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Two's Company: Composition and Performance of Entrepreneurial Pairs

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Abstract

We explore the effects of diverse team composition on the survival and growth of new ventures using the Danish Linked Employer-Employee database. To get cleaner measures of diverse team composition, we focus on entrepreneurial dyads, and also investigate the asymmetric effects of team composition by distinguishing between the ?primary? and the ?secondary? founder. We complement existing work by showing that heterogeneity in team composition is affected by the asymmetric hierarchical structure within the team, and that a unidimensional diversity indicator (which is usually applied) fails to capture a number of performance effects of heterogeneous team composition. Pairs of younger individuals have lower survival chances but higher employment growth. Pairs led by a male tend towards ?jobless growth? in the sense that they have higher growth of profits and sales but not employment. Family firms have lower employment growth, especially when formed with one?s mother.

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1 Introduction

From the late 1980s onwards, we have observed a gradual shift from treating entrepreneurship as an act of one lone individual towards entrepreneurship as a collective activity (Cooney, 2005; Harper, 2008). Consequently, researchers within the field of entrepreneurship started to investigate the composition of these entrepreneurial teams (e.g. Ruef et al., 2003). In close relation to identifying this composition, there is also an interest in investigating whether composition affects the performance of these teams, which varies from member entry and exit to growth and survival, and if so what the nature of this relationship is. Studies have focused on various compositional measures of teams; for example, industry experience (Delmar and Shane, 2006), entrepreneurial experience (Ucbasaran et al., 2003; Delmar and Shane, 2006), and prior affiliations of team members (Beckman et al., 2007). However, inspired by the upper echelon theories on diversity in top management teams (Hambrick and Mason, 1984), there has been an increased focus on diversity in entrepreneurial teams arguing that the heterogeneity of these teams affects how they work together, which ultimately will affect their performance (Gartner, 1985; Ensley et al., 1998). Indeed, Ensley et al. (2002) argue that "the richest and most interesting studies of TMTs are likely to involve new ventures" (p. 381).

Not surprisingly, and in accordance with studies on top management teams, the impact of diversity is inconclusive. Studies have not specified whether, how and why team diversity positively or negatively affects the performance of start-ups. This can attributed to: (i) the assumption that the same level of diversity might have a different impact on various performance indicators, i.e. diversity might be good for firm growth but bad for firm survival, (ii) that the approach in investigating team composition is too ambitious by constructing an overall (scalar) diversity measure, and (iii) studies investigate entrepreneurial teams of different sizes, thereby introducing an undesirable level of complexity, making it even more difficult to estimate the impact of diversity on performance. In this paper, we will focus on a subset of entrepreneurial teams – dyads. This approach will provide us with cleaner measure of heterogeneous team composition, and a focus on dyads is a theoretically meaningful way of analyzing entrepreneurial teams (Harper, 2008). In addition, it is one of the most common forms of entrepreneurial team size (Ruef et al., 2003), which is supported by many studies on entrepreneurial teams report averages sizes between two and three members (Ucbasaran et al., 2003; Chowdhury, 2005; Clarysse et al., 2007) indicating the bulk of the distribution is represented by two-person teams.

In this exploratory paper, we use the Danish Integrated Database for Labour Market Research (IDA) to identify these entrepreneurial pairs. This database provides detailed information on the demographic characteristics of individuals, e.g. age, gender, education, and the dynamics of organizations, i.e. birth, growth and exit of firms, which allows us to analyse the relations that exist between the demographic characteristic of the entrepreneurial team and new venture performance. The direction of the diversity is determined by the position of the individuals in the firm where a higher ranked individual, based on ownership and occupation code, is considered to be the *primus motor* of the start-up. We select a sample of 3777 entrepreneurial dyads in the Danish private sector in the period 1999-2003 and follow these start-ups for five years after founding.

We contribute to the literature in a number of ways. We investigate the effect of diversity on performance using an especially rich dataset that contains details on a number of variables including educational background and family ties. While much previous work has focused on small samples, we provide, as suggested by Vanaelst et al. (2006), representative large-sample evidence using detailed administrative data. We investigate the performance of new businesses in terms of both survival and employment growth. While previous work has grouped together ventures of different ages, we observe new ventures from their first year of business (as indicated by their date of official registration). In response to calls for diversity research to focus more on dynamic effects (Horwitz and Horwitz, 2007), we exploit our longitudinal data to consider lagged effects of diversity (that is, the effects of heterogeneous combinations of start-up and pre-start characteristics on five-year performance). Furthermore, we contribute to the literature by moving on from assuming that power relations are symmetric between team members – we distinguish between the primary and secondary founder, and investigate which characteristics matter for each of the two founders.

The analysis indicates that, when focusing on entrepreneurial pairs, there is indeed a difference in performance depending on the direction of this diversity. With regards to education, the best performing firms are not composed of similar individuals. Ventures with a STEM-educated primary founder, i.e. a founder with a science, technology, engineering or math degree, and a Business-educated secondary founder enjoy relatively high employment growth, while interestingly enough the opposite combination (Business first, STEM second) has low employment growth. Pairs of younger individuals have lower survival chances but higher employment growth. Performance of mixed-race and mixed-gender ventures depends upon the identity of the primary founder. Family firms have equal survival chances but lower employment growth – consistent with suggestions that they persist for an unnecessarily long period of time.

The remainder of the paper is structured as follows. We review the related literature in Section 2 and formulate some propositions. Our methodology is described in Section 3. We present our data in Section 4. Section 5 contains our analysis, where we begin with non-parametric representations of team composition and performance before moving on to parametric regressions. Section 6 contains a synthetic discussion of our findings and revisits our propositions. Section 7 concludes.

2 Background

2.1 Related literature

Issues on team diversity are not a new phenomenon; on the contrary, a survey of the literature indicates that there exists a long tradition in linking the diverse composition of teams with their performance (see, e.g., Williams and O'Reilly (1998) and Horwitz (2005) for a literature review). However, a closer inspection of these studies reveals that the interest is traditionally based upon teams in larger organizational settings, e.g. top management and product development teams (Murray, 1989; Bantel and Jackson, 1989; Pelled, 1996). More recently, studies that investigate the diverse composition of entrepreneurial teams have emerged and an increase in the number of such studies is visible. This steady increase runs parallel with the increased focus on entrepreneurial teams in general (Harper, 2008).

Studies that investigate the composition of entrepreneurial teams (e.g. Baron et al., 1999; Ruef et al., 2003) show that entrepreneurial teams are mainly characterized by homophily, at least regarding gender, ethnicity and occupation (more visible characteristics), while we can observe more heterogeneity in terms of functionality and status. The homophily in these teams can be explained by the social selection mechanism behind recruitment that is often driven by interpersonal attraction (Forbes et al., 2006); not only because these teams rely on social networks (Aldrich and Ruef, 2006), which are homogeneous (McPherson et al., 2001), but also based on the other recruitment channels. The underlying rationale is that interpersonal attraction based on the demographic attributes will cause less (personal) trouble in start-ups (Beckman et al., 2007); consequently, the limited resources will be used to deal with the liability issues that start-ups face.

In contrast to the above-mentioned perspectives on the importance of homophily, there are studies that stress the positive impact of diversity on performance as a result of the unique set of skills, abilities and knowledge that are brought into the team (Hambrick et al., 1996; Williams and O'Reilly, 1998; Horwitz, 2005). This line of argument is similar to other approaches within management theory, in particular the resource-based view of the firm, which argues that a heterogeneous resource composition, including human resources, determines a firm's competitive advantage (Barney, 1991). Within the upper echelon studies on top management teams, which have their origin in Hambrick and Mason (1984), it is widely accepted that it is important that these teams collectively possess the skills that are necessary to run a successful business (Beckman et al., 2007). The majority of studies on entrepreneurial teams share this perspective as their superior performance compared to solo entrepreneurs is believed to be driven by the access to various forms of human capital and the presence of different perspectives (Kamm et al., 1990; Eisenhardt and Schoonhoven, 1990; Watson et al., 1995). Nevertheless, most studies on these entrepreneurial teams focus on human capital theory and look at overall team characteristics (e.g. average level of education or length of experiences) to explain performance (Beckman et al., 2007). This approach is very helpful in explaining the performance of individual entrepreneurs (Davidsson and Honig, 2003) but fails to capture the impact of the diversity in skills that are present in a collective. By adopting an organizational demography approach, we can consider both the average characteristics of the human resources in ventures and the differences between the human resources (Beckman et al., 2007). The above-mentioned theoretical approaches provide sound but contradictory arguments on the potential effect of team diversity on team performance. It is therefore not surprising that empirical studies have found both positive, negative and non-significant effects of diversity in entrepreneurial teams.

