Discussion Paper No. 08-112

Matching of Individuals for Start-Ups – A Test of the O-Ring Theory

Bettina Müller

Zentrum für Europäische
Wirtschaftsforschung GmbH

Centre for European
Economic Research

Discussion Paper No. 08-112

Matching of Individuals for Start-Ups – A Test of the O-Ring Theory

Bettina Müller

Download this ZEW Discussion Paper from our ftp server:

ftp://ftp.zew.de/pub/zew-docs/dp/dp08112.pdf

Das Wichtigste in Kürze

Die Gründung eines Unternehmens ist eine komplexe Angelegenheit, bei der eine Vielzahl von Aufgaben erfüllt werden muss. Dafür sind eine Reihe unterschiedlicher Qualifikationen erforderlich, die vermutlich nicht von einer Person alleine erbracht werden können. Es ist daher zu erwarten, dass Unternehmen in Teams gegründet werden. Gleichzeitig ist anzunehmen, dass die einzelnen Aufgaben im Rahmen einer Gründung in der Weise interdependent sind, dass Fehler bei der Ausführung einer einzigen Aufgabe das gesamte Projekt gefährden können. Z.B. ist die beste Produktidee wertlos, wenn es nicht gelingt, genügend Kunden dafür zu finden. Aus organisationtheoretischer Perspektive können Neugründungen damit aus dem Blickwinkel der Organisation von Teamwork in einem Spezialistenteam betrachtet werden.

Eine Möglichkeit, die Abhängigkeit des Outputs vom Grad der Erfüllung essentieller Aufgaben, die von unterschiedlichen Personen ausgeführt werden, theoretisch zu formalisieren, ist die O-Ring-Produktionsfunktion (Kremer (1993), Fabel (2004)). Die O-Ring-Theorie impliziert, dass sich Teams bilden, in denen alle Mitglieder das gleiche Fähigkeitsniveau haben. Weiterhin sagt die Theorie voraus, dass die Teams umso größer sind und umso mehr Kapital pro Kopf einsetzen, je höher das Fähigkeitsniveau ihrer Mitglieder ist. In diesem Papier wird untersucht, inwieweit sich die Implikationen der O-Ring-Theorie in den Daten wiederfinden lassen. Aus politischer Perspektive ist diese Untersuchung insofern relevant, als dass die O-Ring-Theorie als Grundlage für Handlungsanweisungen zur Förderung junger Unternehmen dienen kann.

Für die Analyse steht ein umfangreicher Datensatz zur Verfügung, der sämtliche Unternehmen, die 1998 in Dänemark gegründet wurden, sowie alle in diesen Unternehmen beschäftigten Individuen umfasst. Um zu bestimmen, wie stark sich die Individuen zur Gründung eines Unternehmens hinsichtlich ihrer Fähigkeiten segregieren, werden statistische Tests konstruiert, die die tatsächlich beobachtete Aufteilung mit einer zufälligen Aufteilung der Individuen auf die Unternehmen vergleichen. Die Ergebnisse zeigen, dass sich, entgegen den Vorhersagen der O-Ring-Theorie, eher Individuen mit unterschiedlichem Fähigkeitsniveau zusammenfinden. Weiterhin gründen fähigere Leute eher kleinere Unternehmen. Als einzige korrekte Vorhersage erweist sich der positive Zusammenhang zwischen Fähigkeitsniveau und Kapital pro Kopf. Insgesamt erscheint die O-Ring-Theorie damit als keine gute Beschreibung junger Unternehmen.

Non-Technical Summary

Setting up a new firm is a complex process, which comprises many tasks. These different tasks require different qualifications. It can be expected that the required qualifications are provided by different persons, since one person alone cannot possess all relevant skills. Presumably, new firms are therefore founded in teams. Further, it can be assumed that the different tasks, which are to be performed in the course of establishing a firm, are interdependent in a way that a failure in the performance of a single task can put the whole project at risk. For example, the best business idea is not worth anything if it is not marketed appropriately to potential consumers. Thus, from the perspective of organisation theory, the establishment of a firm is an example of organising team work in a team of specialists.

A way to formalise the idea of direct impact of the degree of task performance on output is the O-ring production framework (Kremer (1993), Fabel (2004)). The O-ring theory implies the segregation of individuals between firms according to their level of ability. Furthermore, the O-ring approach predicts that firm size and capital per head should increase with employees' average level of ability. In this paper it is analysed to what extent the predictions of the O-ring theory are supported by the data. This study is also relevant from a policy perspective, as the O-ring theory can serve as a basis for guidelines to assist new firms.

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 predictions of the theory, individuals with different levels of ability are more inclined to team up in new firms. Also contrary to the predictions of the theory, firm size and average level of ability of the involved individuals turn out to be negatively correlated. The only relationship that is predicted correctly by the theory is the positive relationship between capital per head and the average level of ability. In summary, the O-ring theory apparently does not provide a good description for the situation of young firms.

Matching of Individuals for Start-Ups – A Test of the O-Ring Theory

Bettina Müller*

December 2008

Abstract

In this paper I analyse how individuals match for for the purpose of setting up a new firm. As a theoretical basis I use the O-ring theory introduced by Kremer (1993) and applied to new firms by Fabel (2004). The O-ring theory predicts that individuals segregate between firms according to their level of ability. Further, the theory implies that a higher average ability level within firms is positively related to both the number of individuals and capital per head. Using a rich employer-employee data set on the whole population of Danish firms founded in 1998 most of the predictions of the O-ring theory are rejected. I find that individuals do not match with individuals with the same level of ability. Furthermore, ability and firm size turn out to be negatively correlated. There is only some support for the hypothesis concerning the positive relationship between ability and capital per head.

Keywords: Entrepreneurship, O-Ring Theory, Theory Test
JEL Classification: D23, L26, M13.

*Bettina.Mueller@zew.de. ZEW Mannheim, Centre for European Economic Research, Research Group Information and Communication Technologies, P.O.Box 103443, D-68034 Mannheim, Germany. The author is thankful to Irene Bertschek, Katrin Schleife, Thorsten Doherr, and Oliver Fabel for many helpful advices. Special thanks go to Statistics Denmark and the Centre for Economic and Business Research in Copenhagen, DK, for providing me with access to the data as well as to Stefan Boeters for many extensive and helpful discussions. Financial support of the Deutsche Forschungsgemeinschaft (DFG) through the research group "Heterogeneous Labor: Positive and Normative Aspects of the Skill Structure of Laborïs gratefully acknowledged. Comments are very welcome.

