr}_{random} has to be simulated again, which was done by 1,000 times randomly assigning the newcomers within a sector to the firms, thereby maintaining the number of newcomers for each firm. In each round, ΔH^{tr}_{random} is calculated and averaged over firms on the industry level. The resulting value is stored. The mean values of the simulated distributions are then used as the reference values for the actual observed development of the Herfindahl-Index.

Randomly assigning newcomers to firms mirrors a situation where firms do not at all search for individuals systematically with respect to disciplines. The other extreme case would be that firms search systematically but focus on individuals which are equal to themselves, i.e. duplicate themselves with respect to disciplines. Therefore, the actually observed difference in the Herfindahl-Index is also contrasted to a situation in which individuals choose clones of themselves with respect to disciplines. The null hypothesis to be tested is

$H1b_0^{dev}$: *The development of the actual observed composition of teams with respect to educations equals a process where the old team members duplicate themselves.*

The simulation of the respective test statistic $\Delta H^{tr}_{duplication}$ is as follows: As many individuals as newcomers entering the firm are drawn with replacement from the individuals already working in the firm. Then the information about the educational attainment of the selected individuals is recorded and $\Delta H^{tr}_{duplication}$ is calculated. Finally, the average value of $\Delta H^{tr}_{duplication}$ on the industry level is stored and the loop is started again. The number of rounds amounts again to 1,000.

Table 3.5 shows the results. The actually observed development of the Herfindahl-Index is reported in columns (1), (4), and (7). The development of the Herfindahl-Index when newcomers are randomly assigned to firms is shown in columns (2), (5), and (8) and the development of the Herfindahl-Index when individuals already in the firm duplicate themselves in columns (3), (6), and (9). The actually observed Herfindahl-Index decreases when new persons join, which means that the diversity

Table 3.5: Diversity of disciplines - changes due to new individuals entering the firm

industry	**all firms**			**firms with univ. graduates**			**firms w/o univ. graduates**		
	observed	with random assignm.	with random dupl.	observed	with random assignm.	with random dupl.	observed	with random assignm.	with random dupl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
total (firms with $n > 1$)	-0.263	-0.341***	0.157***	-0.168	-0.223***	0.162***	-0.291	-0.364***	0.156***
manufacturing									
low-technology	-0.171	-0.227***	0.138***	-0.215	-0.262***	0.130***	-0.196	-0.221***	0.139***
medium-low technology	-0.181	-0.272***	0.160***	-0.064	-0.088**	0.173***	-0.200	-0.293***	0.159***
medium-high technology	-0.308	-0.373***	0.138***	-0.063	-0.109**	0.167***	-0.353	-0.422***	0.133***
high technology	-0.176	-0.190	0.132***	-0.012	-0.014	0.137***	-0.338	-0.366	0.127***
construction work	-0.260	-0.404***	0.144***	-0.158	-0.225***	0.147***	-0.271	-0.415***	0.144***
services									
wholesale trade	-0.285	-0.338***	0.175***	-0.168	-0.195***	0.193***	-0.322	-0.368***	0.171***
retail trade, repair	-0.241	-0.302***	0.179***	-0.191	-0.240***	0.157***	-0.256	-0.309***	0.182***
hotels, restaurants	-0.208	-0.256***	0.159***	-0.127	-0.149***	0.167***	-0.236	-0.270***	0.158***
knowl.-intens. high-tech serv.	-0.366	-0.465***	0.121***	-0.214	-0.273***	0.156***	-0.470	-0.595***	0.098***
knowl.-intens. market serv.	-0.279	-0.340***	0.157***	-0.176	-0.259***	0.164***	-0.358	-0.409***	0.151***
other knowl.-intens. serv.	-0.273	-0.325***	0.168***	-0.102	-0.172***	0.173***	-0.346	-0.383**	0.166***
freight transport	-0.341	-0.380***	0.159***	-0.136	-0.144	0.150***	-0.374	-0.396*	0.15***9

Notes: The diversity of disciplines is measured by the Herfindahl-Index of highest educational attainment. Columns (1), (4), and (7) show the difference between the average Herfindahl-Index before and the average Herfindahl-Index after newcomers joined the firms by industry, based on the actual sorting of individuals. Columns (2), (5), and (8) depict the mean value of the distribution of the difference between the average Herfindahl-Index before and the average Herfindahl-Index after newcomers joined the firms by industry, generated with random assignment of newcomers to firms. Columns (3), (6), and (9) show the difference between the average Herfindahl-Index before and the average Herfindahl-Index after newcomers joined the firms by industry, generated by randomly duplicating already involved individuals in the firms.
***, **, * indicate whether the values in column (2), (5), and (8) respectively (3), (6), and (9) are significantly different from the values in column (1), (4), and (7) at the 1%, 5% and 10% level respectively.
Source: Statistics Denmark, author's calculations.

of skills increases. However, the decrease in the Herfindahl-Index would have been larger if newcomers were randomly assigned to firms. This holds for all industries as well as for both subgroups of firms. In most cases, the discrepancy in the differences between the two situations is highly significant. On the other hand, if the individuals already in the firm would clone themselves, the diversity would decrease substantially as the inspection of the respective columns reveals. This means that individuals actually look for other individuals who enrich their skill basis, but compared to a situation of random assignment they tend to systematically choose newcomers with skills already in the firm. Concerning H1, the rejection is therefore maintained.

3.4.6.2 Degree of homogeneity with respect to ability

Concerning the degree of homogeneity with respect to ability, the conclusion in Section 3.4.2 was that individuals form teams with members of similar ability level. However, the question remained whether they do it systematically since in many cases the actually observed composition of teams does not differ significantly from the composition of teams when individuals are matched randomly, especially for firms with university graduates. To further analyse this question, the same setup as in the previous section is used and the actual development of the standard deviation of log wages due to newcomers is compared to the development when newcomers are randomly assigned to firms as well as when the existing workforce clones itself. The null hypotheses for the respective tests are

$H2a_0^{dev}$: *The development of the actually observed composition of teams with respect to ability equals a random process*

and

$H2b_0^{dev}$: *The development of the actually observed composition of teams with respect to ability equals a process where the old team members duplicate themselves.*

The test statistics are $\Delta std.dev._{random}$ in the case of random assignment of newcomers and $\Delta std.dev._{duplication}$ in the case of random duplication, where $\Delta =$ std. dev.(log wages)_after - std. dev.(log wages)_before. The simulations follow the same procedure as described in the previous Section apart from calculating $\Delta std.dev._{random}$ and $\Delta std.dev._{duplication}$ instead of ΔH^{tr}_{random} and $\Delta H^{tr}_{duplication}$.

Table 3.6: Homogeneity of abilities - change due to new individuals entering the firm

industry	**all firms**			**firms with univ. graduates**			**firms w/o univ. graduates**		
	observed	with random assignm.	with random dupl.	observed	with random assignm.	with random dupl.	observed	with random assignm.	with random dupl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
total (firms with $n > 1$)	0.102	0.132***	-0.041***	0.074	0.098***	-0.043***	0.110***	0.139	-0.040***
manufacturing									
low-technology	0.063	0.126***	-0.035***	0.123	0.193**	-0.028***	0.060	0.116***	-0.036***
medium-low technology	0.072	0.111***	-0.035***	0.012	0.070**	-0.044***	0.081	0.115***	-0.034***
medium-high technology	0.125	0.122	-0.029***	0.023	0.102***	-0.026***	0.144	0.126	-0.030***
high technology	0.029	0.104***	-0.057***	-0.069	-0.013**	-0.055***	0.127	0.220*	-0.059***
construction work	0.099	0.123***	-0.037***	0.042	0.058	-0.040***	0.104	0.127***	-0.036***
services									
wholesale trade	0.105	0.135***	-0.050***	0.071	0.089	-0.056***	0.117	0.145***	-0.049***
retail trade, repair	0.095	0.125***	-0.043***	0.085	0.097	-0.038***	0.097	0.128***	-0.044***
hotels, restaurants	0.096	0.137***	-0.046***	0.060	0.081	-0.046***	0.109	0.144***	-0.046***
knowl.-intens. high-tech serv.	0.155	0.192***	-0.031***	0.084	0.150***	-0.034***	0.205	0.223	-0.029***
knowl.-intens. market serv.	0.113	0.133**	-0.040***	0.095	0.094	-0.046***	0.125	0.166***	-0.035***
other knowl.-intens. serv.	0.100	0.182***	-0.044***	0.037	0.135***	-0.060***	0.123	0.199***	-0.038***
freight transport	0.102	0.132***	-0.040***	0.025	0.041	-0.035***	0.114	0.138***	-0.040***

Notes: Ability is measured by the average lifetime wage (in logs) of an individual corrected for inflation, disciplines, and industry. Columns (1), (4), and (7) show the difference between the average standard deviation of log wages before and the average standard deviation of log wages after newcomers joined the firms by industry based on the actual sorting of individuals. Columns (2), (5), and (8) depict the mean value of the distribution of the the difference between the average standard deviation of log wages before and the average standard deviation of log wages after newcomers joined the firms by industry, generated with random assignment of newcomers to firms. Columns (3), (6), and (9) show the difference between the average standard deviation of log wages before and the average standard deviation of log wages after newcomers joined the firms by industry, generated by randomly duplicating already involved individuals in the firms.