2.2 Development of propositions

The previous literature has generally formulated hypotheses in terms of how diversity in one particular dimension (e.g. age, gender, race, prior professional affiliations) affects the performance of the firm. For example, Pelled et al. (1999) distinguish between task conflict and emotional conflict, while Foo et al. (2005) write in terms of task-based and non-task based diversity. Task-based or job-related diversity attempts to capture diversity of expertise, skills and abilities, and studies link this form of diversity with effective team performance, as these different perspectives lead to a broader relevant knowledge base and superior problem-solving capabilities (Webber and Donahue, 2001; Østergaard et al., 2011). Non-task related diversity, which is diversity based on individual attributes that are not directly linked to the performance of work, will offer no such advantages (Pelled, 1996; Pelled et al., 1999; Webber and Donahue, 2001; Foo et al., 2005). In our analysis, we focus primarily on a number of human capital variables – that is, age, education (level and type), and prior industry experience. Diversity in age can have advantages if energetic youth can be combined with the wisdom that accompanies age.

Diversity measures of functional education and experience are regarded as valid measurement of skills, expertise and abilities according to the literature on task-related diversity (Pelled, 1996; Pelled et al., 1999; Webber and Donahue, 2001). Diversity in education type can lead to a broader set of available skills and benefits of specialization, which research considers as important due to the various complex tasks that need to be solved Hmieleski and Ensley (2007). We do not expect any benefits from diversity in education level, however, because individuals will need a common level of education in order to effectively communicate their diverse perspectives. Diversity in prior industry experience is not expected to be an advantage, although it may be that it is sufficient if one of the partners has prior industry experience. We also control for diverse combinations in terms of gender, nationality, and marital status, although we do not hypothesize any particular advantages for these variables because we classify them as non-task-related characteristics.

Our main theoretical focus, however, is on developing some 'propositions' to loosely guide our empirical investigations, that will be used to evaluate the validity of our empirical approach. To begin with, we deliberately distinguish between the 'primary' and 'secondary' founding entrepreneur in our analysis, and suggest that the effect of diversity on performance is not invariant to which individual has which characteristics. For example, it may be that entrepreneurial pairs need one brash, energetic young individual to take the leading role, with an older and wiser individual acting as a 'guiding hand.' It may also be that the primary founder needs to have sound technical knowledge of the product, while benefitting from commercial advice from a supporting partner. Asymmetries in ownership stakes in the venture may lead to agency problems, whereby the individual with the higher ownership stake needs to monitor the secondary founder and keep moral hazard problems in check. In close connection to selecting a primary and secondary founding entrepreneur is the idea on the presence of a lead entrepreneur. Ensley et al. (2000) have demonstrated in such an individual is present within the setting of a team despite that their findings on the impact on new venture performance is inconclusive.

Proposition 1 *Structures of power and authority within teams are not symmetric, and the 'direction' of heterogeneity moderates the effect of team composition on performance*

We also take a non-standard approach to measuring heterogeneity of team composition, because we suspect that the standard practice of reducing heterogeneity to a single summary scalar index of diversity leads to the loss of considerable information on team composition. Consider the variable age: first of all, we suspect that age has a non-linear effect on performance (from the liability of youth to the 'golden age' to senescence). A second drawback is that it is likely that 10 years difference in age matters more when the two founders are on average 25 years old than when they are both on average 60 years old.

Therefore we posit:

Proposition 2 *Team composition cannot easily be reduced to a single summary scalar index of diversity, because many interesting effects will remain hidden*

Another feature of our paper is that we have two performance indicators: survival and employment growth. While each of these indicators is associated with firm performance, they shed light on different facets of performance. We prefer growth as an indicator of success, because some firms may survive and persist even if they experience poor performance (the so-called 'living dead').

Proposition 3 *Heterogeneity of team composition has different effects for survival and growth*

3 Method

In the majority of studies on team diversity, diversity is defined as a function of differences among team members with respect to a common attribute. Consequently, diversity is often regarded as a unit-level compositional construct (Harrison and Klein, 2007). Overall, diversity on these attributes can be measured on three dimensions: variety, balance, and disparity (Stirling, 2001; Harrison and Klein, 2007).

Variety takes into account the number of categories within a certain attribute where more categories result in higher diversity. With balance, the shares of the specific category are measured and a more equal balance between categories results in a higher degree of diversity. Disparity refers to the distance between the outer boundaries of the various categories within one characteristic. Harrison and Klein (2007) distinguished between separation and disparity where the first relates to horizontal differences (diversity based on opinions or expertise), and the latter on vertical differences (diversity based on hierarchy or power). To study this diversity, we will follow the methods proposed in the existing work on team diversity. The majority of these studies have used the techniques of organizational demography. This means that the level of diversity is measured based on observable demographic characteristics, where demography is defined as: "the composition, in terms of basic attributes such as age, sex, educational level, length of service, race and so forth of the social unit under study" (Pfeffer, 1983, p. 303).

Such an empirical strategy leads to several challenges when investigating the impact of diversity on the performance of the team. First, researchers create a unidimensional summary indicator of diversity for each attribute; this approach does not take into account that diversity might in reality have a 'directional' character, in the sense that the value of an individual's characteristics is moderated by their position in the hierarchy. Such a directionality is expected as research has shown that despite that new ventures are often founded by teams often one individual emerges as the leader of the team (Ensley et al., 2000). Second, there is the challenge on how to find a concise representation of the high dimensionality, i.e. large teams have more nodes leading to a higher level of complexity.

3.1 Focus on pairs only

To keep the dimensionality manageable, we focus on entrepreneurial pairs. Focusing on these dyads is a theoretically meaningful way of simplifying the analysis of entrepreneurial teams (Harper, 2008).

With pairs, there is only one possible relationship in which heterogeneity can be measured – that is, the relationship of A to B. With triads, one may look at the heterogeneity between A and B, or A and C, or B and C; and the analysis of heterogeneity becomes even more complex with four or more founders. Another main reason why we focus on pairs is that, contrary to other studies that investigate entrepreneurial team performance, we consider that entrepreneurial teams of different sizes are qualitatively different. In pairs, for example, there is always the tension of a head-on conflict, and disputes are resolved essentially through the mechanism of 'my word against yours.' In keeping with insights from geometry (that is, the stability of triangular structures), an entrepreneurial team of three founders will have more stability as the dynamics of majority rule is more flexible, with each individual taking turns as the swing voter and arbiter, and being able to move from side to side to form new majority coalitions with one of the two others. With teams of four individuals, there may be a tendency to split into rival groups (of pairs) within the team, for individuals to seek strong pair-bonds within the team, or for minority views to acquiesce relatively easily. In short, there may be nonlinearities between number of team members and the nature of diversity within the team, because integers can be seen as being qualitatively different (Schimmel, 1994). Teams of different sizes have fundamentally different opportunities for specialization, that do not scale up with team size in a linear way. To keep our observations as comparable as possible, we focus only on the most numerous team-size, which is the team of two individuals.

3.2 Quantifying diversity

Table 1 summarizes the most common indicators of diversity used in the literature. We will argue that these measures of diversity have a number of drawbacks. First of all, the numerical value of such an index may have no intuitive interpretation. Second, we may be interested in asymmetric roles (due to power structures in a hierarchy) for individuals i and j, instead of assuming the two to be interchangeable.

Table 1: Indicators of diversity used in the literature

Indicator	Formula	Types of variables	Examples
Coefficient of variation	$c_v = \frac{\sigma}{\mu}$	Continuous	Pelled et al. (1999, p11); Foo et al. (2005, p393)
Herfindahl-Hirschman index	$H = 1 - \sum_{l=1}^{l}(P_i)^2$	Categorical	Pelled et al. (1999, p11); Foo et al. (2005, p393); Beckman et al. (2007, p157)
Shannon index	$H = -\sum_{l=1}^{l} P_i(lnP_i)$	Categorical	Pelled et al. (1999, p16); Ucbasaran et al. (2003, p116); Beckman et al. (2007, p156)

Notes: The Shannon index is referred to as Teachman's index in Pelled et al. (1999, p16) and Ucbasaran et al. (2003, p116). The Herfindahl-Hirschman Index is referred to as Blau's heterogeneity index in Pelled et al. (1999, p11).

Third, the benefits of diversity may vary across the distribution of x (for example, being ten years younger may be more important if your partner is 30 than if your partner is 60). This will be difficult to quantify without making the results difficult to interpret. Therefore, instead of trying to quantify diversity, we instead aim to present information on diverse team compositions in the most accessible way possible.