1 Introduction

New firms are regarded to be of substantial relevance for the development of an economy, especially for innovation, growth, and the creation of jobs. But setting up a new firm is a complex process which comprises many tasks. This especially applies for new firms in research- and knowledge-intensive sectors since in addition to the challenge of setting up a new firm in general there is often an innovation − either a new product, a new service, or a new production technology − at the heart of the new business. It can be expected that complexity requires different qualifications provided by different persons, since one person alone presumably cannot possess all relevant skills. Accordingly, authors like Fabel (2004) assume that it is necessary to have a team composed of specialists to establish a new firm. However, this requirement might also give rise to a particular sort of risk: If all team members are specialists in different areas, a specific task cannot be taken over by other team members in case one of the team members makes a mistake. If the performance of a team member assigned to an essential task is below a critical level therefore the whole project is at risk. Thus, together with fulfilling the requirement of different qualifications, the risk of failure due to the malperformance of certain tasks by one or more team members must be coped with and the choice of appropriate partners is essential for new firms.

A way to formalise this idea of direct impact of the degree of task performance on output is the O-ring production framework which was introduced by Kremer (1993) and applied to new firms by Fabel (2004). The O-ring production function conceptualises the production process as a set of tasks with complementarity in the ability levels of the persons performing these tasks. Complementarity in ability means that the replacement of a person by some other person with slightly higher ability level not only increases the marginal product of the whole project, but the more so the higher the average ability of the other persons involved in the project. The O-ring theory implies segregation of individuals between firms according to their level of ability. Furthermore, the O-ring approach predicts that firm size should increase with the average ability level of the employees and that more capital per head should be employed the higher the average ability level of the employees.

In this paper I analyse to what extent the predictions of the O-ring theory are supported by the data. From a policy perspective the results of this analysis allow to learn more about how to set up networking forums or incubator organisations like technology parks, spin-off centers at universities, or study programs which aim at endowing individuals interested in setting up a firm with relevant skills. Besides providing infrastructure and financial support these institutions also give individuals the opportunity to observe each other's abilities and thus to reduce the asymmetric information with respect to the characteristics of potential partners. If the O-ring theory turns out to provide a reasonable description of the matching of individuals for setting up a new firm, incubators should aim at bringing together persons with the same level of ability. Further, the O-ring theory can be used to derive welfare statements as Fabel and Weber (2005) do.[1]

For my investigation, I use Danish register data covering the whole population of firms founded in 1998 as well as all individuals involved in these new firms in the start-up year and in the following three years. The data provide rich information on the individual side so that it can be determined which characteristics are exhibited by persons who match for setting up a new firm. Special attention is given to firms founded with university graduates since these firms can be expected to have the highest potential of introducing innovative products (Koellinger (2008)), the production of which presumably require knowledge from different fields. For these firms a good matching of individuals might be especially important.

In order to analyse the degree 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 individuals more often choose partners with an equal educational background than could be expected from random assignment. Concerning ability, there is rather evidence against the conjecture that individuals search systematically for other individuals with the same level of ability. Also contrary to the predictions of the theory, firm size and average ability of the involved individuals turn out to be negatively correlated. Capital per head and ability level are positively related in most of the industries as predicted.

The paper is structured as follows: In Section 2 the implications of the O-ring theory are worked out in detail. In Section 3 I check how far existing results can

[1]Fabel and Weber (2005) show on the basis of the O-ring theory, that the welfare effects of incubators depend on the degree of risk aversion in an economy.

be interpreted as evidence in favour of the O-ring theory. Section 4 describes the data. In Section 5 the results are presented. Section 6 concludes.

2 Theoretical Background and Hypotheses

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. This event is an extreme example of production processes which consist of a series of tasks, each of which must be fulfilled at a certain minimum level of quality for the output to have positive market value. 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. For example, the best idea is not worth anything if it is not marketed appropriately to potential costumers. In the following, the O-ring approach is outlined and its empirical implications are worked out.

In the O-ring framework the above outlined idea of ability interdependence is expressed by the following function of expected production:

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

where k refers to physical capital, n to the number of tasks and $q_i \in (0, 1)$ to the ability of the individual assigned to task i. Ability is measured by the probability of perfect task performance: If one of the individuals makes a mistake, which happens with the probability $1 - [\prod_{i=1}^{n} q_i]$, output is zero.

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

$$\max_{\{q_i\},k,n} \frac{pF(k,n)\left[\prod_{i=1}^{n} q_i\right] n - rk}{n} = \max_{q,k,n} p\frac{Y}{n} - \frac{rk}{n}, \tag{2}$$

where p refers to the output price and r to the interest rate. In the literature, for reasons of simplicity, it is usually assumed that each task requires only one worker, i.e. n is also interpreted as the number of individuals. This assumption is debatable since it might be worthwhile to back up critical tasks by several persons or to have one person to execute 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.[2] 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.[3] The reasoning is the following: If individuals have different educations they acquire different knowledge which makes them predestined for certain tasks but not for others. Thus, when several persons are involved in a start-up, it can be expected to observe that different individuals have different educations.[4] Therefore, the first hypothesis analysed in 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:

$$\frac{d^2Y}{dq_i d\left(\prod_{j\neq i} q_j\right)} = F(k,n)n > 0. \tag{3}$$

This also holds for output per head Y/n and means that abilities are complementary.[5] 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 for them. 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.[6] (Formally, this means that $[\prod_{i=1}^{n} q_i]$ can be replaced by q^n). Accordingly, the second hypothesis is:

[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 e.g. Fabel (2004) follows him in this respect.