***, **, * indicate whether the values in column (2), (5), and (8) respectively (3), (6), and (9) are significantly different from the values in column (1), (4), and (7) at the 1%, 5% and 10% level respectively.

Source: Statistics Denmark, author's calculations.

The results are shown in Table 3.6. Interestingly, the actually observed standard deviation of log wages increases when newcomers are engaged (columns (1), (4), and (7)). This means that, contrary to the expectations based on the O-ring theory, the degree of homogeneity with respect to ability decreases through new team members. However, the actual decrease in homogeneity is in many cases not as strong as under random assignment of newcomers to firms (columns (2), (5), and (8)). However, also here, some insignificant differences between the two situations appear among firms with university graduates. If the old workforce had cloned itself, the homogeneity would have increased as can be seen in columns (3), (6), and (9). In summary, individuals choose partners systematically but do not look for partners with similar ability levels. H2 can therefore be rejected.[24]

3.4.6.3 Relationship between ability and team size

In Section 3.4.3 it is shown that from the perspective of the O-ring theory, the "wrong" firms, i.e. firms with a lower average ability level, employ a higher number of individuals. However, as argued, a reason may be that individuals first have to figure out the optimal team size. If this is the case, we should observe that the correlation becomes positive over time. However, as Table 3.7 shows, this does not happen. The Table displays the estimated coefficients of equation (3.16) separately for the years 1999 to 2001. Over the whole timespan, the relationship between average ability and firm size remains negative. And, and as can be seen from the size of the coefficients, it even becomes stronger. This holds for almost all industries as well as for firms with university graduates and firms without university graduates (not shown). The negative relationship between ability and team size is obviously stable.

[24]The firms with university graduates in high-technology represent the only exception of the overall pattern. In these firms, the actual observed homogeneity with respect to ability increases and the increase is even stronger than under duplication. This might be an indication that the O-ring theory applies best to this subset of firms in this sector. However, the sector high-technology is the one with the smallest number of firms.

Table 3.7: Relationship between ability and team size

dep. var.: log(employment)	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
	1999		**2000**		**2001**	
average ability	-0.190***	0.014	-0.293***	0.019	-0.354***	0.023
average ability in ...						
low-technology	-0.544***	0.126	-0.628***	0.154	-0.665***	0.178
medium-low technology	-0.249*	0.135	-0.547***	0.164	-0.503***	0.162
medium-high technology	-0.159	0.176	-0.544***	0.209	-0.847***	0.278
high-technology	-0.236	0.305	0.038	0.430	-0.149	0.317
construction work	-0.299***	0.055	-0.523***	0.072	-0.634***	0.082
wholesale trade	-0.106***	0.034	-0.244***	0.049	-0.308***	0.054
retail trade, repair	-0.182***	0.031	-0.297***	0.045	-0.383***	0.053
hotels, restaurants	-0.580***	0.105	-0.757***	0.134	-0.964***	0.157
knowl.-intens. high-tech serv.	-0.124***	0.024	-0.168***	0.041	-0.164***	0.044
knowl.-intens. market serv.	-0.126***	0.023	-0.163***	0.028	-0.210***	0.034
other knowl.-intens. serv.	-0.091**	0.038	-0.035	0.055	-0.095*	0.056
freight transport	-0.113***	0.043	-0.186***	0.058	-0.205***	0.069
constant	2.351***	0.494	2.740***	0.602	2.897***	0.694
industry dummies	YES		YES		YES	
R^2	0.072		0.081		0.092	
number of observations	11,322		8,650		7,028	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level.
Source: Statistics Denmark, author's calculations.

3.5 Conclusions

In this paper, I analyse whether there are complementarities between the abilities of individuals in newly founded firms. Hypotheses are derived from the O-ring theory (Kremer (1993)), which provides a basis to formulate predictions of firms characterised by these type of complementarities. Using a rich employer-employee data set covering all firms established in 1998 in Denmark, I find the following results

- If firms are founded by a team, individuals match more often with other individuals who have the same education than under random matching.

- If firms are founded by a team, individuals match more often with other individuals who have the same level of ability than when randomly matched. However, this holds only for the start-up year. When the firms mature, the degree of homogeneity decreases. And it decreases even more than it would be the case under random recruitment of new employees. Thus, diversification in ability turns out to be the recruitment strategy of young firms.
- The average level of ability in firms is negatively correlated with firm size.
- The average level of ability in firms is positively correlated with capital per head.

These results do not change when industries are considered separately or when the analysis is restricted to firms founded with university graduates. Except for the very last finding all results contradict the O-ring theory. Thus, new firms seem not to be characterised by complementarities in the abilities of their workforce, at least not as formalised by the O-ring theory.

Why do the hypotheses fail? There are at least three potential reasons. First, the theory is adequate but there are measurement problems. Although the data set is very comprehensive, it is possible that the information does not suffice to measure the key variables of the O-ring theory – the number of essential tasks and the probability to make a failure while performing these tasks – adequately. If individuals performing unessential tasks have systematically different ability levels than individuals performing essential tasks the estimations are biased. The same is the case if the probability to make a failure is not very well reflected in the wages. Second, the theory is right, but only holds in the long run. It might be the case that individuals systematically commit errors when assembling the human capital basis of their firms or are hindered by imperfect information to find the right partners at once. Third, the theory is not adequate. The O-ring theory relies on the extreme assumption that mistakes of one person cannot be compensated by other persons. This makes an additional person an additional source of risk for the firm and neglects possible risk reducing effects.

However, I presume that the last reason applies. The measurement problems are probably not as severe as to invalidate the qualitative results. The new firms are so small that it is reasonable to assume that each individual performs an essential task. This should hold at least for the start-up year. And wages should reflect to a sufficient extent whether individuals make mistakes with high probability. The analyses performed in Section 3.4.6 also give first evidence that the theory also does not hold in the long run. In Müller (2009), I worked further on this point by estimating how the survival probabilities of the firms are affected by team size and the degree of homogeneity in educations and in abilities are determined for the survival probabilities of the firms. It turns out that team size has a positive effect on survival, but the degree of homogeneity has no effect. This suggests that the reason of the rejection of most of the hypotheses in this paper is that an additional person in the firm does not increase but reduces the risk of firm failure.