In our view, the standard scalar indicators of diversity suffer from problems related to extreme reductionist simplification. For example, a team of two men and one women is treated as having an identical gender composition as a team of two women and one man, or even a team of four women and two men (because firm size is seldom interacted with the diversity indices). The maximum possible amount of diversity also depends on the group size (e.g. the maximum score for gender diversity in a team of three is not the same as the maximum score for a team of four). With regards to information on educational background, standard diversity measures provide information on the number of different backgrounds but they remain mute on *which* backgrounds are represented. For example, when looking at the diversity of educational backgrounds, a team where everyone has a STEM background is indistinguishable (to the econometrician) from a team where everyone has a business background (both teams would have zero diversity). To deal with these problems, we develop a less parametric approach to investigating diversity and performance, by representing heterogeneity in terms of coordinates in an n-dimensional Euclidean disparity space (Stirling, 2007).

3.3 Empirical strategy

We begin with some non-parametric illustrative statistics of the performance of pairs to give the reader an intuitive grasp of the composition of teams and their performance outcomes. Anticipating that most readers will not have a 3D printer, and furthermore in recognition of the fact that the human brain is not well adapted to considering graphs containing three or more dimensions (which would be problematic if we had more than two team members), we plot the two founders on two axes and report the outcome in the resulting two-dimensional disparity space, using contour plots and cross-tabulations.

We then complement our 'raw' non-parametric results with parametric regressions, that have the advantage of allowing us to include control variables. In our parametric regressions, we prefer not to collapse information on diversity into a single summary diversity index, because this might not have a ready or 'intuitive' interpretation. Instead, we include a dummy variable for each category of combinations of partners. This gives us a different problem – that of having to include a large number of dummy variables for each pair-wise combination of characteristics. To deal with this latter issue, we adopt a 'stepwise' regression approach, whereby we repeat our regressions in iterative progression, at each step removing the least significant variable, and proceed until all of the remaining explanatory variables are above a minimum threshold level of significance.

4 Data

To investigate whether the direction of the employment diversity affects the performance of the new venture, we make use of the information gathered from Danish government registers. This database, which is maintained by Statistics Denmark, is known under the name Danish Integrated Database for Labor Market Research (from now on referred to by its Danish acronym IDA). IDA is suitable for the analysis as its longitudinal characteristic allows us to follow individuals, establishments and firms over time. As a result, firm dynamics (birth, death and growth rate of firms) and the employment history of the active labor force can be identified. The database holds information on various demographic characteristics, such as gender, age, country of origin, type and level of education, which university the individuals attended, occupation and work experience. Because these individuals can be matched to a firm at any given year, it is possible to observe the team composition of the start-up and address individual level processes that can help us understand not only the founding of new businesses, as proposed by Shane and Khurana (2003), but also growth and disbanding of these new ventures.

4.1 Start-ups, Entrepreneurial Pairs, and Directionality

To conduct the various analyses, we created a sample of all start-ups in the period 1999 to 2003 where we exclude all start-ups in the primary and public sector.[1] The motivation for selecting the time-period is two-fold. First, we want to be able to use the growth in sales as one of the firm growth measures; due to the break in the data between 1998 and 1999 it is problematic to include start-ups founded prior to 1999. Second, we want to follow the start-up for a number of years after founding to identify whether they survive and to establish their growth rates. The current dataset has data up to 2008, which allows us to follow each start-up for up to at least five years after founding.

To select our sample of start-ups it is important to identify the founding year. To do so, we use information on the firm's founding date from the company register in combination with the plant and firm identification number. We identify a start-up as a one-plant firm with no prior firm and plant identification number, which is in line with Dahl and Reichstein (2007). Furthermore, to select genuinely new firms, we exclude all start-ups that are the result of a separation or merger of previously existing plants. Based on the above-mentioned selection criteria we identify 12,861 start-ups in the period 1999-2003.

To identify the disparity we need to identify the persons that are involved in the start-up in the year of founding. These persons are identified by merging two datasets: i.e. (i) the entrepreneurship database, which provides detailed information on who is the owner of the start-up; and (ii) the employee dataset that provides information on a person's primary workplace. We add all these individuals to identify the size of the start-up in the year of founding. Due to the nature of linked employer-employee databases we are limited to only identify individuals that have a formal attachment to the new venture, i.e. registered to be part of the organizations through governmental registers. For that reason, our concept of entrepreneurial pair varies from the definition of entrepreneurial teams that exist in the literature. Nevertheless, this approach of identifying entrepreneurs in small new ventures in IDA is similar to Nanda and Sørensen (2010) that use these entrepreneurs to investigate peer effects of entrepreneurship. Furthermore, the motivation for identifying all the individuals in the first year as crucial stakeholders is: (i) the observation that most firms start small and hardly change in size during their lifetime (Aldrich and Ruef, 2006); (ii) the initial resource profile can be used to predict start-up performance, including failure (Cooper et al., 1994); and (iii) founder characteristics (Boeker, 1989), early hiring decisions (Baron et al., 1999), and strategies at start-up (Romanelli and Tushman, 1994) have lasting consequences for new organizations. The operational definition of an entrepreneurial pair in this paper are thus two individual that have a formal affiliation to the new venture in the year of founding.

[1] Start-ups that are not within the 15 and 75 two-digit level NACE code are excluded. Within these two two-digit codes there is one classification, 40 to 45 (energy), that is a mix of both public and private firms, which also will be omitted.

As explained in Section 3 we will focus only on two-person start-ups.[2] Similarly to the studies reported in Section 3, entrepreneurial pairs is the most common team size. This selection criteria will decrease the sample to 4002 new ventures.

Since we investigate the directionality of the disparity, we need to assign a *primus motor* (individual i) for each two person start-up. To do so, we conduct several steps to find this individual, which is a combination of ownership, occupation code and the length of the attachment to the workplace. In this case we argue that the position of lead entrepreneur is based on either a having a higher rank or a longer tenure. The majority of the our primary individuals are identified as the owner of the new venture, i.e. 2487. In 183 pairs the primary individual is identified as a director of the business and 1070 cases both are registered as an employee but then the highest employee rank in combination with the number of days of employment enables us to identify a primary individual. For 225 cases it is not possible to identify a direction and these cases are excluded from our sample; consequently, we end up with a sample of 3777 entrepreneurial pairs. Afterwards, we identify the disparity of this pair in terms of age, education (both degree and discipline) and industry experience, as well as other common diversity indicators (gender, nationality, and civil status).

4.2 Survival and Growth

As mentioned above, we investigate the impact of this directional disparity on firm performance. The first performance measure is firm survival – due to the unique identification number associated to firms and plants we can follow the status of these organizational units in all years up to a change in this identification number. A change in this identification number is always connected to a variable that indicates the status; when this status is identified as being a closure we consider it to be a non-survivor. In reality, firms might re-enter into the same or in different industries; however, for analytical purposes we will not consider this as a new entry and these firms do not re-appear in the sample. In addition to the closure of a business a firm might continue in another form, e.g. as a result of a merger or acquisition. We will treat these firms as survivors but these observations will be censored due to the structural change of these firms. This is the case for 114 firms in the sample. In total, 1256 firms (that is, 33.33%) survive up to the fifth year.

We also investigate the impact of team composition on employment growth. We measure growth in terms of number of employees, and track the employment growth of the firm after 5 years. It is straightforward for us to measure the employment growth of our firms, because they all start with two individuals – we need only consider the number of employees in year 5.

5 Analysis

5.1 Non-parametric analysis

In the following subsections we will present the non-parametric analysis that provides us with a first indication of the effect of team composition on new venture performance. We will start with the impact of age, followed by education (both the level and the type of education), and industry experience.

[2] We only restrict our sample where two individuals have a primary attachment to the new venture in the founding year. Other individuals might be connected to this new venture but this venture is not their primary employment. Ntheote also that it is possible that a team of two founders takes their first employee within the first year.