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

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

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

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

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. Normalising output price p to one and specifying output per team member $F(k,n)$ as $k^{\alpha}n^{(1-\alpha)}$ as in Fabel (2004) the first order conditions of the optimisation problem given in equation (2) with respect to n and k are:

$$(1-\alpha)k^{\alpha}n^{-\alpha}q^{n} + k^{\alpha}n^{(1-\alpha)}q^{n}log(q) + \frac{rk}{n^2} = 0 \quad (4)$$

and

$$\alpha k^{(\alpha-1)}n^{(1-\alpha)}q^{n} - \frac{r}{n} = 0 \quad (5)$$

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

$$\frac{1}{n^*} = -log(q) \quad (6)$$

and

$$\frac{k^*}{n^*} = \left(\frac{\alpha q^{n^*}}{r}\right)^{\frac{1}{1-\alpha}} (n^*)^{\frac{1}{1-\alpha}} \quad (7)$$

From equation (6) we get:

H3: Given that each tasks requires one person, team size and ability level are positively correlated.

Note from equation (6) 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 done by Fabel (2004), the ability level for a team foundation has to be above average.

The fourth hypothesis is based on equation (7):

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

Intuitively, more able workers have a lower probability of failing why 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. However, the O-ring theory suggests to use wages as a representation of ability. To see this, consider a firm that maximises expected profit:

$$\max_{q,k,n} \pi(q,k,n) = F(k,n)q^n - w(q) - rk \tag{8}$$

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:

$$F(k,n)q^{(n-1)}n = \frac{dw(q)}{dq}, \tag{9}$$

i.e. if marginal revenue of changing the ability level equals marginal costs. Integration and insertion of $k^{\alpha}n^{(1-\alpha)}$ yields:

$$w^*(q) = (1-\alpha)\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} - (n^*)^{\frac{1}{1-\alpha}} q^{\frac{n*}{1-\alpha}}. \tag{10}$$

Thus, the optimal wage is a monotonously increasing function of ability. In the empirical analysis wages are therefore used as a measure for ability.

3 Related Literature

There are some papers providing facts which are in line with the predictions of the O-ring theory, although they do not aim at directly testing the theory. In the following, these papers are presented and related to the predictions of the O-ring theory.

3.1 Sorting of individuals according to ability

Davis and Haltiwanger (1991) as well as Dunne, Foster, Haltiwanger, and Troske (2004) examine the development of the wage dispersion in US manufacturing firms in the years 1963 to 1986 and 1975 to 1992 respectively. Interpreting wages as a reflection of abilities, their framework also provides an indication how the sorting of workers according to their abilities has evolved over time. By means of a variance decomposition they divide the total variation in wages into the variation within plants and the variation between plants. A larger between- than within-plant component can be taken as an indication that workers are sorted between firms. The authors find that the between-plant component accounts for more than 50 percent of the total variance in each of the considered years. Additionally, they find that a considerable part of the increase in the wage dispersion can be attributed to an increase in the variation of wages between plants.

However, as Iranzo, Schivardi, and Tosetti (2008) argue, using raw wages as a measure of ability might give misleading results concerning the segregation of workers by ability. The reason is that raw wages also include firm-specific effects which can be due to different compensation policies, such as efficiency wages and rent sharing, which do not reflect individual ability (Kramarz, Lollivier, and Pelè (1996)). Not correcting the wages for these firm-specific components might lead to greater between-firm variation of wages which has no analogy in a greater between-firm variation of ability. In fact, as Iranzo et al. (2008) show for the Italian manufacturing sector, the between-plant component is by some 10 percentage points higher when raw wages are used instead of wages corrected for firm fixed effects. Using corrected wages, they find that the between-plant component is rather low.[7] For all workers it fluctuates around 17 percent of total variation over the period 1982 to 1996. For nonproduction workers it is even lower, around 8 percent for the same time period. Moreover, there is no tendency of an increase in segregation over time detectable.

There are also efforts to determine the segregation of skills on the basis of observable skill characteristics other than wages. Kramarz et al. (1996) show segregation indices which are defined as the fraction of the between-plant variation in total variation of the share of unskilled blue-collar workers, skilled blue-collar workers, foremen, clerks, technicians as well as of engineers, professionals, or managers in the years 1986 and 1992 for France. The fraction of the between-plant component for all these groups has risen between the considered years, so that members of the different groups work together more often in the same firm. The same tendency is reported by Kremer and Maskin (1996) for similar worker groups as considered by Kramarz et al. (1996) in Great Britain in the years 1984 and 1990. Thus, there are some hints that individuals increasingly sort

[7]Iranzo et al. (2008) also correct the wages for individual time variant effects like age and seniority. This is disputable since these effects can also be considered as ability components.

themselves into firms according to their ability.

3.2 Relationship between ability and firm size

Concerning H3 it is a well documented fact that large firms pay higher wages (e.g. Mellow (1982), Oi (1983), Brown and Medoff (1989), and Troske (1999)). Brown and Medoff (1989), for example, report that on average employees working in firms with log employment being one standard deviation above average get 6 to 15 percent higher wages than similar workers in firms with log employment being one standard deviation below average, depending on the data set. Similarly, Troske (1999) estimates that workers in firms with log employment being one standard deviation above average get 13 respectively 11 percent more than workers in firms with log employment being one standard deviation below average, depending on whether plant or firm size is considered.

There has been considerable discussion about the question why workers in larger firms get higher wages since these differences even appear after controlling for observable worker and firm characteristics. However, as Abowd, Kramarz, and Margolis (1999) show, the by far biggest fraction of the employer size-wage effect can be explained by a pure person effect, which is the workers' ability net of observable individual and firm characteristics. Additionally, Abowd et al. (1999) find that the higher the average levels of the observable skill characteristics as well as the average level of pure ability the larger is the firm in terms of employees. Thus, it can be inferred that it is higher ability that leads to higher wages for individuals working in larger firms, which corresponds to the prediction formulated in H3.

3.3 Relationship between ability and capital employment

Abowd et al. (1999) also provide evidence that ability and capital employment are positively related, which is formulated in H4 above. The average levels of observable skill characteristics as well as the average level of pure ability come along with higher total capital employment as well as with higher capital input per head.

In summary, there are several facts that are consistent with the predictions of the O-ring theory. However, doubts can be put forward whether the O-ring theory explains the observed facts 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. Additionally, the studies were not undertaken to explicitly test the O-ring theory. An exception is the recently released working paper by Yu and Orazem (2008). The authors actually find that skills leading to higher wages are also positively correlated with firm size and technological complexity.[8] However, they cannot determine which individuals work together in firms, which is at the heart of the O-ring theory.