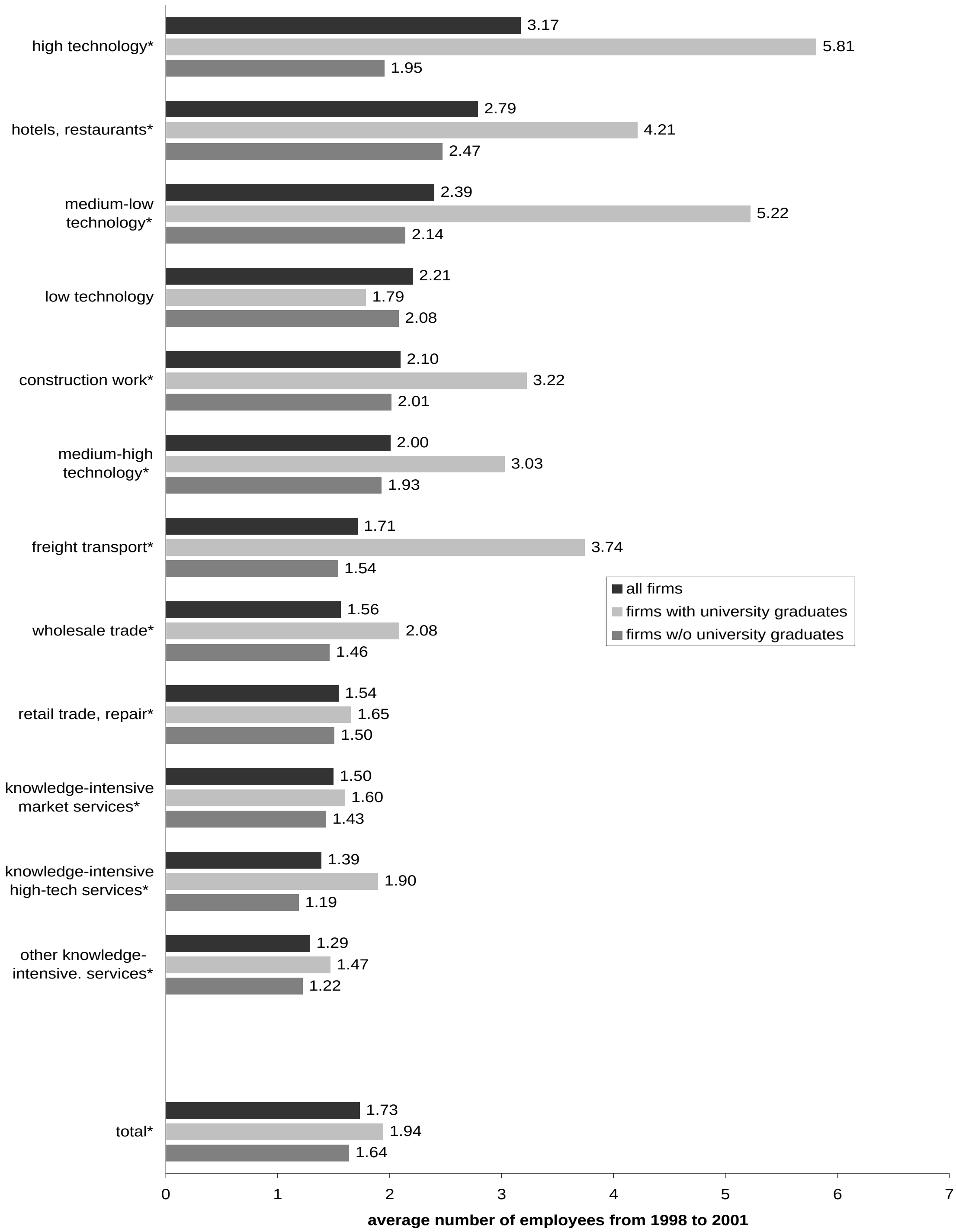
Appendix

Table 3.8: Definition of industries

	NACE - code	description
low-technology	15, 16	food, beverages and tobacco
	17, 18, 19	textile and clothing
	20, 21, 22	wood, pulp, paper products, printing and publishing
	36, 37	other manufacturing and recycling
medium-low technology	23	coke, refined petroleum products and nuclear fuel
	25	rubber and plastic products
	26	non-metallic mineral products
	27	basic metals
	28	fabricated metal products
	351	shipbuilding
medium-high technology	24, excl. 24.4	chemicals excl. pharmaceuticals
	29	non-electrical machinery
	31	electric machinery
	34	motor vehicles
	352, 354, 355	other transport equipment
high-technology	244	pharmaceuticals
	30	computers, office machinery
	32	electronics, communication
	33	scientific instruments
	353	aerospace
knowledge-intensive high-tech services	64	post and telecommunications
	72	computer and related activities
	73	research and development
knowledge-intensive market services (excl. financial intermediation)	61	water transport
	62	air transport
	70	real estate activities
	71	renting of machinery and equipment w/o operator, and of personal and household goods
	74	other business activities
other knowledge-intensive services	80	education
	85	health and social work
	92	recreational, cultural and sporting activities

Source: OECD (2003).

Figure 3.3: Average number of employees during the period 1998 to 2001



Reading aid: Firms in the knowledge-intensive market services have on average of 1.50 individuals during the period 1998 to 2001.

A * at the sector names indicates whether firms with university graduates differ significantly from firms without university graduates at the 5% level.

Source: Statistics Denmark, author's calculations.

Table 3.9: Heterogeneity of educations in start-up year – 95% confidence intervals (CI)

industry	**all firms**		**firms with univ. graduates**		**firms w/o univ.graduates**	
	observed value	95%-CI under random assignm.	observed value	95%-CI under random assignm.	observed value	95% CI-under random assignm.
	(1)	(2)	(3)	(4)	(5)	(6)
total (firms with $n > 1$)	0.131***	[0.042; 0.057]	0.084***	[0.018; 0.030]	0.145***	[0.048; 0.066]
manufacturing						
low-technology	0.143***	[0.045; 0.121]	0.103**	[0.028; 0.091]	0.164***	[0.045; 0.134]
medium-low technology	0.088*	[0.020; 0.092]	0.065*	[0.011; 0.071]	0.092	[0.017; 0.106]
medium-high technology	0.086	[0.003; 0.111]	0.033	[0.000; 0.100]	0.098	[0.000; 0.145]
high technology	0.099	[0.012; 0.195]	0.063	[0.012; 0.102]	0.148	[0.000; 0.300]
construction work	0.223***	[0.044; 0.081]	0.199***	[0.013; 0.056]	0.228***	[0.045; 0.087]
services						
wholesale trade	0.125***	[0.014; 0.055]	0.027	[0.004; 0.038]	0.150***	[0.015; 0.068]
retail trade, repair	0.107***	[0.033; 0.067]	0.045**	[0.011; 0.043]	0.116***	[0.034; 0.072]
hotels, restaurants	0.103***	[0.044; 0.078]	0.039	[0.019; 0.053]	0.110***	[0.046; 0.085]
freight transport	0.082**	[0.022; 0.078]	0.044	[0.009; 0.052]	0.090**	[0.021; 0.087]
knowl.-intens. high-tech serv.	0.112***	[0.008; 0.068]	0.068***	[0.003; 0.043]	0.169**	[0.000; 0.167]
knowl.-intens. market serv.	0.128***	[0.014; 0.049]	0.120***	[0.010; 0.032]	0.137***	[0.010; 0.098]
other knowl.-intens. serv.	0.033	[0.000; 0.089]	0.000	[0.000; 0.067]	0.050	[0.000; 0.126]

Notes: The diversity of educations is measured by the Herfindahl-Index of highest educational attainment. Columns (1), (3), and (5) show the average Herfindahl-Index by industry, based on the actual sorting of individuals to firms. Columns (2), (4) and (6) depict the mean value of the distribution of the average Herfindahl-Index by industry, generated with random assignment of individuals to firms.
***, **, * indicate whether the values in column (1), (3), and (5) are significantly different from the values in column (2), (4), and (6) at the 1%, 5% and 10% level respectively.
Source: Statistics Denmark, author's calculations.

Table 3.10: Homogeneity of abilities in start-up year – 95% confidence intervals (CI)

industry	**all firms**		**firms with univ. graduates**		**firms w/o univ.graduates**	
	observed value	95%-CI under random assignm.	observed value	95%-CI under random assignm.	observed value	95% CI- under random assignm.
	(1)	(2)	(3)	(4)	(5)	(6)
total (firms with $n > 1$)	0.276***	[0.301; 0.314]	0.300**	[0.301; 0.329]	0.266***	[0.297; 0.314]
manufacturing						
low-technology	0.292*	[0.291; 0.345]	0.260***	[0.279; 0.389]	0.304	[0.281; 0.350]
medium-low technology	0.261**	[0.272; 0.341]	0.284	[0.247; 0.397]	0.255*	[0.254; 0.349]
medium-high technology	0.236**	[0.247; 0.347]	0.260	[0.184; 0.401]	0.230*	[0.218; 0.384]
high technology	0.438	[0.309; 0.601]	0.534	[0.267; 0.656]	0.309	[0.209; 0.734]
construction work	0.236***	[0.265; 0.291]	0.253	[0.233; 0.319]	0.232***	[0.264; 0.292]
services						
wholesale trade	0.319	[0.297; 0.344]	0.340	[0.274; 0.371]	0.312	[0.290; 0.352]
retail trade, repair	0.262***	[0.277; 0.304]	0.275	[0.249; 0.341]	0.258***	[0.274; 0.306]
hotels, restaurants	0.291***	[0.313; 0.343]	0.338	[0.290; 0.377]	0.279***	[0.310; 0.345]
freight transport	0.291***	[0.313; 0.372]	0.343	[0.290; 0.436]	0.264***	[0.304; 0.376]
knowl.-intens. high-tech serv.	0.283	[0.270; 0.331]	0.279	[0.256; 0.332]	0.287	[0.231; 0.401]
knowl.-intens. market serv.	0.288***	[0.299; 0.338]	0.292**	[0.297; 0.347]	0.283	[0.266; 0.359]
other knowl.-intens. serv.	0.305	[0.271; 0.398]	0.351	[0.231; 0.453]	0.282	[0.244; 0.418]

Notes: Ability is measured by the average lifetime wage (in logs) of an individual corrected for inflation, disciplines and industry. Columns (1), (3), and (5) show the average standard deviation of ability by industry, based on the actual sorting of individuals to firms. Columns (2), (4), and (6) depict the mean value of the distribution of the average standard deviation by industry, generated with random assignment of individuals to firms.
***, **, * indicate whether the values in column (1), (3), and (5) are significantly different from the values in column (2), (4), and (6) at the 1%, 5% and 10% level respectively.
Source: Statistics Denmark, author's calculations.

4 Ability Matching and Survival of Start-Ups

4.1 Introduction

New firms are regarded to be of substantial importance for the development of an economy, especially for innovation, growth, and the creation of jobs. However, new firms also face a high risk of failure. For example, Mata and Portugal (1994) report that only about half of the firms in their data set survived the first four years and Audretsch (1991) finds that only a third is still in operation after ten years. Thus, there seems to be a high risk connected with the establishment of firms. In order to reduce this risk and to create general conditions which help young firms to be in business for longer periods, it is important to know what determines the survival of new firms in the first years of their existence.

New firms are typically human-capital intensive, and the individuals involved are regarded to be one crucial success factor (see e.g. Gompers and Lerner (2001)). As Fabel (2004a,b) and Fabel and Weber (2005) note, a particular sort of risk may arise in organising human-capital intensive activities: If the skills necessary for running the firm are provided by several individuals who are each a specialist in one particular skill and if the performance of one of these specialists is below a critical level, the whole project can fail. That is: Human-capital intensive activities are likely to be characterised by complementarities in the abilities of the individuals performing the essential tasks. These complementarities could be a reason for the observed high failure rates of young firms.