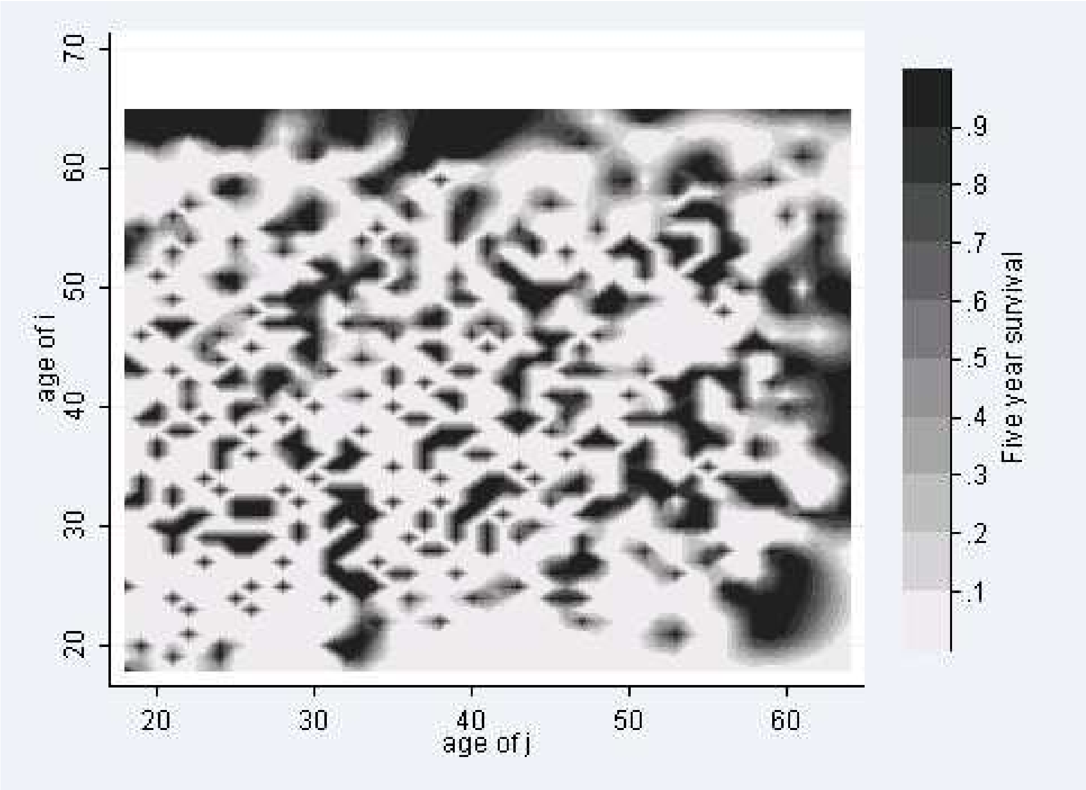

Figure 1: Contour plot of the survival of entrepreneurial pairs. z-axis: average survival after 5 years. Contour plot produced using thin-plate-spline interpolation.

5.1.1 Age

We start with presenting some non-parametric analysis on the age of the founders. As presented in Table H.1 in the Appendix, the average age of the individuals in the sample is around 35 years of age.

Figure 1 shows the survival rates of entrepreneurial pairs, conditional on the age of individuals i and j. On the whole, there appears to be a rather uniform pattern – the survival of startups seems to be constant across the distribution of ages of i and j. That said, we observe a slightly longer survival of firms depending on the age of the entrepreneurial team, i.e. where either i or j is old.

Figure 2 shows the employment growth outcomes associated with different partnership combinations according to age. A first observation is that the best performing ventures, in terms of employment growth, are those where the primary founder has an age of around 20, while the secondary partner has an age of around 30. This suggests that both partners should be relatively young, to cope energetically with the workload of starting a new venture, although the secondary founder should be noticeably older than the first. Hence, some diversity in age can be valuable. Other regions associated with high employment creation are also visible, such as when age_i=45 and age_j=40, or when age_i=55 and age_j=30. A second observation is that job creation generally seems to decrease with age of both the primary and the secondary partner, although the relationship is not smooth or linear. To the extent that the best outcomes are not on the $45°$ line (the 'diagonal'), Figure 2 provides early evidence that diversity in age can be beneficial.

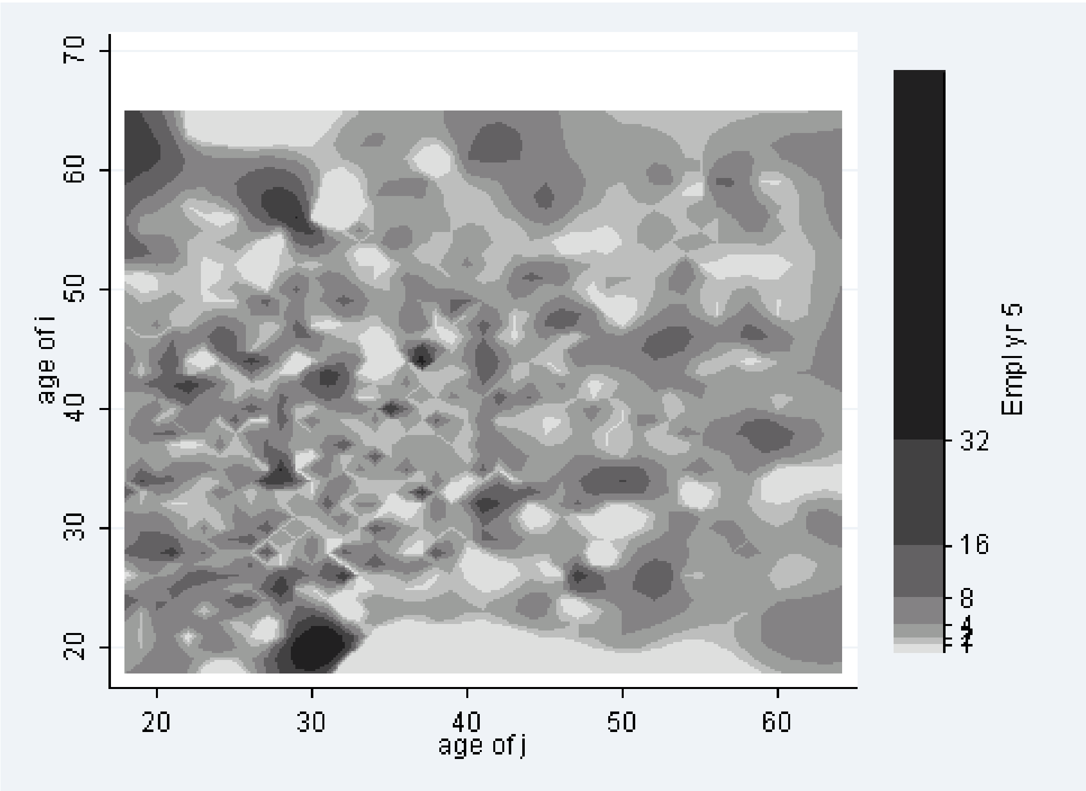

Figure 2: Contour plot of the outcomes associated with entrepreneurial pairs. z-axis: employment after 5 years, measured in terms of number of employees at the date of annual compulsory registration (in November of each year). Contour plot produced using thin-plate-spline interpolation.

		j 1	2	3	4	5
i	1	0.241	0.327	0.353	0.286	0.227
	2	0.319	0.441	0.457	0.385	0.350
	3	0.373	0.520	0.409	0.235	0.125
	4	0.341	0.448	0.444	0.565	0.353
	5	0.241	0.333	0.273	0.154	0.625

		j 1	2	3	4	5
i	1	3.909	4.677	4.111	3.833	5.000
	2	4.411	4.224	4.952	4.500	7.714
	3	4.760	5.654	5.111	9.750	2.000
	4	4.696	3.821	6.875	4.269	5.333
	5	3.846	4.923	7.000	6.250	10.080

Figure 3: Performance after 5 years, by education level, for individuals i (primary founder) and j. Cells with above-median values are highlighted. Left: survival; right: means of numbers of employees.

5.1.2 Education

In our analysis of the impact of directional disparity in education, we would like to take into account both the level of education and the type of education. The structure of the education variable in IDA allows us to identify the level of education (based on the first two-digits of an eight-digit code) and the discipline being taught (digit three and four of the eight-digit education code). We begin by considering education level before moving on to education type.

Education level In preparing the sample for the non-parametric analysis on education, we have merged the different education codes in five education level dummies, i.e.: for all up to (and including) high-school (1); vocational training (2); Vocational short cycle education (3); Bachelor (4), which includes professional and academic bachelor; Post graduate (5), which includes Master and PhD graduates. For this analysis we also drop individuals for who we do not know the education they obtained.

In Table 3 we present the survival rates of the start-ups based on the combination of education levels of the founders and the directionality of these education levels. We observe that those with the least education (i.e. public/primary school) generally seem to have the lowest survival rates. Paradoxically, pairs where one individual belongs to the highest education category also have, in a number of cases, lower survival rates, presumably because highly-educated entrepreneurs have attractive outside options that may lure them away (Gimeno et al., 1997). We also observe that diversity in education level is not necessarily an encumbrance, because high survival rates are also observed away from the diagonal.