In the following it is pursuit whether the O-ring theory is a good description for the situation of young firms.

4 Data

The data used in this paper are provided by Statistics Denmark, Denmark's federal statistical office. At the end of 1998 Statistics Denmark took stock of all new firms which had been set up in Denmark. On an annual basis, these firms were followed until 2001 or until they shut down.[9] The data are register data, which cover the whole population of firms that were set up in 1998 and that were still in operation at the end of that year. Firms that had started in 1998 and shut down within the same year are not contained in the data set. Firm-level information collected in the start-up year comprises industry of business, legal form, location, total number of employees, total annual exports, total annual purchases, and total annual sales. At the end of each year during the follow-up period, the current number of employees and the current amount of exports, purchases, and sales are recorded.

[8] Yu and Orazem (2008) interpret the O-ring theory differently than it is done in this paper. They equate n with the number of technologies used and take output Y as a measure of size.

[9] 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 for determining the degree of homogeneity between team members it is essential 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.

Via a combination of a firm and a personal identification number (ID) it is possible to link the firm-level information to information on individuals 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. These can be used to generate the relevant variables for the individuals involved in the new firms in the start-up year. 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 following analysis comprises the highest level of education attained, wages, labour market experience, unemployment spells, prior self-employment experience, and leadership experience.

A drawback of the data is that it is not possible to distinguish between persons who are in fact founders of the respective firm and persons who are solely employees. It is only known which person registered the firm with the authorities. However, as the great majority of the new firms are small entities – 80 percent have five or less persons and the modus is one person – the characteristics of each person might be important regardless of whether the person is a founder or not.[10]

The data are adjusted in two respects. First, in some cases the person who registered the firm with the authorities has been included in the number of employees by Statistic Denmark but in others it has not. To correct this, the number of employees raised by Statistics Denmark is increased by one in case the registering person was not counted as an employee. This needs to be done since otherwise some firms would not have had any employees. Second, for some firms not all employees can be identified, i.e. the number of employees recorded in the respective variable in the firm data is greater than the number of personal IDs that can be merged to the firm data. Firms for which either no personal ID can be matched at all, which lack all personal IDs for the start-up year, or for which personal IDs can only be merged with gaps (e.g. all individuals both in 1998 and 2000 are identified but not in 1999) are removed from the data set. In the case where the number of employees recorded differs from the number of personal IDs that

[10]Figure 3 in the appendix shows the average number of individuals over the whole period of consideration. The average firm size is 1.7 individuals. With 1.9 persons firms with university graduates are slightly larger than firms without university graduates (1.6 persons). Manufacturing firms are bigger than firms in the service sectors.

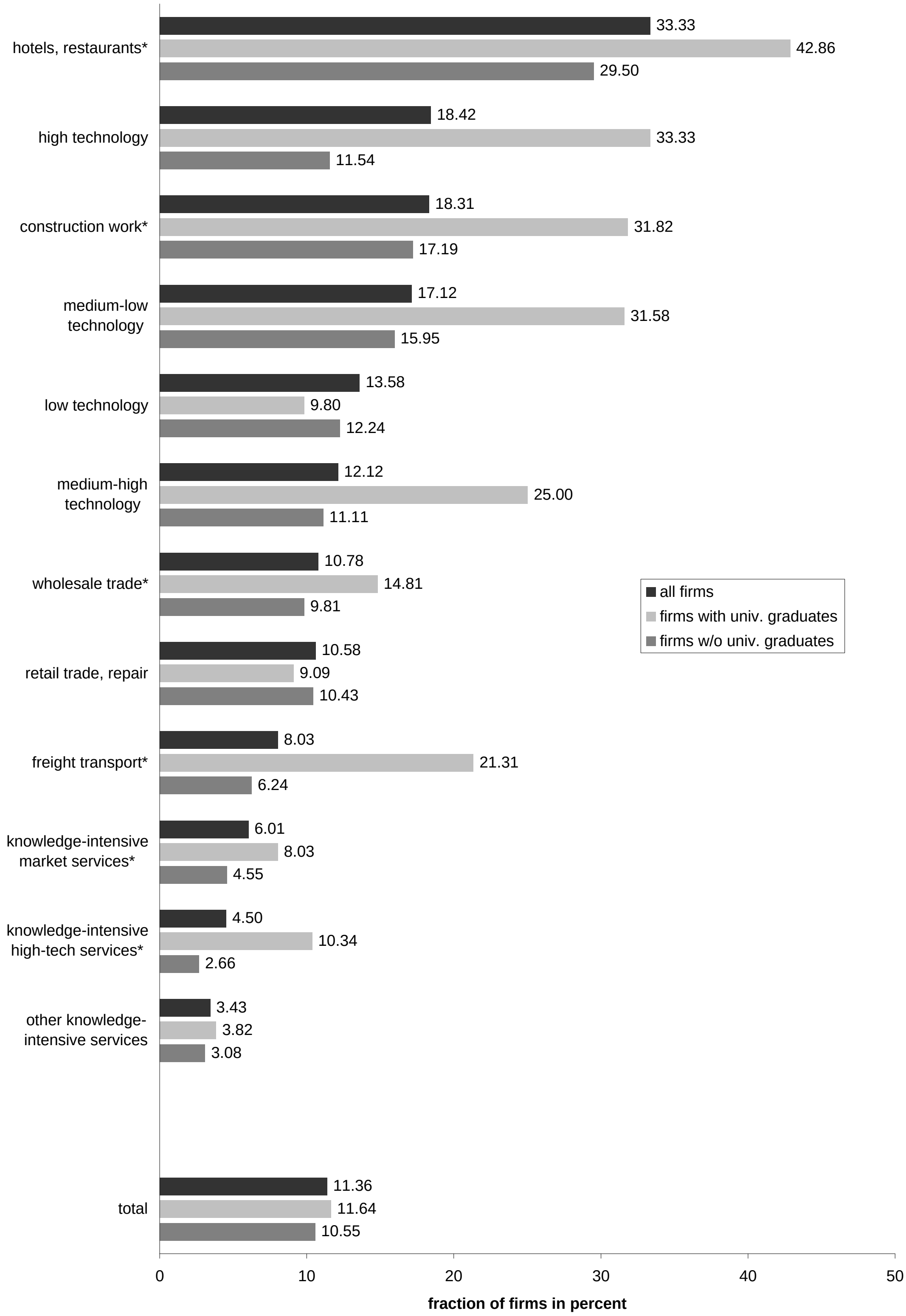
can be merged for each year without gaps, the number of personal IDs is used instead of the number of employees recorded. From the 16,063 firms founded in 1998, 14,171 are used for the subsequent analyses.