One way to formalise complementarities in ability is given by the O-ring production approach by Kremer (1993). The O-ring theory assumes that a project consists of several tasks, each of which must be fulfilled at a certain minimum level of quality for the whole project to have success.[1] In Müller (2008), I determined to what extent the equilibrium effects of the O-ring theory can be confirmed by the data. The results were mixed. In this paper, I therefore try to answer the question why we do not get much support for the theory.

In order to do this, I focus on the movements to the equilibrium that can be inferred from the O-ring theory. The theory proposes several ways how these movements will occur. The first follows directly from the assumed production function. The O-ring theory conceptualises the ability of workers in a firm by the probability to perform an assigned task sufficiently well and assumes that these abilities enter the production function multiplicatively. The joint probability that all individuals perform their tasks sufficiently well can be interpreted as the survival probability of the firm. Assuming that each task is assigned to a single person, this means that, given team size, higher average ability in the team is associated with a higher survival probability and, given ability, larger team size is associated with a lower survival probability. These are the first two hypotheses tested in this paper.

The O-ring theory further entails that individuals segregate between firms according to their level of ability. In labour market equilibrium, this results in homogeneous workforces within firms. Observing inhomogeneous teams may therefore only be interpreted as a transitory phenomenon caused by imperfect information about each others' abilities. Hence, I additionally analyse how the degree of homogeneity with respect to team members' ability influences the probability of firm survival. Finally, it is investigated how the degree of heterogeneity in educations affects the survival chances of new firms. This originates from the assumption that for the different tasks knowledge from different fields is necessary.

The approach followed in this paper is in the spirit of Alchian (1950), who conceptualises the evolution of the stock of firms in an economy as a continuous selection process. New firms are an input into this process and the surviving ones are those who fit best to the prevalent economic environment. The O-ring theory describes the mechanisms with which this selection will occur. If the data do not confirm these selection mechanisms, it can be concluded that the O-ring theory is not well suited

[1] Its name originates from the accident of the space shuttle Challenger which exploded in 1986 because of the malfunctioning of only one of its components: the O-rings of the booster.

for describing new firms because complementarities in ability are not an important characteristic of these firms.

For the analysis in this paper, I draw on register data covering the entire population of firms founded in Denmark in 1998 as well as all individuals involved in these firms. This results in a data set of more than 14,000 firms which are distributed over all sectors of the economy. The data provide rich information on the individual side allowing to determine the characteristics of the persons who are involved in the new firms. Ability can be measured by the average hourly wage that the individuals receive over their working life.

The results show that both team size and ability have a positive effect on the survival probability of young firms. Most important is the very fact of founding in a team. Concerning homogeneity, it turns out that neither homogeneity with respect to ability nor heterogeneity with respect to educations affect the probability of firm survival. The main reason why most of the hypotheses in Müller (2008) fail is that an additional person does not increase the risk of firm failure.

The paper is organised as follows: In Section 4.2, the hypotheses for the empirical analysis are derived from the O-ring theory. In Section 4.3, the data are described. Section 4.4 presents the empirical strategy and Section 4.5 the results. Section 4.6 concludes.

4.2 Theoretical Background and Hypotheses

The O-ring theory goes back to Kremer (1993) and applies to production processes which consist of a series of tasks each of which must be performed at a certain minimum level of quality for the output to have positive market value. Individual ability corresponds to the probability that an individual performs her task sufficiently well. The project as a whole only has a positive outcome if all team members perform their tasks at a certain minimum level of quality. Otherwise, output is zero. This is modelled by including individual abilities multiplicatively in the production function

$$Y = F(k, n) \left[\prod_{i=1}^{n} q_i \right] n, \tag{4.1}$$

where k refers to physical capital, n to the number of tasks and $q_i \in (0,1)$ to the probability that the individual assigned to task i works sufficiently well, which is her ability. Following the literature, it is assumed that each task requires one person, i.e. n is also the number of individuals.[2] According to the exposition above, $[\prod_{i=1}^{n} q_i]$ can be interpreted as the survival probability of the firm.

The survival probability exhibits the following two properties. First, for a given team size, the survival probability increases in the ability level of each individual in the team

$$\frac{\partial([\prod_{i=1}^{n} q_i])}{\partial q_i} = \prod_{j \neq i} q_j > 0, \tag{4.2}$$

And second, for a given ability level, the survival probability decreases in the size of the team[3]

$$\frac{\partial([\prod_{i=1}^{n} q_i])}{\partial n} = ln(q)q^n < 0. \tag{4.3}$$

Formulated as empirical hypotheses, equation (4.2) and (4.3) yield

H1a: Given team size, the probability of firm survival increases in the ability level of the team members.

H1b: Given the ability level of the team members, the probability of firm survival decreases in team size.

One can argue that the effect of insufficient task performance on survival depends on the phase of a firm's life cycle. In the conception phase of the business idea the product might have no market value at all if one of the involved team members does not perform her task sufficiently well. Consequently, the firm might have no basis anymore and therefore has to give up. In contrast, if the firm already reached its operation phase, it is no longer inevitable that the firm dissolves if someone makes a mistake. Low-level performance during contract fulfillment for one client can be compensated by normal-level performance for another. The firm can make a loss but this loss is not necessarily threatening for the whole business. Nevertheless,

[2] In his seminal paper, Kremer (1993) explicitly mentions that n indicates the number of tasks and not necessarily the number of employees. But his exposition of the theory uses the assumption of one person per task and Fabel (2004b) follows him in this respect.

[3] In equilibrium, these two effects are balanced and there is a unique failure probability for optimally composed firms. It is even possible to give a value for this failure probability: 0.632.

the effects concerning ability level and team size on the survival rate should also be observed in the operation phase of the firm, albeit weaker.

The assumption of the O-ring theory that team size is negatively related to firm survival cannot easily be reconciled with the results already established in the literature.[4] The existing studies almost unanimously come to the conclusion that size is positively related to survival. The positive relationship between size and survival is sometimes even regarded as a stylized fact (Geroski (1995), Sutton (1997), Caves (1998)). However, most of the papers cannot control for ability due to data restrictions. Taking equation 4.2 and 4.3 together, it is possible that the effect of size appears to be positive as in most of the previous empirical studies. This is the case when higher able persons build larger teams. As shown by Kremer (1993), the O-ring theory implies that ability and team size are positively correlated. Thus, the positive effect of team size found empirically could result because ability is not controlled for.

Team size also appears to be positively related to survival when human capital variables such as length of education, educational degrees or labor market experience are included in the regressions (Brüderl et al. (1996), Prantl (2003), and Jørgensen (2005)). However, human capital variables only capture part of individuals' ability and may not fully represent the q of the O-ring theory. The theory itself suggests to use wages as representation of ability. To see this, consider a firm that maximizes expected profits and employs only individuals of one ability level[5]

$$\max_{q,k,n} \pi(q,k,n) = pF(k,n)q^n n - w(q)n - rk \tag{4.4}$$

For the following, a specific functional form for $F(k,n)$ is needed. Normalising output price p to one and specifying output per team member $F(k,n)$ as $k^\alpha n^{1-\alpha}$ as in Fabel (2004b) the firm does not want to change the ability level of its workers if

$$\frac{\partial \pi(q,k,n)}{\partial q} : k^\alpha n^{1-\alpha} q^{n-1} n = \frac{dw(q)}{dq}, \tag{4.5}$$

[4]Evans (1987a,b), Dunne et al. (1989), Phillips and Kirchhoff (1989), Mata and Portugal (1994), Mata, Portugal, and Guimarães (1995), Audretsch and Mahmood (1995), Brüderl, Preisendörfer, and Ziegler (1996), Cabral and Mata (2003), Prantl (2003), and Jørgensen (2005).

[5]As will be explained below, the O-ring theory actually implies the sorting of individuals according to their ability, which results in homogeneous workforces within firms.

i.e. if marginal revenue of changing the ability level equals marginal costs. The first order condition with respect to capital k is

$$\frac{\partial \pi(q,k,n)}{\partial k} : \alpha k^{\alpha-1} n^{1-\alpha} q^{n} = r. \tag{4.6}$$

Solving equation 4.6 for k, inserting it into equation 4.5, and integration yields[6]

$$w^{*}(q) = (1-\alpha)\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} (n^{*})^{\frac{1}{1-\alpha}} q^{\frac{n^{*}}{1-\alpha}}. \tag{4.7}$$

This is a monotonously increasing function of ability, i.e. each ability level is unambiguously reflected in a certain wage and a higher ability level comes along with a higher wage. In the empirical analysis, wages are therefore used as a measure of ability.