Table 3 (right) shows the number of employees after 5 years by education level. It would appear that post-entry growth is low when $Educ_i = 1$ or $Educ_j = 1$ (that is up to and including high school) and relatively high when $Educ_i$ or $Educ_j$ are equal to 3 (vocational short cycle education) or 5 (post graduate education).

Education type From the level of education we try to identify whether the type of education matters for survival and growth. The education types are divided in four categories. One type are all the programmes in vocational training and below ($\leq$ Voc Tr) and three where the educational programmes above this level have been divided in: degrees within science technology, engineering and mathematics (STEM), business related degrees (Business); and other degrees (Other). Figure 4 contains a number of interesting results, among which some evidence that the direction of diversity matters. The best performing teams (in terms of survival and growth) occur when $EducType_i$=STEM. $\{EducType_i$=STEM, $EducType_j$ = Business$\}$ has a high survival rate (0.571) while $\{EducType_i$ = Business, $EducType_j$ = STEM$\}$ has a low survival rate (0.222). t-tests with unequal variance reveal that this difference is significant at the 10% level (p-value = 0.0942). This pattern is also visible in the right panel of Figure 4, which pertains to growth. The highest employment growth (mean of 17.5 employees after 5 years) is associated with $\{EducType_i$=STEM, $EducType_j$ = Business$\}$; while the employment growth associated with $\{EducType_i$=Business, $EducType_j$ = STEM$\}$ is lower (but the difference is not significant). This suggests that STEM and Business education backgrounds complement each other in complex ways, in line with our propositions.

		j			
		$\leq$ Voc Tr	STEM	Business	Other
	$\leq$ Voc Tr	0.318	0.408	0.488	0.263
i	STEM	0.465	0.556	0.571	0.542
	Business	0.397	0.222	0.412	0.231
	Other	0.311	0.000	0.500	0.345

		j			
		$\leq$ Voc Tr	STEM	Business	Other
	$\leq$ Voc Tr	4.263	4.897	5.400	4.371
i	STEM	5.414	6.600	17.500	4.231
	Business	6.074	12.500	4.857	14.667
	Other	3.842	.	3.750	6.684

Figure 4: Performance after 5 years, by education type, for individuals i (primary founder) and j. Cells with above-median values are highlighted. Left: survival; right: means of numbers of employees.

		j		
		None	2-digit	4-digit
	None	0.265	0.311	.
i	2-digit	0.331	0.428	.
	4-digit	0.412	.	0.429

		j		
		None	2-digit	4-digit
	None	4.798	4.197	.
i	2-digit	5.652	4.618	.
	4-digit	4.395	.	4.149

Figure 5: Performance after 5 years, by industry experience, for individuals i (primary founder) and j. Cells with above-median values are highlighted. Left: survival; right: means of numbers of employees.

5.1.3 Industry experience

Results for prior industry experience are shown in Figure 5. A first observation is that not all combinations of industry experience are observed. The worst outcome for survival is when neither i nor j have any industry experience – pairwise t-tests with respect to the baseline case of $\{indexp_i = indexp_i = 0\}$ show that the differences are all highly significant. The performance outcomes associated with industry experience for i at the 2-digit level are not considerably lower than those obtained for experience at the 4-digit level, which suggests that experience at the 2-digit level may be sufficient.[3] For growth, high employment growth can occur even if j= no prior industry experience. It seems that it is not necessary for both founders to have prior industry experience in order to grow.

5.2 Regressions

The non parametric analysis we presented above give an indication of the role of team composition on new venture performance. To study this effect in more detail, we apply other estimation techniques to control for other factors that might explain new venture performance. To do so, we estimate the following regression equation:

$$\begin{aligned} Y_k \quad = \quad & \beta_0 + \beta_1 \cdot \sum_{i=1...3} \sum_{j=1...3} AgeGroup_{ij} + \beta_2 \cdot \sum_{i=0,11} \sum_{j=0,11} Education_{ij} \\ & + \beta_3 \cdot \sum_{i=0,2} \sum_{j=0,2} IndustryExp_{ij} + \beta_4 \sum_{i=0,1} \sum_{j=0,1} Gender_{ij} \\ & + \beta_5 \cdot \sum_{i=0,1} \sum_{j=0,1} Danish_{ij} + \beta_6 \cdot \sum_{i=0,1} \sum_{j=0,1} Married_{ij} \\ & + \beta_7 \cdot VentureCharacteristics_k + \varepsilon_k \end{aligned} \qquad (1)$$

The unit of observation is the performance of venture k, and the explanatory variables include a constant term β_0, characteristics of the two founders i and j, as well as some venture-specific controls. A closer analysis of non-linearities and interdependencies affecting team composition is enabled by mapping the

[3] t-tests reveal that there are no significant differences between the outcomes for i when industry experience is measured at the 2-digit or 4-digit level, with the exception of survival when $indexp_j$=0 (that is, the mean values 0.412 and 0.331 are significantly different at the 5% level).

two-dimensional disparity space with a set of dummy variables for each combination of characteristics for individuals i and j.

We recoded the age categories by dividing age in three separate, approximately equipopulated classes, i.e. less or equal to 30; age between 31-45 years, and 45 years and over. This gave us $3 \times 3 = 9$ possible configurations for i and j which are represented by 8 dummy variables (with the omitted base dummy corresponding to a team of young partners). In each case, the omitted dummy variable (corresponding to the base case) is the combination of lowest values for i and j.

We recoded our education variables to take into account the interdependence of education level and education type. Those with the lowest educational qualifications have not had the opportunity to specialize, and therefore the types of education refer only to those above a minimum level of education. To take this into account, we recoded our education variables $Education_{ij}$ such that i and j can take the following values: 1 for all up to (and including) high-school; 2 for vocational training; 3_1, 3_2 and 3_3 for vocational oriented short-cycle education programmes that specialize in either STEM, Business or other (respectively); 4_1, 4_2 and 4_3 for undergraduate (both academic and professional bachelor degrees), that specializes in either STEM, Business or other, respectively, and 5_1, 5_2 and 5_3 graduate and PhD education that specializes in either STEM, Business or other, respectively.

Industry experience is calculated with respect to the individual's work experience in the previous 5 years. Individuals can either have no prior experience, industry experience at the 2-digit NACE industry class, or industry experience at the 4-digit level (following Dahl and Sorenson, 2012).

$VentureCharacteristics_k$ includes a set of control variables. The first control variables we include are industry controls. In some industries, such as manufacturing, we have only a few firms present. To deal with this, we regroup some sectors together, following the Eurostat industry classification scheme for manufacturing sectors. We also have few firms in two-digit NACE sectors 65 and 67 (banking, insurance, etc) and so we merge these sectors together with 66 (life insurance, pensions, etc) to generate a new industry group which corresponds to the Eurostat definition of "Knowledge-intensive financial services." Second, the entrepreneurial pairs might be based on family relationships. As this relationship can influence the performance of the firms in different ways we included four dummies making a distinction whether the entrepreneurial pairs are spouses, siblings, father and son/daughter, or mother and son/daughter. The inability of previous work to control for spousal relations has in fact been identified as a weakness of previous work (Hellerstedt et al., 2007). Family firms account for around 20% of our sample. Third, similar industry experience is an important factor that explains new venture performance, in particular survival (Dahl and Reichstein, 2007). To control for this factor we created two variables that indicate whether the two entrepreneurs have common industry experience in the previous 5 years.[4] Fourth, we introduce cohort dummies, which correspond to the year (1999-2003) in which the firm was founded. Finally, to control for the regional dimension, we created a set of five region dummies that correspond to the five Danish administrative regions.[5]

Equation (1) corresponds to a cross-sectional regression setup, where we explain performance at time $t + 5$ as a function of characteristics at startup (time t). When the dependent variable is survival, we apply a logit regression model (Jenkins, 1995).[6] When the dependent variable is employment growth, we measure this by taking the (natural logarithm of) number of employees after five years. Indeed, a meaningful indicator of the growth of new ventures is their size at the end of the period of observation (Eisenhardt and Schoonhoven, 1990; Storey, 1994; Colombo and Grilli, 2005). Although final size con-

[4] That is, whether one or both have worked in the same 4-digit NACE industry class.

[5] These regions are: Capital Region of Denmark, Zealand, North Denmark, Southern Denmark, and Central Denmark.

[6] An additional advantage of logit regression in our context is that it can be implemented inside our stepwise regression algorithm.

founds the effects of initial size and post-entry growth, nonetheless all the firms in our sample have the same initial size of two employees.