The O-ring theory is formulated for production environments in which tasks are complementary. This certainly 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, the sample is split up into twelve industries and the results are separately presented for each industry.[11] 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 and therefore with more complex technologies which require specialists in different fields. Good matching might therefore be especially important for these firms.

The analyses concerning H1 and H2 only apply to firms which are founded by teams. Figure 1 shows the proportion of firms that are founded with at least two persons by industry, separately for all firms, for firms with university graduates, and for firms without university graduates. To determine whether there are significant differences in the fraction of team foundations between firms with university graduates and firms without university graduates a t-test on the equality of means is performed. It turns out that only 11 percent of all firms have more than one employee at the end of the start-up year. In general, the need for several persons is higher in manufacturing than in services. The sectors with the three highest proportions of team foundations are hotels, restaurants (33 percent), high technology (18 percent), and construction work (18 percent). This rank order holds also for firms founded with university graduates. Among the firms founded without university graduates construction work ranks second (17 percent) followed by medium-low technology (16 percent). Comparing the two groups it turns out that firms founded with university graduates are in total 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.

[11] For a detailed description of the combined industries see Table 8 in the appendix.

Figure 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.

5 Methods and Results

The presentation of results below follows the order of the hypotheses derived in Section 2. First, the results on the heterogeneity of educations are shown, then those regarding the degree of homogeneity with respect to ability, and finally the results referring to the relation between the ability level within firms and team size as well as capital input. Section 5.1 to 5.5 refer to the situation in the start-up year. In Section 5.6 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.

5.1 Heterogeneity of educations

H1 states that each person of a founding team has attained a different education. To determine the degree of heterogeneity 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:

$$H = \sum_{i=1}^{n} s_i^2, \tag{11}$$

where s_i denotes the share of education i.

The underlying education variable could 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 was not aggregated in any respect for calculating the Herfindahl-Index. 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.

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, e.g. 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 (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:

$$H^{tr} = \left(H - \frac{1}{n}\right)\frac{n}{n-1} \quad \in [0, 1]. \tag{12}$$

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. 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 (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 diversity in educations is low, high or on an average level. To make such a judgement possible a statistical test is constructed where 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 the test is:

$H1_0$: *The composition of the actual observed teams with respect to disciplines 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 taken 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.

Table 1 shows the actual average (transformed) Herfindahl-Index per industry for all firms (column (1)) as well as for firms with university graduates (column (3)) and firms without university graduates (column (5)) respectively.[12] 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.[13] 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.

[12] Because there are only around ten percent team foundations, as shown in Figure 1, and the firms are unevenly distributed over industries, some numbers are based on only a few firms. E.g. the average Herfindahl-Index of all firms in the high technology sector is based on six firms and the one for firms with university graduates in the sector medium-high technology on only two firms.

[13] Table 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 1 do not lie in the middle of the interval.

Table 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.

5.2 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 of 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 the average hourly wages are corrected for inflation, disciplines and industry effects. Then the average lifetime hourly wage of an individual starting from the year of labour market entry until 2001 is calculated. Correcting the wages that way aims at excluding all components which do not represent ability.[14]

As in Section 5.1, 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 has to 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.[15] In order to get a reference point how good the observed standard deviation meets the theoretical value of zero a similar procedure as in Section 5.1 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 distribution of the standard deviation in the case of random matching is simulated again since mean and standard deviation can only be derived analytically for a given team size. The simulation method is the same as in Section 5.1: Individuals are randomly assigned to firms, then the standard deviation of the wages per firm is calculated and averaged on the industry level. The resulting values are stored. This is done 1,000 times.

The results are presented in Table 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

[14]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. A further discussion of the procedure for correcting the wages is given in Section 5.5.

[15]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. Standard deviations greater than zero are impossible to observe under this null hypothesis.

Table 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.

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.[16] That is, more often than

[16] The 95%-confidence intervals of the standard deviation of log wages are given in Table 10 in the appendix. Again, the distributions are not symmetric. Thus, the mean value given in Table 2 does not lie in the middle of the interval.

it could have been 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.

5.3 Relationship between ability and start-up size

The low fraction of team foundations observed (Figure 1) is not necessarily evidence against the O-ring theory, as explained in Section 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 can be used. Remember that the (equilibrium) equation for the relationship between team size n and ability q is:

$$\frac{1}{n^*} = -log(q) \Leftrightarrow n^* log(q) = -1. \tag{13}$$

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:

$$w^*(q) = (1-\alpha)\left(\frac{\alpha}{r}\right)^{\frac{\alpha}{1-\alpha}} (n^*)^{\frac{1}{1-\alpha}} q^{\frac{n}{1-\alpha}}, \tag{14}$$

logarithmise, and solve for $nlog(q)$:

$$n^* log(q) = (1-\alpha)log(w^*(q)) - (1-\alpha)log(1-\alpha) - \alpha log\left(\frac{\alpha}{r}\right) - log(n^*). \tag{15}$$

Inserting this expression into equation (13) gives after rearranging:

$$log(n^*) = 1 - (1-\alpha)log(1-\alpha) - \alpha log\left(\frac{\alpha}{r}\right) + (1-\alpha)log(w^*(q)). \tag{16}$$

This equation can be estimated by regressing the log of the number of employees on the log of wages treating $1 - (1 - \alpha) log(1 - \alpha) - \alpha log(\alpha/r)$ as 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 (14) is multiplied by n^*:

$$n^* w^*(q) = (1 - \alpha)(k^*)^\alpha (n^*)^{1-\alpha} q^{n^*} n^* = (1 - \alpha)Y. \tag{17}$$

Table 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 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 (geometric) average wage leads to a 0.307% lower employment). 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. Interestingly, this result is not only contrasts with the predictions of the O-ring theory but also with the existing evidence on the relationship between wages and firm size. Apparently, the positive relationship between these two variables, as found for large and established firms, does not hold for new firms. Future research will be devoted at finding explanations for this observation.