Besides insufficient ability, the O-ring theory implies a further reason why a firm can fail: better outside options for at least one team member. These can arise when teams are built with the wrong partners. In the production function (4.1), the marginal product of ability of the individual assigned to task i is increasing in the average ability levels of the individuals assigned to the other tasks

$$\frac{d^2 Y}{dq_i d\left(\prod_{j \neq i} q_j\right)} = F(k,n)n > 0. \tag{4.8}$$

This means that skills are complementary.[7] If labour markets are competitive, this implies that firms which have started to employ individuals with the highest ability in the population (and still have suboptimal size) can attract other individuals of the highest ability level since they can pay them the highest wage. Firms with medium ability individuals cannot successfully compete for higher able individuals but are successful in attracting medium ability individuals compared to firms with lower average ability level. This leads to homogeneity in the ability levels of all individuals within firms.

As a theory for describing an equilibrium, the O-ring theory implies that heterogenous teams are not formed at all since abilities are publicly observable and heterogeneous teams are unattractive for high-ability individuals. Thus, in equilibrium it

[6] The constant of integration is zero since an individual with zero ability destroys the product with certainty and therefore cannot receive positive wages.

[7] This is the same concept of complementarity as applied e.g. by Milgrom and Roberts (1990, 1995) in order to explain the joint usage of certain technologies.

is useless to search for an effect of the degree of homogeneity on firm survival. But, as shown in Müller (2008), the ability levels of team members in just established firms exhibit a considerable amount of heterogeneity although not as much as in randomly assembled teams. It is possible that this is partly due to measurement error, since ability always has to be approximated somehow. But it might also be the case that abilities are not perfectly observable so that individuals mistakenly choose the wrong partners. Moreover, each individual might only overlook a small set of potential partners. Thus, teams with similar but not the same level of ability are built. If real abilities and suitable partners become known over time only, better outside options for some team members can arise and a firm can close down because of too much diversity in the abilities. Thus, a further hypothesis is

H2: Given average ability and team size, the probability of firm survival increases in the degree of homogeneity with respect to the ability of the team members.

As mentioned above, in the literature on the O-ring theory, it is assumed that each task requires one person. This is a rather strong assumption as it rules out the cases where one individual can perform several tasks and several individuals are assigned to one task. But under this assumption, it can be expected that individuals are qualified for certain tasks but not for others due to their field of education. Presumably, a firm with a team consisting of individuals with different educational backgrounds can rely on a broader basis of knowledge and therefore has a higher probability of survival. Hence, a third hypothesis is

H3: Given average ability and team size, the probability of firm survival increases in the degree of heterogeneity in educations of the team members.

With H2 and H3, this paper is also related to the literature of the so called "upper echelons research" in business administration (Hambrick and Mason (1984)), which analyses the impact of team composition on firm performance.[8] However, the focus of the upper echelons research lies mainly on well established and rather big firms.[9] Moreover, none of these studies looks at homogeneity in ability as it is done in

[8]For overviews, see Carpenter et al., 2004, Finkelstein and Hambrick, 1996 or Jackson, 1992.

[9]Roure and Madique (1986), Roure and Keeley (1990), Ensley et al. (1998), Ensley and Amason (1999), Ensley and Amason (1999), Beckman et al. (2007), and Zimmerman (2008) condsider new firms.

this paper and all papers that consider new firms are interested in other outcome variables than survival.

4.3 Data

The data used in this paper are provided by Statistics Denmark, Denmark's federal statistical office. These are register data, which cover the whole population of firms which are set up in Denmark in 1998 and that were still in operation at the end of that year.[10] The total number of new firms at the end of 1998 amounts to 16,063. On an annual basis, these firms were observed until 2001 or until they shut down.[11] In the start-up year industry of business, legal form and location of the firm are registered. Additionally, the current number of employees and the current amount of exports, purchases, and sales are recorded in the start-up year and at the end of each year during the follow-up period.

By a combination of firm and personal identification numbers (ID), it is possible to link the firm-level information to information on individuals which is stored in the Integrated Database for Labour Market Research (IDA). The IDA database covers a wide range of variables on the total Danish population from 1980 onwards, including the complete education and employment history. The latter can be used to generate the relevant variables for the individuals involved in the new firms in all years. Due to missing information about the employees for some firms, 14,171 firms of the original 16,063 firms can be used for the subsequent analysis.

A drawback of the data is that it is not possible to identify the persons who perform the necessary tasks in the firm. However, as the great majority of the new firms are

[10]Firms that started in 1998 and shut down within the same year are not contained in the data set.

[11]The same procedure has been applied to all firms founded in 1994. However, for these firms it is only possible to merge individual information for the person who registered the firm with the authorities for the start-up year. Since it is essential for determining the degree of homogeneity between team members to either have information on all individuals or to have at least a representative sample of the individuals, the analysis is restricted to the 1998 cohort.

small entities, each person can be considered to be important.[12] In the following, firms with at least two persons involved are referred to as "team foundations".

4.4 Empirical Approach

The effects of the variables relevant for this paper are determined by estimating a duration model. In principle, the exit of a firm can occur at any time during the year, i.e. survival time is continuous. However, in the data at hand it is only reported whether the respective firm still exists at the end of the year. Since spell lengths are only observed in intervals, a model for interval censored data is estimated. The relevant hazard rate is the probability of exit during year j given survival up to year $j-1$

$$h_j(X) = P(j-1 < T \leq j | T > j-1, X), \tag{4.9}$$

where j denotes the half-open interval $(year_{j-1} - year_j]$. Duration models based on this type of data can be estimated by applying methods for standard binary outcome models (see e.g. Sueyoshi (1995) and Jenkins (2005)). The dependent variable contains the information whether or not firm i survived year j

$$S_{ij} = \begin{cases} 1 & \text{if firm } i \text{ survives year } j \\ 0 & \text{if firm } i \text{ does not survive year } j \end{cases}. \tag{4.10}$$

The likelihood function is constructed as follows: The probability that firm i survives year j is given by $P(S_{ij} = 1) = 1 - h_{ij}(X_{ij}, \beta)$. Correspondingly, the probability that firm i does not survive year j is given by $P(S_{ij} = 0) = h_{ij}(X_{ij}, \beta)$. Considering only one firm, the probability for the sequence of outcomes s_{ik} over the whole period of observation amounts to

$$P(S_{i1} = s_{i1}, S_{i2} = s_{i2}, \ldots, S_{ij} = s_{ij}) = \prod_{k=1}^{j} (1 - h_{ik}(X_{ij}))^{s_{ik}} h_{ik}(X_{ij})^{1-s_{ik}}. \tag{4.11}$$

Since this holds for all firms, the likelihood function for the whole sample is

$$\mathcal{L} = \prod_{i=1}^{n} \left[\prod_{k=1}^{j} (1 - h_{ik}(X_{ij}))^{s_{ik}} h_{ik}(X_{ij}))^{1-s_{ik}} \right]. \tag{4.12}$$

[12]Figure 4.1 in the appendix shows the average number of individuals per firm over the whole period of consideration by industry. The total average firm size is 1.7 persons.

Taking logs, the loglikelihood function is

$$\log \mathcal{L} = \sum_{i=1}^{n} \sum_{k=1}^{j} [s_{ik} \log(1 - h_{ik}(X_{ij}))) + (1 - s_{ik}) \log(h_{ik}(X_{ij})))]. \tag{4.13}$$

One observation is a firm-year combination and the probability of surviving the following year is estimated.

To make the model estimable, a functional form for the hazard rate $h_{ik}(X_{ij})$ must be chosen. In principle, any continuous distribution function can be used. As it is known from practical applications of binary choice models, the results are not very sensitive to the functional form of the distribution functions. Therefore, the choice of the functional form for the hazard rate reduces to the question what can be implemented easiest. For this paper, the logistic distribution is chosen which turns equation (4.13) into a likelihood function of a pooled logit model. In order to allow the hazard rate to vary with survival time (duration dependence), year dummies are added to the list of regressors.

To account for firm heterogeneity which is not captured in the observable variables, a random effects logit is estimated. In this case the hazard rate becomes

$$h_{ik} = \frac{exp(X_i'\beta + c_i)}{1 + exp(X_i'\beta + c_i)}, \tag{4.14}$$

where c_i reflects the unobservable firm effect. In random effects models for binary variables, it is assumed that this effect is sampled along with the dependent variable and observable independent variables and it is removed by integrating it out.[13] Here, the distribution of c_i is assumed to be $N \sim (0, \sigma_c)$ and the removal of this effect is carried out with the default approximation routine implemented in STATA's xtlogit command.

In Table 4.1, the distribution of the life duration of the firms in the data set is shown. At the end of the observation period in 2001, only about half of the firms still exist. The largest number of exits occurs in the second year after foundation.

[13]For details, see e.g. Wooldridge (2002), pp. 482.

Table 4.1: Survival and hazard rates

	surviving firms	number of exits	survival rate	hazard rate
1998	14,171	0	1.000	0
1999	11,822	2,349	0.834	0.166
2000	8,994	2,828	0.635	0.239
2001	7,369	1,625	0.520	0.181

Source: Statistics Denmark, author's calculations.

Measurement and Specification

As mentioned in Section 4.2, wages are used to measure ability. Statistics Denmark provides the average hourly wage once per year for each year the individual was wage employed. For the analyses in this paper, these wages are corrected for inflation, disciplines, and industry effects. The goal of correcting the wages this way is to exclude all components which do not represent ability.[14] After the correction, the average lifetime hourly wage of an individual is calculated, starting with her year of labour market entry until 2001. Thus, for the estimations in this paper, the ability level in a team is the average of the corrected lifetime wages across all team members. The degree of homogeneity of abilities is determined by calculating the standard deviation of the corrected lifetime wages. For easier interpretation, the negative of the standard deviations is included in the regressions.