Altogether, we will have an unusually rich set of variables in our initial regressions – too many to fit in a conventional results table. To maintain clarity, we adopt a stepwise algorithm for iterative removal of the least significant variable, and then repeating the regression until only the most significant variables remain. We take the full model in Equation (1) as a starting point before stepwise removal of the least significant explanatory variable. We stop when the least significant explanatory variable is significant at the 15% level. As a result, it can be expected that our stepwise algorithm will give a different set of significant variables for different dependent variables and for different subsamples. This implies that it is not possible for us to report all of our results as adjacent columns in the same regression table – instead each regression of Equation (1) will be reported in a separate results table.

5.2.1 Survival

Table 2 contains the regression results for survival after 5 years. Teams that include old founders tend to have a higher survival rate (compared to the base case of two young founders). The two best performing age combinations (in terms of survival) are when the secondary founder is in the 45 years and over category.

Education seems to help survival, because all of the significant education dummies are positive (with respect to the omitted baseline case corresponding to two founders with minimal education). Interestingly enough, many (but not all) of the significant education dummies correspond to symmetric configurations where both founders are in the same education category. (However, this symmetry with respect to education is not found for employment growth, as we shall see). Industry experience has a positive effect on survival – because all of the significant dummies are positive with respect to the omitted baseline category of no experience for both founders.

In terms of ethnicity, we observe that teams of two Danes have the highest expected survival. Higher survival is observed for ventures where both the founders are in a registered partnership. However, there are no significant differences in the survival of family businesses.

5.2.2 Employment growth

Table 3 contains the regression results for number of employees after 5 years. A first observation is that we have a larger number of significant variables when employment growth is the dependent variable.[7]

For age, we observe results that contrast to our findings for survival – the base case (youngest age category for both founders) has the highest expected employment growth, judging by the fact that all of our significant dummies are negative. In fact, teams of two old founders have the coefficient with the largest magnitude, which indicates the lowest employment growth. Combining our results for survival and growth, firms with older pairs demonstrate stronger persistence, but firms composed of young founders demonstrate higher growth (conditional on survival). This mirrors the well-known result that younger *firms* grow faster (i.e. firm age measured as years since start-up; at the business-level rather than at the level of individuals).

With regards to education, we have a mixed bag of results, considering that some education dummies are positive and others are negative. Furthermore, many are not significant at the usual 5% significance level.

[7] A practical implication of the difficulty of finding variables that predict survival, but not growth, is that it will not be easy to apply a two-stage Heckman selection model (which requires the existence of variables that predict survival but not growth).

We observe that $\{i = 3\_1, j = 3\_2\}$ has a large positive effect on employment growth, while the opposite configuration, $\{i = 3\_2, j = 3\_1\}$, has a large negative effect on employment growth. This echoes our earlier findings from Figure 4 (right). This asymmetry between STEM and Business education is not always observed however, the cases of post-graduate education levels, $\{i = 5\_1, j = 5\_2\}$ and $\{i = 5\_2, j = 5\_1\}$ are the combinations with the highest employment growth. More generally, teams where the primary founder has a post-graduate education often have higher employment growth.

With regards to industry experience, it is puzzling to see that *ceteris paribus* the few significant dummies are all negative. It is not clear why businesses without prior industry experience would not outperform those without such knowledge capital. Although we include industry dummies in our linear regression framework, it could be that more complex interactions of industry, experience, and employment growth are driving these findings.

Regarding ethnicity, the highest-growth ventures are those led by a Dane (although it matters little whether the second founder is a Dane or a foreigner). Family firms consistently have negative coefficients – whether we consider businesses formed with the father, with the spouse, or with the mother. This likely reflects the particularities of the 'business plan' of family firms, which puts more emphasis on guaranteeing a relaxed family lifestyle rather than the pursuit of commercial ambitions. The lowest-growth businesses are formed with one's mother.

Another interesting finding is that the R^2 from the growth equation is higher than what is usually found for growth regressions (Coad, 2009, Table 7.1), perhaps because of the level of detail in our explanatory variables, and perhaps because we have a homogenous subset of firms (pairs) for which growth is measured over 5 years instead of annually. Moreover, the growth regression R^2 is much higher than the psuedo-R^2 obtained from the survival equation.[8]

6 Discussion

In this section we will seek to 'digest' our findings by referring to our three propositions.

Proposition 1 stated that the effects of diversity on the outcomes of new businesses were heavily moderated by the 'position' or 'status' within the hierarchy. We find considerable support for this hypothesis because our results were far from 'symmetric' in a number of cases. This suggests that beneficial characteristics of the primary founder are not necessarily those that would best befit the secondary founder. With regards to age, growth tends to be higher if the primary founder is younger than the second. With regards to type of education, we obtained a mixed set of results, although businesses with a commercially-minded individual playing a secondary role performed better in terms of survival and growth than when a commercially-minded individual was the primary founder. More generally, our results for education type were far from symmetric. With some of our other variables, however, symmetry in characteristics space was associated with better outcomes (such as two Danes as founders; or where both founders are married (positive effects for firm survival); or two founders with low education having the worst survival chances).

Proposition 2 stated that the effects of diversity were non-linear and complex and could not easily be represented using a linear unidimensional indicator. We observed that the 'optimal' position in characteristics space was not monotonically increasing – for example, low education was associated with

[8]Note however that an OLS R^2 and a logit pseudo-R^2 are not strictly comparable. A comparison of the Nagelkerke R^2 statistics for both equations (obtained from estimation of the full model in equation (1), without stepwise elimination of insignificant coefficients, yields estimates of the Nagelkerke R^2 of 0.152 for the survival regression and 0.217 for the growth regression.

Table 2: Stepwise logit regression of equation (1), where the binary dependent variable is survival after 5 years.

	Coefficient	Robust Std. Error	z-stat
Age group dummies			
agegrp_dummy_21	0.255	0.108	2.36
agegrp_dummy_22	0.224	0.106	2.12
agegrp_dummy_23	0.336	0.153	2.20
agegrp_dummy_32	0.236	0.155	1.53
agegrp_dummy_33	0.348	0.157	2.21
Education			
education_dummy_1__3_2	0.837	0.535	1.56
education_dummy_2__2	0.307	0.096	3.18
education_dummy_3_1__2	0.834	0.278	3.00
education_dummy_4_1__2	0.598	0.415	1.44
education_dummy_4_1__4_1	1.544	0.724	2.13
education_dummy_4_3__2	0.473	0.281	1.68
education_dummy_4_3__4_3	0.904	0.408	2.22
education_dummy_4_3__5_2	2.042	0.956	2.14
education_dummy_5_1__5_1	2.106	0.588	3.58
education_dummy_5_3__5_3	1.623	1.102	1.47
Industry experience			
indexp_dummy_1_0	0.215	0.144	1.50
indexp_dummy_1_1	0.622	0.164	3.80
indexp_dummy_2_0	0.697	0.106	6.60
indexp_dummy_2_2	0.632	0.111	5.69
Non-task characteristics			
dane_dummy_11	0.621	0.116	5.34
marr_dummy_01	0.209	0.122	1.71
marr_dummy_10	0.310	0.099	3.13
marr_dummy_11	0.506	0.107	4.75
Industry dummies	yes		
Region dummies	yes		
Year dummies	yes		
β_0: Constant term	-2.146	0.183	-11.70
Obs	3604		
Pseudo-R^2	0.0808		

Table 3: Stepwise OLS regression of equation (1), where the dependent variable is (log of) the number of employees after 5 years. Robust standard errors obtained from the Huber/White/Sandwich estimator.