5.4 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:

$$\frac{k^*}{n^*} = \left(\frac{\alpha q^{n^*}}{r}\right)^{\frac{1}{1-\alpha}} (n^*)^{\frac{1}{1-\alpha}} \tag{18}$$

Table 3: Relationship between ability and team size

dep. var.: log(employment)	all firms coeff.	all firms std.err.	firms with univ. graduates coeff.	firms with univ. graduates std.err.	firms w/o univ.graduates coeff.	firms w/o univ.graduates std.err.
average log(wages)	-0.081***	0.009	-0.070***	0.023	-0.068***	0.009
average log(wages) 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.

Taking logs and inserting equation (15) for $nlog(q)$ yields after some rearrangements:

$$log\left(\frac{k^*}{n^*}\right) = log\left(\frac{\alpha}{r(1-\alpha)}\right) + log(w^*(q)). \tag{19}$$

According to the theory the coefficient of $log(w(q))$ has to be one. Estimating equation (19) by regressing the balance sum per head on average wages on the firm level, treating $log\left(\frac{\alpha}{r(1-\alpha)}\right)$ as regression constant, gives the results shown in Table 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.

Table 4: Relationship between ability and capital employment per head

	all firms		firms with univ. graduates		firms w/o univ.graduates	
dep. var.: log(balance sum per head)	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
average log(wages)	0.444***	0.043	0.767**	0.104	0.379***	0.048
average log(wages) 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.

This is the case in low-, medium-low, medium-high technology, and in the knowledge-intensive services.[17] Thus, there is some evidence that the relationship between ability and capital input per head is predicted correctly by the O-ring theory.

[17]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.

5.5 Discussion

Up to now the results are mixed concerning the O-ring theory providing 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. 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.

My procedure of correcting wages differs in two respects from the one used by Iranzo et al. (2008). First, Iranzo et al. (2008) only take the pure person effect net of observable characteristics as ability. In contrast, in my analysis also observable characteristics like level of education, labour market experience, or age are regarded as determinants of ability and therefore not corrected for. Second, unobservable firm effects are not excluded from the wages because the O-ring effect is a firm effect: Successful firms might be successful just because they employ good workers which in turn is then again reflected in the wages. Ultimately, the correction of wages is also arbitrary to some degree. 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, there were only level effects 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 considerable 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 5.1 to 5.4 is that the hypotheses derived in Section 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.

5.6 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).[18]

- 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 relevant, all firms are treated as a pooled sample and the cases (firms and years) where newcomers joined the firm are selected.[19]

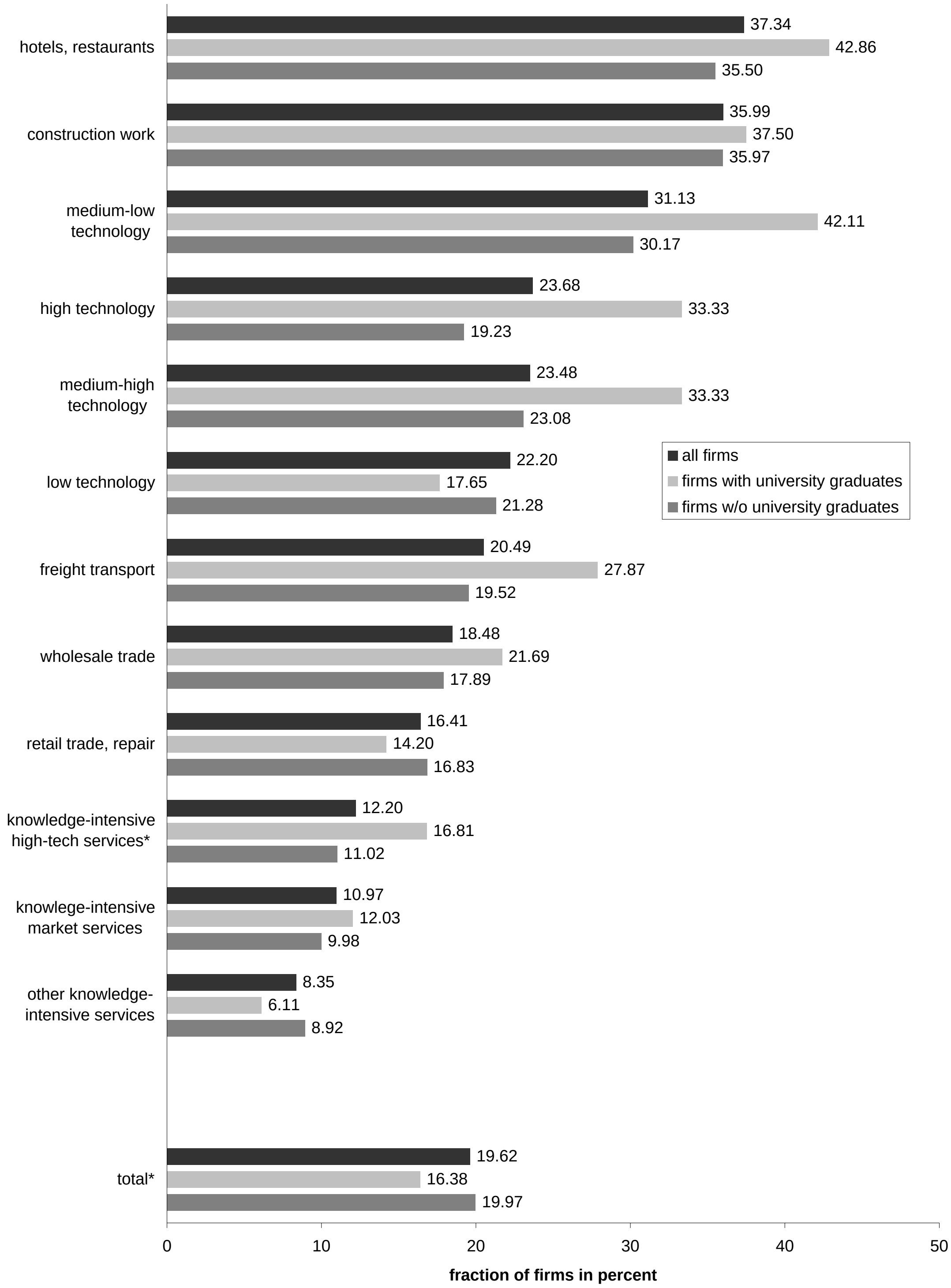
Figure 2 shows the fraction of firms which get newcomers in the period 1999 to 2001. In total, 20 percent of all firms have newcomers whereby the fraction of firms which take on new persons is significantly higher among firms without university graduates than among firms with university graduates (20 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.[20] The only sector in which firms with university graduates differ significantly from firms without university graduates is 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.