As a measure of the degree of heterogeneity in education, the Herfindahl-Index of the highest education attained is calculated for each team. The Herfindahl-Index is a measure of concentration. For the purpose of this paper, it is computed as

$$H = \sum_{i=1}^{n} s_i^2, \tag{4.15}$$

where s_i denotes the share of education i in a team.

The range of possible values of the Herfindahl-Index depends on the number of individuals in a team. To correct for this and to make the Herfindahl-Index better

[14] The effects of disciplines and industries were corrected for to take out demand effects: If, for example, engineers are in short supply, their wages rise due to the working of the market forces and not due to an increase in their abilities in the first line. See Müller (2008) for further discussion of the wage correcting procedure.

comparable between teams of different size, the index is transformed to the $[0,1]$-interval in the following way

$$H^{tr} = 1 - \left(H - \frac{1}{n}\right)\frac{n}{n-1} \quad \in [0,1]. \tag{4.16}$$

As a result, it takes on the value zero if all individuals have the same education and becomes one if each individual attained a different education. With this transformation, teams in different firms are treated as equally diverse if all individuals have different educations, independently of team size.

The variable the Herfindahl-Index is based on can take on more than 1,000 values, i.e. it provides highly detailed information on the education of the individuals. Since the educational degree is only a crude measure for the task actually fulfilled in the firm, there is no obvious level of aggregation for this variable. In this paper, the variable has not been aggregated in any respect for calculating the Herfindahl-Index.

The empirical model is estimated in two different versions: In the first, only characteristics of the start-up year are considered. This takes account of the fact that the conditions at start have a lasting effect on the organisation and the outcome of young firms (e.g. Mata and Portugal (1994) or Baron, Burton, and Hannan (1996)). The second version allows the regressors to take on different values over time.

As control variables, the share of exports in sales and regional as well as industry dummies are used. Since it is assumed that all relevant observable and unobservable abilities of the individuals are reflected in the wages, no further ability measures are included in the regressions. In order to account for the conjecture that the marginal effect of the first partner is different from the marginal effect of a second or a third partner, a dummy which takes the value one if at least two persons are involved in the firm is included in addition to the variable "team size".

Table 4.2 and Table 4.3 show descriptive statistics of the variables used in the regressions. The numbers are based on firm-year combinations. Table 4.2 shows the figures for characteristics in the start-up year whereas in Table 4.3 it is allowed that the variables change over time. Surviving firms exhibit a higher average ability, but also have more employees than non-surviving firm. And teams in surviving firms are less homogeneous with respect to ability and less heterogeneous with respect to educations than in non-surviving firms.

Table 4.2: Descriptive statistics - Start-up year characteristics

variable	**all firms**		**surviving firms**		**non-surviving firms**	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
avg. ability	3.731	0.325	3.735	0.321	3.714	0.340
team size	1.456	1.830	1.511	1.941	1.215	1.189
team (y/n)	0.133	0.340	0.147	0.355	0.069	0.253
homogeneity in abilities	-0.036	0.113	-0.040	0.118	-0.019	0.087
heterogeneity in educations	0.115	0.308	0.127	0.321	0.061	0.232
share of exports in sales	0.020	0.123	0.022	0.126	0.015	0.108
copenhagen	0.429	0.495	0.422	0.494	0.459	0.498
city	0.299	0.458	0.297	0.457	0.306	0.461
rural	0.273	0.445	0.281	0.450	0.234	0.424
low-technology	0.020	0.141	0.022	0.148	0.011	0.106
medium-low technology	0.010	0.099	0.011	0.103	0.007	0.081
medium-high technology	0.002	0.049	0.002	0.049	0.002	0.047
high technology	0.135	0.342	0.146	0.353	0.089	0.284
construction	0.099	0.298	0.100	0.300	0.091	0.288
wholesale trade	0.034	0.180	0.035	0.183	0.030	0.169
retail trade	0.197	0.397	0.184	0.388	0.252	0.434
hotels, restaurants	0.062	0.242	0.057	0.232	0.084	0.278
knowl.-intens. high-tech serv.	0.108	0.310	0.104	0.306	0.124	0.330
knowl.-intens. market serv.	0.199	0.399	0.202	0.402	0.183	0.387
other knowl.-intens. serv.	0.033	0.179	0.035	0.183	0.027	0.163
freight transport	0.101	0.301	0.101	0.302	0.100	0.300
number of observations	31,992		26,129		5,863	

Notes: The numbers are based on firm-year combinations.
Source: Statistics Denmark, author's calculations.

Table 4.3: Descriptive statistics - Time-varying characteristics

variable	**all firms**		**surviving firms**		**non-surviving firms**	
	mean	std.dev.	mean	std.dev.	mean	std.dev.
avg. ability	3.724	0.322	3.727	0.319	3.713	0.337
team size	1.697	2.621	1.804	2.819	1.199	1.230
team (y/n)	0.178	0.382	0.204	0.403	0.055	0.227
homogeneity of ability	-0.051	0.134	-0.059	0.142	-0.016	0.079
heterogeneity in educations	0.153	0.347	0.176	0.366	0.048	0.207
share of exports in sales	0.022	0.126	0.023	0.129	0.014	0.109
number of observations	31,895		26,273		5,622	

Notes: The numbers are based on firm-year combinations.
Source: Statistics Denmark, author's calculations.

4.5 Results

Table 4.4 shows the estimation results. The figures are the marginal effects calculated at the mean of the independent variables. For the estimations in columns (1) and (2), only the values of the respective variables in the start-up year are considered. Columns (3) and (4) show the results when the values of the variables are updated each year. As can be seen from the critical value of the LR-test ($\bar{\chi}^2_{01}$), the hypothesis that unobserved effects do not play a role can be rejected for both versions of the empirical model. Therefore, only the results from the RE logit are considered in the following.

Concerning the effect of ability and team size, it turns out that both the average ability in a team and the size of the team have a positive impact on the survival probability. Additionally, having a team at all has a much stronger effect on survival than including a further person in a team. Considering only start-up year characteristics, an increase of the average ability by one standard deviation increases the probability of survival by 1 percentage point. An additional team member yields a 0.5 percentage points higher survival rate but the first partner increases the survival probability by 12 percentage points. Allowing for time varying characteristics, the effects remain roughly the same both regarding sign and magnitude. H1a cannot

Table 4.4: Results (marginal effects)

dep. var.: survival of the following year (yes/no)								
	start-up year characteristics				**time-varying characteristics**			
	pooled logit		RE logit		pooled logit		RE logit	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
	(1)		(2)		(3)		(4)	
avg. ability	0.031***	0.006	0.033***	0.007	0.028***	0.006	0.030***	0.007
team size	0.004**	0.002	0.005**	0.002	0.002	0.002	0.004***	0.002
team (y/n)	0.114***	0.017	0.118***	0.017	0.149***	0.014	0.118***	0.015
homogeneity in abilities	0.015	0.041	0.016	0.044	-0.022	0.040	-0.021	0.034
heterogeneity in educations	-0.022	0.030	-0.024	0.032	-0.007	0.031	-0.012	0.025
share of exports in sales	0.050**	0.021	0.052***	0.021	0.047**	0.020	0.044**	0.019
regional dummies (ref.cat. copenhagen)								
city	0.012**	0.005	0.013**	0.005	0.009*	0.005	0.011**	0.005
rural	0.038***	0.005	0.041***	0.006	0.036***	0.005	0.039***	0.005
industry dummies (ref.cat. low-technology)								
medium-low technology	0.056***	0.016	0.058***	0.016	0.039**	0.017	0.038***	0.014
medium-high technology	0.040*	0.022	0.043*	0.022	0.035*	0.021	0.036**	0.017
high technology	-0.016	0.047	-0.015	0.053	-0.015	0.045	-0.005	0.052
construction	0.041***	0.012	0.041***	0.012	0.022*	0.012	0.021*	0.012
wholesale trade	-0.011	0.014	-0.013	0.016	-0.014	0.014	-0.018	0.017
retail trade	-0.074***	0.015	-0.083***	0.019	-0.074***	0.015	-0.100***	0.023
hotels, restaurants	-0.130***	0.020	-0.150***	0.029	-0.155***	0.021	-0.230***	0.042
knowl.-intens. high-tech serv.	-0.034***	0.015	-0.037**	0.017	-0.030**	0.014	-0.036**	0.019
knowl.-intens. market serv.	0.002	0.013	0.001	0.014	0.006	0.012	0.004	0.014
other knowl.-intens. serv.	0.026*	0.015	0.027*	0.016	0.031**	0.014	0.029**	0.013
freight transport	-0.015	0.014	-0.016	0.016	-0.025*	0.014	-0.028	0.018
time dummies (ref.cat. 1999)								
2000	-0.091***	0.005	-0.111***	0.018	-0.087***	0.005	-0.173***	0.014
2001	-0.044***	0.006	-0.083**	0.035	-0.044***	0.006	-0.232***	0.036
pseudo-R^2	0.036				0.057			
log likelihood	-14,686.789		-14,685.742		-14,005.661		-13,979.795	
$\bar{\chi}^2_{01}$			2.09*				51.73***	
number of observations	31,992		31,992		31,895		31,895	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Marginal effects are calculated at the means of the independent variables. For the calculation of the marginal effects of the RE logit, the random effect is set to its mean value zero. For a detailed description of the combined industries, see Table 4.5 in the appendix.
Source: Statistics Denmark, author's calculations.

be rejected but H1b can. Thus, I cannot find the countervailing effect of team size and ability in the failure probability suggested by the O-ring theory. Instead, I can corroborate the finding of earlier studies stating that firms founded with a higher number of persons have higher survival chances. Interestingly, this result appears *even when* ability is controlled for.