	Coefficient	Robust Std. Error	t-stat
Age group dummies			
agegrp_dummy_12	-0.236	0.132	-1.79
agegrp_dummy_13	-0.271	0.139	-1.95
agegrp_dummy_21	-0.239	0.082	-2.90
agegrp_dummy_22	-0.400	0.081	-4.93
agegrp_dummy_23	-0.492	0.098	-5.01
agegrp_dummy_31	-0.460	0.124	-3.71
agegrp_dummy_32	-0.487	0.109	-4.48
agegrp_dummy_33	-0.715	0.099	-7.19
Education			
education_dummy_1__3_3	-0.651	0.360	-1.81
education_dummy_2__4_1	0.377	0.146	2.57
education_dummy_3_1__3_1	0.601	0.106	5.67
education_dummy_3_1__3_2	1.364	0.145	9.38
education_dummy_3_1__3_3	0.342	0.115	2.97
education_dummy_3_1__4_3	-0.856	0.225	-3.81
education_dummy_3_1__5_3	-0.807	0.203	-3.98
education_dummy_3_2__3_1	-1.200	0.162	-7.42
education_dummy_3_3__2	0.634	0.290	2.18
education_dummy_3_3__3_2	-0.575	0.171	-3.36
education_dummy_4_1__1	0.555	0.271	2.05
education_dummy_4_1__3_2	1.443	0.151	9.55
education_dummy_4_3__3_3	-1.529	0.102	-14.97
education_dummy_4_3__5_2	-0.583	0.195	-2.98
education_dummy_5_1__3_3	0.581	0.225	2.58
education_dummy_5_1__4_1	-0.540	0.119	-4.53
education_dummy_5_1__4_3	0.907	0.114	7.94
education_dummy_5_1__5_1	0.455	0.254	1.79
education_dummy_5_1__5_2	1.374	0.552	2.49
education_dummy_5_2__2	0.653	0.249	2.62
education_dummy_5_2__4_3	0.842	0.127	6.61
education_dummy_5_2__5_1	2.027	0.103	19.67
education_dummy_5_2__5_3	-0.377	0.128	-2.94
education_dummy_5_3__3_3	1.024	0.099	10.37
education_dummy_5_3__5_2	0.440	0.122	3.61
Industry experience			
indexp_dummy_0_1	-0.108	0.064	-1.68
indexp_dummy_2_2	-0.143	0.063	-2.29
Non-task characteristics			
dane_dummy_10	0.283	0.140	2.02
dane_dummy_11	0.255	0.099	2.56
marr_dummy_10	0.124	0.060	2.06
marr_dummy_11	0.115	0.061	1.89
Family-firm dummies			
mom	-0.568	0.107	-5.3
spous	-0.323	0.082	-3.96
dad	-0.218	0.120	-1.82
Industry dummies	yes		
Region dummies	yes		
Year dummies	yes		
β_0: Constant term	3.010	0.220	13.68
Number of obs	1207		
R^2	0.174		

low survival, but there was little dependence of survival on education above a certain threshold. We also observed that the 'optimal' position in characteristics space depended on the characteristics of the partner – a powerful illustration of this idea is that, controlling for other factors, a configuration of education types $\{i = 3\_1, j = 3\_2\}$ had high expected employment growth, while the inverse configuration $\{i = 3\_2, j = 3\_1\}$ yielded a negative coefficient (with respect to the base case of minimal education), and furthermore, changing the characteristics of the 'second fiddle' turned the coefficient from strongly positive to negative (compare e.g. employment growth for $\{i = 5\_1, j = 4\_1\}$ with $\{i = 5\_1, j = 4\_3\}$). Finally, another problem is that diversity will probably interact with firm size (this was not examined here because all businesses in our sample have the same start-up size of 2 individuals).

Taken together, our support for Propositions 1 and 2 provides justification for our new methodology, which has identified effects of team composition on performance that could not have been uncovered using the standard diversity indicators.

Proposition 3 predicted that diversity has different effects on survival and employment growth (even though these two could be considered as indicators of firm performance). In the case of family firms, we observe that they generally have an average performance for survival (because we observe no significant coefficients apart from a positive coefficient for spouses), although family firms are associated with slower employment growth. Regarding our employment growth regressions, we observe the largest negative effects for firms founded with mothers, then fathers, then spouses. This is consistent with the notion that family firms are under pressure to keep the family 'tradition' alive (perhaps even in the face of prolonged poor performance), although they do not seek employees either through a mistrust of 'outsiders' or an aversion to the perceived risks or growth. Similarly, firms composed of older founders have better survival rates, but lower employment growth. Pairs of young founders have the highest employment growth. This could be because pairs of older founders do not want to take risks or over-exert themselves, but would prefer to 'coast along' before retirement. Younger pairs seem to be more willing to 'experiment' in their businesses, having higher exit hazards but often experiencing faster employment growth. In further analysis, we complemented our employment growth results with findings relating to growth of sales and profits. Among our results, we found that ventures led by a male had higher growth of sales and profits, but not of employment, suggesting that ventures led by males have different priorities and seem to prefer jobless growth.

7 Conclusion

This exploratory study on 3777 entrepreneurial pairs, and the amount of detail that is provided by the Danish register data on these pairs, provide interesting insights into how team composition affects performance. In particular it places question marks on the way diversity is treated in the various studies that exist on the topic. First, we provided evidence that the effects of diversity are moderated by the hierarchy that exist in the firm. Second, diversity is clearly not a linear and unidimensional indicator. This calls for an overall re-evaluation of the existing approaches to investigating diversity of team composition. Third, diversity has a different impact on different performance measures.

Our results offer insights concerning the stereotype (to be found in venture capital circles or the university spinout literature) that startups have good technical ideas but poor business/commercial skills (and hence need VC business guidance to succeed). For example, Wennberg et al. (2011, p. 1138) write about the "important imperative to assist USOs in building viable teams that have the requisite commercial experience to succeed." We observed that it is better, in terms of employment growth, to be configured with STEM first and business second, than to have a business-educated founder first and STEM second. This hints that there may be problems if the focus is on commercial aspects, with the technical side taking a back seat. Our analysis provides tentative evidence that while commercial skills are important, they should not dominate the technical aspects. Commercial viability should, perhaps, be seen as a constraint to be satisfied, rather than the primary aim of the new venture.

Our results show that family firms generally have lower performance, and policy-makers seeking to have a more efficient entrepreneurship policy should perhaps rethink the specific benefits these firms get. For example, it is not clear why, in the UK, family firms get implicit subsidies (such as relief from inheritance tax) even though they are observed to be noticeably unproductive (Bloom and Van Reenen, 2010).

Finally, we would like to provide some suggestions for further work. First, we consider that there is still plenty of opportunity for finding richer quantitative tools for analyzing diverse entrepreneurial teams. It seems slightly ironic to us that it is frequently acknowledged that diversity is a 'double-edged sword' and often yields mixed results, and yet researchers generally compress the numerous dimensions of diversity into a single indicator and then calculate the 'average effect' through standard regressions. We would like to see more 'diversity' in quantitative research into the role of diversity in teams. For example, future work could try to decompose the two edges of the 'sword' to investigate which factors affect conflict more than creativity (that is, distinguishing between the 'gross' and the 'net' costs and benefits of diversity). Second, it would be interesting to see if the degree of diversity in an entrepreneurial team affects the likelihood that the founder will stay with the firm in later years. Although there does exist literature on team member exit (Ucbasaran et al., 2003; Chandler et al., 2004; Hellerstedt et al., 2007), the time span of these studies are limited.

References

Aldrich, H. E. and Ruef, M. (2006). *Organizations Evolving*. SAGE publications ltd, second edition.

Bantel, K. and Jackson, S. (1989). Top management and innovations in banking: Does the composition of the top team make a difference? *Strategic Management Journal*, 10:107–124.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, 17(1):99–120.

Baron, J., Hannan, M., and Burton, M. (1999). Building the iron cage: Determinants of managerial intensity in the early years of organizations. *American Sociological Review*, 64(4):527–547.

Beckman, C. M., Burton, M., and O'Reilly, C. (2007). Early teams: The impact of teams demography on vc financing and going public. *Journal of Business Venturing*, 22(147-173).

Bloom, N. and Van Reenen, J. (2010). Why do management practices differ across firms and countries? *Journal of Economic Perspectives*, 24(1):203–224.

Boeker, W. (1989). The development and institutionalization of subunit power in organizations. *Administrative Science Quarterly*, 34(3):388–410.

Chandler, G. N., Honig, B., and Wiklund, J. (2004). Antecedents, moderators, and performance consequences of membership change in new venture teams. *Journal of Business Venturing*, 20:705–725.

Chowdhury, S. (2005). Demographic diversity for building an effective entrepreneurial team: is it important? *Journal of Business Venturing*, 20:727–746.

Clarysse, B., Knockaert, M., and Lockett, A. (2007). Outside board members in high tech start-ups. *Small Business Economics*, 29(3):243–259.

Coad, A. (2009). *The growth of firms: A survey of theories and empirical evidence*. Edward Elgar Publishing.

Colombo, M. and Grilli, L. (2005). Founders' human capital and the growth of new technology-based firms: A competence-based view. *Research Policy*, 34(6):795–816.

Cooney, T. M. (2005). Editorial: What is an entrepreneurial team. *International Small Business Journal*, 23(3):226–235.

Cooper, A. C., Gimeno-Gascon, F. J., and Woo, C. Y. (1994). Initial human and financial capital as predictors of new venture performance. *Journal of Business Venturing*, 9:371–395.

Dahl, M. S. and Reichstein, T. (2007). Are you experienced? prior experience an the survival of new organizations. *Industry and Innovation*, 14(5):497–511.