[18] 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.

[19] 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 "aftervariable. If a firm gets newcomers both in 1999 and 2000 the situation in 1999 is considered once as the "aftersituation (with respect to 1998) and once as the "beforesituation (with respect to 2000).

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

Figure 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.

5.6.1 Heterogeneity of qualifications

As shown in Section 5.1, individuals match in a way that they choose partners with an educational background from the same field leading to rejection of H1. Does this also hold for the recruitment of new employees? Or do newcomers tend to add to the existing skill stock by providing skills which are not yet existent in the firm? To analyse this question 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:

$H1a_0^{dev}$: *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 industry level. The resulting value is stored. The mean values of the resulting 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 disciplines equals a process where 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 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 actual observed Herfindahl-Index decreases when new persons join, which means that the diversity 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 persons 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.

5.6.2 Degree of homogeneity with respect to ability

Concerning the degree of homogeneity with respect to ability the conclusion in Section 5.2 was that individuals form teams with members of similar ability level. However, the question remained whether they do it systematically, i.e. not randomly, 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

Table 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.

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 disciplines equals a process where 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 Δ = 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 $\Delta H^{tr}_{duplication}$.

The results are shown in Table 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.

The firms with university graduates in high-technology represent The only exception of the overall pattern. In these firms the 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 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.

Table 7: Relationship between ability and team size

dep. var.: log(employment)	coeff.	std.err.	coeff.	std.err.	coeff.	std.err.
	1999		**2000**		**2001**	
average log(wages) 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, own calculations.

5.6.3 Relationship between ability and team size

In Section 5.3 it was shown that, from the perspective of the O-ring theory, the “wrongffirms, i.e. firms with a lower average ability level, employ a higher number of individuals. However, a reason be, as argued, 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 7 shows this does not happen. The numbers display the estimated coefficients of equation (16) separately for the years 1999 to 2001. Over the whole timespan the relationship between average ability and firm size remains negative. 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.

6 Conclusion

At first sight it seems compelling to assume that new firms have a team composed of specialists what requires to rely on sufficient task performance of each team member. The O-ring theory then seems to provide an obvious theoretical basis, from which hypotheses regarding the characteristics of new firms can be derived. However, as the results in this paper show the O-ring theory does not provide a good description of the situation of young firms. Using a rich employer-employee data set covering all firms established in 1998 in Denmark, the following is discovered:

- Only about one tenth of all firms founded in 1998 are set up with more than one person. Manufacturing firms are more likely to be founded by a team than service sector firms. Over the whole period considered, the average number of employees amounts to 1.7, whereby firms with university graduates are larger than firms without university graduates. Thus, for the majority of firms the risk of matching is not relevant.
- If firms are founded by a team, the matching occurs systematically with respect to the degree of educational attainment such that individuals with the same educations team up. Thus, teams are not composed of specialists in *different* areas.
- Matching also occurs systematically with respect to ability but individuals do not choose partners with the same level of ability, as predicted by the O-ring theory.
- Also contrary to the predictions of the O-ring theory, the average level of ability in firms is negatively correlated with firm size.
- The average ability on the firm level is positively correlated with capital input per head. This is the only result that is in line with the predictions of the O-ring theory.

The question left open by the analysis of this paper is whether individuals systematically commit errors by assembling the human capital basis of their firms, e.g. that individuals do not behave in line with the O-ring theory although it would be good for them. If this is the case, there would be a strong argument in favour of fostering ability matching, e.g. through incubators, on the policy side. To determine whether there are reasons for such a policy intervention an analysis determining the performance consequences of the team composition needs to be conducted. This will be done in an additional paper.

If it turns out that also there is no reason to stick to the O-ring theory from the normative perspective either, a submodular function instead of a supermodular function like the O-ring production function might be considered as alternative. As Grossman and Maggi (2000) argue, for many creative or problem solving tasks it suffices that only one person comes up with a new idea or a solution for a problem. Having several high-ability individuals employed is therefore a waste of resources. Submodular functions imply matching of high-ability individuals with low-ability individuals. This would correspond betterwith the decrease in the degree of homogeneity with respect to ability over time observed in the Danish data.

References

Abowd, J., Kramarz, F., and Margolis, D. (1999). High Wage Workers and High Wage Firms. *Econometrica*, *67*(2), 251–333.

Brown, C., and Medoff, J. (1989). The Employer Size-Wage Effect. *The Journal of Political Economy*, *97*(5), 1027–1059.

Davis, S., and Haltiwanger, J. (1991). Wage Dispersion between and within U.S. Manufacturing Plants, 1963-86. *Brookings Papers on Economic Activity. Microeconomics*, 115–200.

Dunne, T., Foster, L., Haltiwanger, J., and Troske, K. (2004). Wage and Productivity Dispersion in United States Manufacturing: The Role of Computer Investment. *Journal of Labor Economics*, *22*(2), 397–429.

Fabel, O. (2004). Spin-Offs of Entrepreneurial Firms: An O-Ring Approach. *Journal of Institutional and Theoretical Economics*, *160*, 416–438.

Fabel, O., and Weber, T. (2005). *Entrepreneurial Èlites: Industry Structure and Welfare Effects of Incubating New Businesses* (Discussion paper No. 05/09). DFG Research Group Heterogeneous Labor: Positive and Normative Aspects of the Skill Structure of Labor.