The effects of homogeneity in abilities and heterogeneity in educations can be found in row three and four of Table 4.4. Obviously, the degree of homogeneity in abilities and the degree of heterogeneity do not have any effect on the survival probability of young firms. This result casts doubt an the assumption that team heterogeneity is an important variable to explain firm performance as put forward in the upper echelons literature. These doubts concern at least new firms. What is striking about the previous studies on new firms is that it is obviously difficult to identify any effect of team heterogeneity at all. However, this could also be a small number-problem as the authors of the previous studies rely on rather few firms and selected industries. In contrast, the analysis in this paper uses a high number of observations but also finds no effect. This suggests that team heterogeneity is rather unimportant for firm performance.

A possible reason for the missing effect of team heterogeneity is that diversity is a double-edged sword (Hambrick et al. (1996), Ensley and Amason (1999)). Concerning ability, it is attractive for a high ability individual to look for other high ability individuals because of their lower failure probability. On the other hand, high ability individuals also demand a high compensation for their labour input. Thus, if not all tasks are essential for the success of the project − and it seems that they are not − it could simply be cheaper to employ an individual with low ability. Concerning educations, heterogeneity may provide a broader basis of knowledge. But on the other hand, different educations also represents different modes to interpret the world what could lead to misunderstandings and even to conflict among the team members. Overall, the effects can cancel out.

With the results presented in Table 4.4, the O-ring theory does not describe the situation in young firms very well. However, one can argue that the theory only applies to a subset of industries. Task complementarity might only be particular for the production environments in certain sectors. However, this is not confirmed in the data. To account for the probable limited applicability of the theory the regressions are performed separately for different industries. This differentiation does not lead to any results systematically different from those found for all firms. However, as can be seen in Table 4.6 and Table 4.7 in the appendix, the main results are driven by the firms in the service sectors.

Moreover, it might be the case that firms founded with university graduates are better described by the O-ring theory than firms founded without university graduates. The reason is that firms with university graduates are more likely to deal with innovative products and therefore with more complex technologies which require specialists in different fields. Good matching might therefore be particularly important for these firms. However, as shown in Table 4.8 in the appendix, regressions run for firms founded with university graduates only, again do not lead to major differences compared to the effects for all firms. The only deviation from the results for all firms is that for team with university graduates it is only important to have a team at all. A further team member has no additional effect. This again confirms the conjecture that the step from a single entrepreneur to a team is the crucial step to increase the probability of survival of young firms.

4.6 Conclusions

In this paper, I analyse how the survival of young firms is affected by the average level of ability in a team, the team size, team members' homogeneity with respect to ability, and team members' heterogeneity with respect to educations. The aim was to determine whether the selection mechanisms assumed by the O-ring theory of production can be confirmed by the data. It turns out that the average level of ability in a team and the team size have positive effects on a firms' probability to survive the next year. Most important is having a team at all. In contrast, homogeneity with respect to ability and heterogeneity with respect to educations do not have any effect on the probability of survival. With these results, the selection mechanisms of the O-ring theory can not be supported. Together with the results in Müller (2008), it can be concluded that the O-ring theory does not adequately describe the project "firm foundation". The observed data do not correspond to the equilibrium implied by the theory and it is also not likely that the firms will reach this equilibrium in the long run.

Presumably, the main reason why the O-ring theory does not seem to apply to young firms is that it does not allow for redundancies. One good worker cannot be substituted by two mediocre workers in the theory. This is an extreme assumption. If tasks are really critical, it might be worthwhile to back up these tasks with a second person who checks the work output of the first. Furthermore, it is probably always possible to absorb mistakes in the course of the project at least to some extent.

For policy, the results of this paper suggest that young firms can be supported in their longevity by making sure that several persons are involved and the ability of the persons is as high as possible. However, the degree of diversity in ability and educations can be neglected.

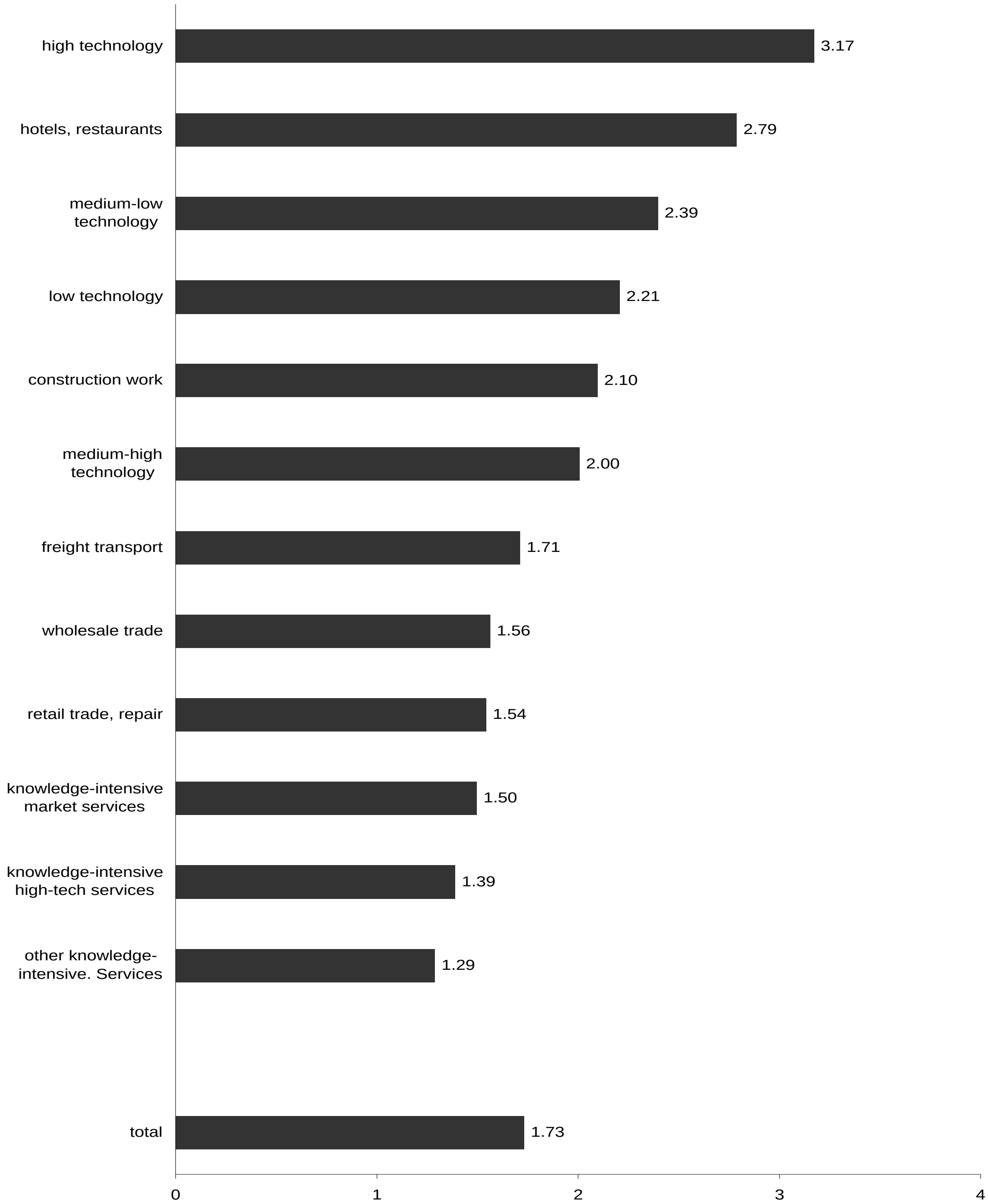
Appendix

Table 4.5: Definition of industries

	NACE - code	description
low-technology	15, 16	food, beverages and tobacco
	17, 18, 19	textile and clothing
	20, 21, 22	wood, pulp, paper products, printing and publishing
	36, 37	other manufacturing and recycling
medium-low technology	23	coke, refined petroleum products and nuclear fuel
	25	rubber and plastic products
	26	non-metallic mineral products
	27	basic metals
	28	fabricated metal products
	351	shipbuilding
medium-high technology	24, excl. 24.4	chemicals excl. pharmaceuticals
	29	non-electrical machinery
	31	electric machinery
	34	motor vehicles
	352, 354, 355	other transport equipment
high-technology	244	pharmaceuticals
	30	computers, office machinery
	32	electronics, communication
	33	scientific instruments
	353	aerospace
knowledge-intensive high-tech services	64	post and telecommunications
	72	computer and related activities
	73	research and development
knowledge-intensive market services (excl. financial intermediation)	61	water transport
	62	air transport
	70	real estate activities
	71	renting of machinery and equipment w/o operator, and of personal and household goods
	74	other business activities
other knowledge-intensive services	80	education
	85	health and social work
	92	recreational, cultural and sporting activities

Source: OECD (2003).