Dahl, M. S. and Sorenson, O. (2012). Home sweet home: Entrepreneurs' location choices and the performance of their ventures. *Management Science*, 58(6):1059–1071.

Davidsson, P. and Honig, B. (2003). The role of social and human capital among nascent entrepreneurs. *Journal of Business Venturing*, 18:301–331.

Delmar, F. and Shane, S. (2006). Does experience matter? the effect of founding team experience on the survival and sales of newly founded ventures. *Strategic Organization*, 4(3):215–247.

Eisenhardt, K. and Schoonhoven, C. (1990). Organizational growth: Linking founding team, strategy, environment, and growth among U.S. semiconductor ventures, 1978-1988. *Administrative Science Quarterly*, 35(3):504–529.

Ensley, M., Carland, J., and Carland, J. (2000). Investigating the existence of the lead entrepreneur. *Journal of Small Business Management*, 38(4):59–77.

Ensley, M., Pearson, A., and Amason, A. (2002). Understanding the dynamics of new venture top management teams: cohesion, conflict, and new venture performance. *Journal of Business Venturing*, 17:365–386.

Ensley, M. D., Carland, J. W., and Carland, J. C. (1998). The effect of entrepreneurial team skill heterogeneity and functional diversity on new venture performance. *Journal of Business and Entrepreneurship*, 10(1):1–15.

Foo, M. D., Wong, P. K., and Ong, A. (2005). Do others think you have a viable business idea? team diversity and judges' evaluation of ideas in a business plan competition. *Journal of Business Venturing*, 20:385–402.

Forbes, D., Borchert, P., and Zellmer-Bruhn, M. (2006). Entrepreneurial team formation: An exploration of new member addition. *Entrepreneurship Theory and Practice*, pages 225–246.

Gartner, W. B. (1985). A conceptual framework for descriing the phenomenon of new venture creation. *The Academy of Management Review*, 10(4):696–706.

Gimeno, J., Folta, T., Cooper, A., and Woo, C. (1997). Survival of the fittest? entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly*, pages 750–783.

Hambrick, D., Cho, T., and Chen, M. (1996). The influence of top management team heterogeneity on firms' competitive moves. *Administrative Science Quarterly*, 41:659–684.

Hambrick, D. and Mason, P. (1984). Upper echelon: The organization as a reflection of its top managers. *The Academy of Management Review*, 9:193–206.

Harper, D. (2008). Towards a theory of entrepreneurial teams. *Journal of Business Venturing*, 23(6):613–626.

Harrison, D. and Klein, K. (2007). What's the difference? diversity constructs as separation, variety, or disparity in organizations. *The Academy of Management Review*, 32(4):1199–1228.

Hellerstedt, K., Aldrich, H., and Wiklund, J. (2007). The impact of past performance on the exit of team members in young firms: The role of team composition. Frontiers of Entrepreneurship Research 27 (11), article 2.

Hmieleski, K. and Ensley, M. (2007). A contextual examination of new venture performance: entrepreneur leadership behavior, top management team heterogeneity, and environmental dynamism. *Journal of Organizational Behavior*, 28(7):865–889.

Horwitz, S. (2005). The compositional impact of team diversity on performance: Theoretical considerations. *Human Resource Development Review*, 4(2):219–245.

Horwitz, S. and Horwitz, I. (2007). The effects of team diversity on team outcomes: A meta-analytic review of team demography. *Journal of Management*, 6:987–1015.

Jenkins, S. (1995). Easy estimation methods for discrete-time duration models. *Oxford Bulletin of Economics and Statistics*, 57(1):129–136.

Kamm, J., Shuman, J. C., Seeger, J., and Nurick, A. J. (1990). Entrepreneurial teams in new venture creation: A research agenda. *Entrepreneurship Theory and Practice*, Summer 1990:12.

McPherson, M., Smith-Lovin, L., and Cook, J. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27:415–444.

Murray, A. (1989). Top management heterogeneity and firm performance. *Strategic Management Journal*, 10:125–141.

Nanda, R. and Sørensen, J. (2010). Workplace peers and entrepreneurship. *Management Science*, 56(7):1116–1126.

Østergaard, C., Timmermans, B., and Kristinsson, K. (2011). Does a different view create something new? the effect of employee diversity on innovation. *Research Policy*, 40(3):500–509.

Pelled, L. H. (1996). Demographic diversity, conflict, and work group outcomes: An intervening process theory. *Organization Science*, 7(6):615–631.

Pelled, L. H., Eisenhardt, K., and Xin, K. (1999). Exploring the black box: An analysis of work group diversity, conflict, and performance. *Administrative Science Quarterly*, 44(1):1–28.

Pfeffer, J. (1983). Organizational demography. In Staw, B. and Cummings, L., editors, *Research in Organizational Behavior*, volume 5, pages 299–357. Greenwhich, CT: JAI press.

Romanelli, E. and Tushman, M. (1994). Organizational transformation as punctuated equilibrium: an empirical test. *Academy of Management Journal*, 37(5):1141–1166.

Ruef, M., Aldrich, H., and Carter, N. (2003). The structure of founding teams: Homophily, strong ties, and isolation among U.S. entrepreneurs. *American Sociological Review*, 68(2):195–222.

Schimmel, A. (1994). *The Mystery of Numbers*. Oxford University Press.

Shane, S. and Khurana, R. (2003). Bringing individuals back in: the effects of career experience on new firm founding. *Industrial and Corporate Change*, 12(3):519–543.

Stirling, A. (2001). A general framework for analyzing diversity in science, technology and society. *SPRU Working Papers 156*.

Stirling, A. (2007). A general framework for analysing diversity in science, technology and society. *Journal of the Royal Society Interface*, 4(15):707–719.

Storey, D. (1994). The role of legal status in influencing bank financing and new firm growth. *Applied Economics*, 26(2):129–136.

Ucbasaran, D., Lockett, A., Wright, M., and Westhead, P. (2003). Entrepreneurial founder teams: Factors associated with member entry and exit. *Entrepreneurship Theory and Practice*, Winter 2003:1042–2587.

Vanaelst, I., Clarysse, B., Wright, M., Lockett, A., Moray, N., and S'Jegers, R. (2006). Entrepreneurial team development in academic spinouts: An examination of team heterogeneity. *Entrepreneurship Theory and Practice*, 30(2):249–271.

Watson, W., Ponthieu, L., and Critelli, J. (1995). Team interpersonal process effectiveness in venture partnerships and its connection to perceived success. *Journal of Business Venturing*, 10:393–411.

Webber, S. and Donahue, L. (2001). Impact of highly and less job-related diversity on work group cohesion and performance: A meta-analysis. *Journal of management*, 27(2):141–162.

Wennberg, K., Wiklund, J., and Wright, M. (2011). The effectiveness of university knowledge spillovers: Performance differences between university spinoffs and corporate spinoffs. *Research Policy*, 40(8):1128–1143.

Williams, K. and O'Reilly, C. (1998). Demograhpy and diversity in organizations: A review of 40 years of research. In Staw, B. and Cummings, L., editors, *Research in Organizational Behavior*, pages 77–140. JAI Press, Greenwich.

8 Appendix

Table H.1: Summary statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
age i	3777	36.967	10.263	15	91
age j	3777	33.615	11.941	15	79
male i	3777	0.700	0.458	0	1
male j	3777	0.617	0.486	0	1
dane i	3777	0.881	0.324	0	1
dane j	3777	0.867	0.340	0	1
educ_level (i)	3678	1.997	1.097	1	5
educ_level (j)	3639	1.722	0.977	1	5
educ_type (i)	3777	0.387	0.900	0	3
educ_type (j)	3777	0.260	0.770	0	3
survival	3777	0.333	0.471	0	1
empl (t=5), November headcount	1259	4.563	5.310	0	88
empl (t=5), FTE	1259	3.223	3.919	0	60
turnover (100k DKK) (t=5)	892	50.597	114.642	0.960	2007.530
family firm: brother	3777	0.032	0.175	0	1
family firm: spouse	3777	0.073	0.261	0	1
family firm: mother	3777	0.030	0.170	0	1
family firm: father	3777	0.049	0.216	0	1
family firm	3777	0.184	0.387	0	1
2-digit industry experience (i)	3777	0.443	0.497	0	1
2-digit industry experience (j)	3777	0.387	0.487	0	1
4-digit industry experience (i)	3777	0.317	0.465	0	1
4-digit industry experience (j)	3777	0.262	0.440	0	1
same_school	3777	0.045	0.207	0	1
Copenhagen	3777	0.449	0.497	0	1