Grossman, G., and Maggi, G. (2000). Diversity and Trade. *The American Economic Review*, *90*(5).

Iranzo, S., Schivardi, F., and Tosetti, E. (2008). Skill Dispersion and Firm-Productivity: An Analysis with Employer-Employee Matched Data. *Journal of Labor Economics*, *26*(2), 247–285.

Koellinger, P. (2008). Why are some entrepreneurs more innovative than others? *Small Business Economics*, *31*, 21–37.

Kramarz, F., Lollivier, S., and Pelè, L.-P. (1996). Wage Inequalities and Firm Specific Compensation Policies in France. *Annales d'Èconomie et de Statistique*(41/42), 369–386.

Kremer, M. (1993). The O-Ring Theory of Economic Development. *The Quarterly Journal of Economics*, *108*, 551–575.

Kremer, M., and Maskin, E. (1996). *Wage Inequality and Segregation by Skill* (Working paper No. 5718). NBER.

Mellow, W. (1982). Employer Size and Wages. *The Review of Economics and Statistics*, *64*(3), 495–501.

Milgrom, P., and Roberts, J. (1990). The Economics of Modern Manufacturing:

Technology, Strategy, and Organization. *The American Economic Review*, *80*(3), 511–528.

Milgrom, P., and Roberts, J. (1995). Complementarities and Fit: Strategy, Structure and Organizational Change in Manufacturing. *Journal of Accounting and Economics*, *19*, 179–208.

OECD. (2003). *OECD Science, Technology and Industry Scoreboard.* Paris: OECD.

Oi, W. (1983). The Fixed Employment Costs of Specialized Labor. In Jack E. Triplett (Ed.), *The Measurement of Labor Costs.* Chicago: University of Chicago Press for NBER.

Prat, A. (2002). Should a team be homogeneous? *European Economic Review*, *46*, 1187–1207.

Troske, K. (1999). Evidence on the Employer Size-Wage Premium from Worker-Establishment Matched Data. *The Review of Economics and Statistics*, *81*(1), 15–26.

Yu, L., and Orazem, P. (2008). *Human Capital, Complex Technologies, Firm Size and Wages: A Test of the O-ring Production Hypotheses* (Working paper No. 08029). Iowa State University.

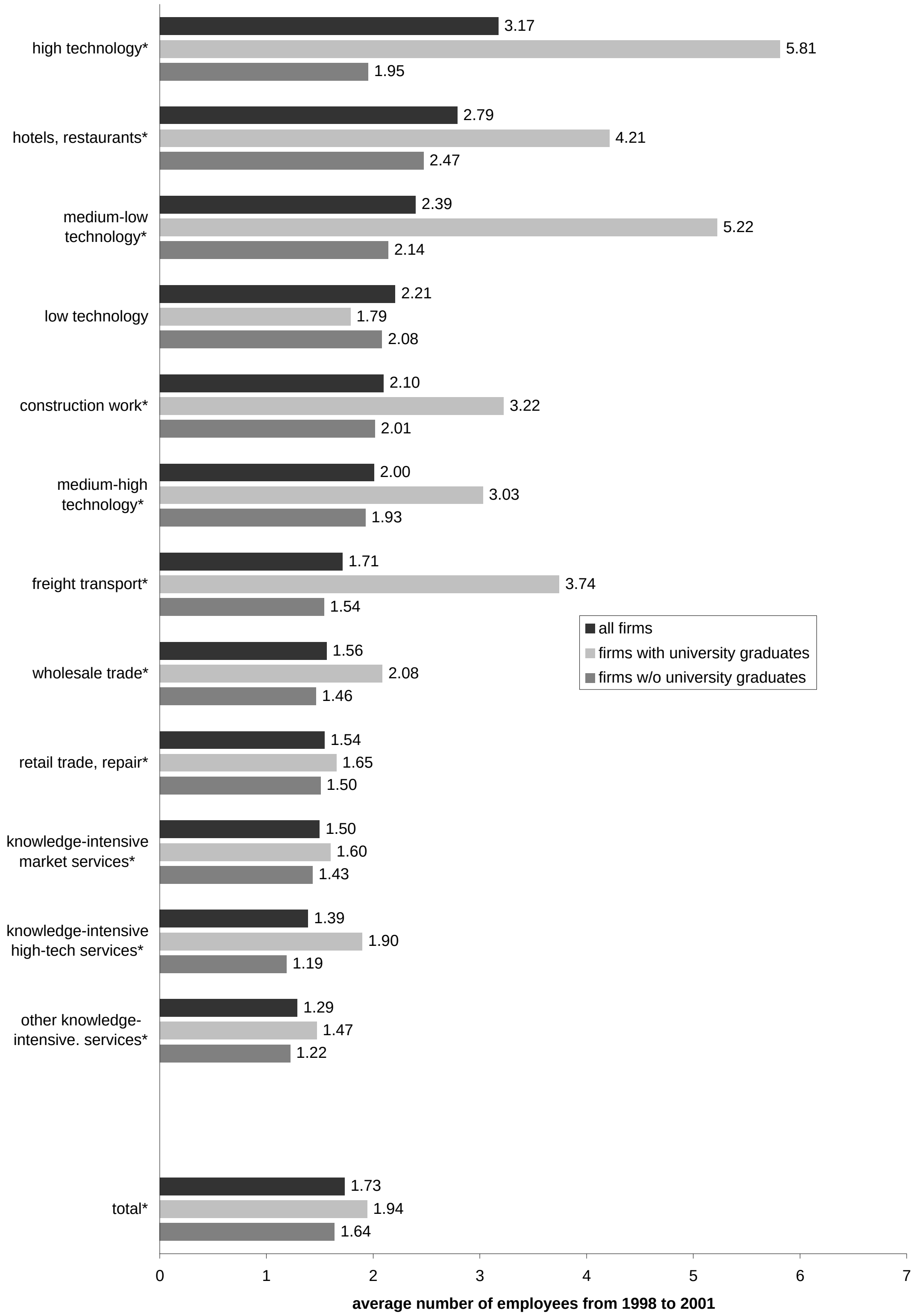
Appendix

Table 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: 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 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 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, own calculations.