Figure 4.1: Average number of employees during the period 1998 to 2001



Reading aid: Firms in the knowledge-intensive market services have on average 1.50 individuals during the period 1998 to 2001.
A * at the sector names indicates whether firms with university graduates differ significantly from firms without university graduates at the 5% level. For a detailed description of the combined industries, see Table 4.5.
Source: Statistics Denmark, author's calculations.

Table 4.6: Results (marginal effects) for firms founded in the manufacturing sector

dep. var.: survival of the following year (yes/no)								
	start-up year characteristics				**time-varying characteristics**			
	pooled logit		RE logit		pooled logit		RE logit	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
	(1)		(2)		(3)		(4)	
avg. ability	0.035	0.024	0.004*	0.003	0.023	0.023	0.014	0.012
team size	0.004	0.004	0.000	0.000	-0.001	0.003	0.000	0.001
team (y/n)	-0.059	0.078	-0.003	0.012	0.169***	0.064	0.061*	0.034
homogeneity in abilities	-0.095	0.119	-0.010	0.012	0.076	0.128	0.027	0.048
heterogeneity in educations	0.092	0.063	0.007	0.008	-0.126	0.149	-0.047	0.041
share of exports in sales	0.040	0.072	0.003	0.005	0.040	0.060	0.019	0.025
regional dummies (ref.cat. copenhagen)								
city	0.020	0.016	0.002	0.001	0.014	0.016	0.007	0.008
rural	0.035**	0.016	0.003*	0.002	0.026*	0.016	0.014	0.009
industry dummies (ref.cat. low-technology)								
medium-low technology	0.048***	0.015	0.004**	0.002	0.034**	0.015	0.015*	0.009
medium-high technology	0.032*	0.018	0.002*	0.001	0.029*	0.017	0.012	0.008
high technology	-0.014	0.038	-0.001	0.005	-0.008	0.035	0.000	0.017
time dummies (ref.cat. 1999)								
2000	-0.106***	0.021	-0.049***	0.014	-0.095***	0.020	-0.095***	0.022
2001	-0.078***	0.023	-0.180***	0.045	-0.075***	0.022	-0.180***	0.038
pseudo-R^2	0.040				0.049			
log likelihood	-814.614		-811.340		-783.096		-778.218	
$\bar{\chi}^2_{01}$			6.55***				9.76***	
number of observations	2,124		2,124		2,131		2,131	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Marginal effects are calculated at the means of the independent variables. For the calculation of the marginal effects of the RE logit, the random effect is set to its mean value zero. For a detailed description of the combined industries see Table 4.5.
Source: Statistics Denmark, author's calculations.

Table 4.7: Results (marginal effects) for firms founded in the service sectors

dep. var.: survival of the following year (yes/no)								
	start-up year characteristics				**time-varying characteristics**			
	pooled logit		RE logit		pooled logit		RE logit	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
	(1)		(2)		(3)		(4)	
avg. ability	0.036***	0.007	0.039***	0.009	0.032***	0.007	0.038***	0.009
team size	0.003	0.003	0.003	0.003	0.006**	0.003	0.009***	0.003
team (y/n)	0.130***	0.021	0.138***	0.021	0.134***	0.020	0.121***	0.016
homogeneity in abilities	0.045	0.049	0.052	0.054	-0.035	0.048	-0.034	0.045
heterogeneity in educations	-0.009	0.040	-0.011	0.043	0.046	0.038	0.034	0.034
share of exports in sales	0.065***	0.023	0.072***	0.025	0.064***	0.023	0.068***	0.024
regional dummies (ref.cat. copenhagen)								
city	0.011**	0.006	0.013**	0.007	0.009	0.005	0.013*	0.007
rural	0.040***	0.006	0.044***	0.007	0.038***	0.006	0.045***	0.006
industry dummies (ref.cat. retail trade)								
wholesale trade	0.054***	0.007	0.060***	0.009	0.051***	0.007	0.056***	0.007
hotels, restaurants	-0.048***	0.011	-0.056***	0.015	-0.067***	0.011	-0.083***	0.018
knowl.-intens. high-tech serv.	0.035***	0.007	0.041***	0.009	0.038***	0.007	0.046***	0.007
knowl.-intens. market serv.	0.069***	0.006	0.076***	0.008	0.072***	0.006	0.079***	0.007
other knowl.-intens. serv.	0.084***	0.009	0.090***	0.010	0.085***	0.008	0.081***	0.009
freight transport	0.052***	0.007	0.059***	0.009	0.043***	0.007	0.050***	0.007
time dummies (ref.cat. 1999)								
2000	-0.100***	0.006	-0.130***	0.026	-0.095***	0.006	-0.199***	0.023
2001	-0.045***	0.007	-0.103**	0.049	-0.043***	0.007	-0.253***	0.053
pseudo-R^2	0.032				0.054			
log likelihood	-12,297.512		-12,296.266		-11,705.559		-11,688.144	
$\bar{\chi}^2_{01}$			2.49*				34.83***	
number of observations	25,543		25,543		25,434		25,434	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Marginal effects are calculated at the means of the independent variables. For the calculation of the marginal effects of the RE logit, the random effect is set to its mean value zero. For a detailed description of the combined industries see Table 4.5.
Source: Statistics Denmark, author's calculations.

Table 4.8: Results (marginal effects) for firms founded with university graduates

dep. var.: survival of the following year (yes/no)								
	start-up year characteristics				**time-varying characteristics**			
	pooled logit		RE logit		pooled logit		RE logit	
	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
	(1)		(2)		(3)		(4)	
avg. ability	0.056***	0.015	0.056***	0.015	0.049***	0.015	0.052***	0.016
team size	0.001	0.003	0.001	0.003	0.004	0.003	0.004	0.003
team (y/n)	0.158***	0.054	0.158***	0.045	0.126***	0.046	0.111***	0.037
homogeneity in abilities	0.088	0.085	0.088	0.098	0.028	0.102	0.014	0.092
heterogeneity in educations	-0.037	0.136	-0.037	0.117	0.048	0.097	0.039	0.081
share of exports in sales	0.050	0.035	0.050	0.034	0.043	0.032	0.042	0.031
regional dummies (ref.cat. copenhagen)								
city	0.014	0.011	0.014	0.011	0.009	0.010	0.008	0.011
rural	0.034***	0.013	0.034***	0.012	0.032***	0.012	0.031***	0.012
industry dummies (ref.cat. low-technology)								
medium-low technology	-0.007	0.068	-0.007	0.068	-0.026	0.069	-0.033	0.085
medium-high technology	-0.070	0.082	-0.070	0.096	-0.078	0.079	-0.063	0.117
high technology	-0.215***	0.079	-0.215*	0.125	-0.234***	0.070	-0.267	0.206
construction	-0.046	0.043	-0.046	0.043	-0.046	0.042	-0.058	0.055
wholesale trade	-0.013	0.033	-0.013	0.033	-0.019	0.031	-0.021	0.037
retail trade	-0.041	0.031	-0.041	0.031	-0.034	0.029	-0.043	0.037
hotels, restaurants	-0.161***	0.055	-0.161***	0.057	-0.175***	0.056	-0.223**	0.095
knowl.-intens. high-tech serv.	-0.023	0.028	-0.023	0.029	-0.014	0.027	-0.013	0.031
knowl.-intens. market serv.	-0.009	0.025	-0.009	0.026	-0.006	0.024	-0.010	0.027
other knowl.-intens. serv.	-0.023	0.035	-0.023	0.035	-0.012	0.032	-0.017	0.038
freight transport	-0.037	0.047	-0.037	0.045	-0.055	0.048	-0.077	0.065
time dummies (ref.cat. 1999)								
2000	-0.095***	0.013	-0.095***	0.013	-0.078***	0.012	-0.123***	0.033
2001	-0.071***	0.014	-0.071***	0.014	-0.058***	0.013	-0.160**	0.078
pseudo-R^2	0.038				0.048			
log likelihood	-2,614.543		-2,614.543		-2,484.622		-2,483.193	
$\bar{\chi}^2_{01}$			0.00				2.86**	
number of observations	5,844		5,844		5,825		5,825	

Notes: ***, **, * depict significance at the 1%, 5% and 10% level respectively. Marginal effects are calculated at the means of the independent variables. For the calculation of the marginal effects of the RE logit, the random effect is set to its mean value zero. For a detailed description of the combined industries see Table 4.5.

Source: Statistics Denmark, author's calculations.

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