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ABSTRACT

Team Heterogeneity in Startups and its Development over Time*

We investigate the workforce heterogeneity of startups with respect to education, age and wages. Our explorative study uses data on the population of 1,614 Danish firms founded in 1998. We track these firms until 2001 which enables us to analyze changes in workforce composition over time. Such a dynamic analysis constitutes a hitherto neglected area of entrepreneurship research. To assess relative workforce heterogeneity, we construct a simulated benchmark to which we compare observed workforce heterogeneity. We find that the initial workforce is relatively homogeneous compared to our benchmark. Our result holds both for non-knowledge-based and, to a lesser extent, knowledge-based startups. This seems surprising since a vast management literature advocates heterogeneous teams. The difficulties associated with workforce heterogeneity (like affective conflict or coordination cost) as well as "homophily" (people's inclination to bound with others with similar characteristics) hence appear to generally overweigh the benefits of heterogeneity (like greater variety in perspectives or more creativity). We also document that workforces become more heterogeneous over time – startups add workers with skills different from the workforce at startup. The initial supposedly "poor" mix of workforce characteristics is hence adjusted as the startup matures. This increase in workforce heterogeneity is, however, smaller compared to our benchmark but substantially larger than is team additions had the same characteristics as the initial team members.

JEL Classification: C10, L26, M13

Keywords: entrepreneurship, start-ups, skill heterogeneity, team dynamics

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1 Introduction

Management scholars often emphasize the benefits of startup team heterogeneity for performance. These benefits include the consideration of a greater variety of options to solve problems (Amason et al. 2006; Beckman et al. 2007; Ensley et al. 1998; Zimmerman 2008) which should lead to fewer errors in decision making processes (Roure and Keeley 1990) and more innovation (Bantel and Jackson 1989; Ruef 2000; Wiersema and Bantel 1992; Østergaard et al. 2011). These advantages advocated by management theory are, however, not consistently reflected by the empirical studies (Brouwers et al. 2000; Coad and Timmermans 2012). We review these studies in Section 2.

Existing empirical work on team heterogeneity often focuses on a very narrowly defined and heavily selected sets of industries. In addition, the employment *dynamics*, the type of individuals that are added as team members or that are hired as employees are not well understood (Horwitz and Horwitz 2007; Ucbasaran et al. 2003). Indeed, Ucbasaran et al. (2003, p. 107) even speak about a "neglected" area in entrepreneurship research.

The main aims of our exploratory paper are threefold: first, we seek to document whether or not startup workforces are heterogeneous or homogeneous in terms of observed characteristics using a very comprehensive data set that tracks *all* startups in Denmark in 1998 for a period of three years. We hence provide evidence on a *population* of startups as opposed to often heavily selected samples previously used in the literature.[1] Given that we provide evidence for a very broad set of startups we hope to generate "stylized facts" which may subsequently be found helpful in informing management theory. Our final data set consists of 1,614 firms that were founded by teams. We separately consider "knowledge–based" startups and contrast them with other startups, defining startups as "knowledge–based" if they belong to a high-technology sector like high–tech manufacturing or technology-oriented services or, alternatively, if they were co-founded by at least one university graduate (or both).

Second, we seek to document what types of individuals startups take on board in the first years of their existence. Parker (2009) proposes a Bayesian learning model that considers two types of cognitive biases,

[1]Existing studies consider very high growth firms (Ensley et al. 1998; Kamm et al. 1990), firms founded by US MBA graduates (Ruef 2000), high technology firms (Clarysse and Moray 2004; Eisenhardt and Bird Schoonhoven 1990; Higgins and Gulati 2003; Roberts 1991; Roure and Maidique 1986; Shrader and Siegel 2007), firms that eventually went public (Zimmerman 2008), venture capital backed firms (MacMillan et al. 1985; Zacharakis and Meyer 1998) and university spin–offs (Forbes et al. 2006; Vanaelst et al. 2006). Ruef et al. (2003) provide a critical discussion of existing empirical sociological studies of team assembly.

overoptimism and self-serving attributions, and that imply that teams tend to be founded by homogeneous founders and that founders' choices are state–dependent, i.e. their "poor" (given the positive link between team heterogeneity and firm performance that many management scholars suggest) initial team member choices are reinforced or may even become more pronounced over time. Our paper provides empirical regularities on state–dependence in startup workforce formation.

Third, we offer a methodological innovation to the literature on startup team heterogeneity by suggesting a benchmark for heterogeneity. The definition of a benchmark is important since we would otherwise not be able to discuss if workforces were "heterogeneous" or "homogeneous". Our benchmark allows us to determine degree of workforce heterogeneity. A natural choice is a random assembly of startup workforces among the individuals we observe in our data, which we refer to as "random matching" hereafter. Our benchmark simulation approach basically comes down to writing down the names of each startup workforce member in our data on slips of paper, mixing them up, and throwing them into buckets (where each bucket represents firms of the original sample in terms of workforce size and sector of economic activity). The names of the initial startup members in each bucket constitute randomly assembled startup teams, representing the distribution of all possible startup teams. We subsequently compare the characteristics of those randomly generated startup teams to the characteristics of the team members we actually observe in our data. We describe our method more thoroughly in Section 5.[2]

We also employ a broader and more inclusive definition of team foundations compared to existing studies: startups are team ventures if they are founded by at least two individuals. We consider both the original founder and her first manager(s) as well as rank–and–file employees as "founding" members of the startup. The great majority of new firms start very small which means that workers, founders, and employees will all have a substantial impact on strategic decisions, a conjecture we share with Dahl and Klepper (2008), Laursen et al. (2005) as well as Østergaard et al. (2011) who, like us, are unable to differentiate founders from employees.

A paper close to ours in terms of methodology and content is Ruef et al. (2003) who focus on the actual combination of team members in terms of gender and ethnicity (e.g. male/male, male/male/female,

[2] Our methodology is best compared to Ellison and Glaeser's (1997) "dartboard approach" of geographic industry concentration. Their thought experiment is to write down the identity of each firm in their data on a dart and to throw these darts on a map of the US, thereby generating a random distribution of firms across the US which they compare to the actual and observed distribution of firms.

female/female, female/female/male etc.). They find that homophily — "the tendency of agents to associate disproportionately with those having similar traits" (Golub and Jackson 2012, p. 1287) — and network constraints — the presence of prior ties to team members like family membership —, are the main determinants of team assembly. Ruef et al.'s (2003) benchmark is the unconditional theoretical probability that a team with a particular composition is observed. They base their probability calculations on a Poisson distribution. The main methodological difference to our approach is that ours does not involve the prediction of any probabilities and that we therefore do not need to make any distributional assumptions — our approach is non–parametric. We hence do not risk biased simulation results caused by a potential mis-specification of the underlying probability distribution. In terms of content, we differ from Ruef et al. (2003) by studying workforce heterogeneity across technology–based and non technology–based firms while they do not distinguish different types of startups. They also do not analyze the development of startup workforce heterogeneity over time.[3]

Teams may be heterogeneous in various dimensions. We characterize startup workforces by an "ascribed" (Forbes et al. 2006) characteristic, namely age, and an "achieved" characteristic, namely education. We choose these two characteristics since they received considerable attention in the literature. We also introduce a hitherto unexplored measure of heterogeneity to the team diversity literature — differences in wages workforce members received prior to joining the startup. This measure condenses a wide range of ascribed and achieved characteristics of individuals like labor market experience, gender, education or tenure that individuals possess in a single variable (Heckman et al. 2003; Mincer 1958).

Our main findings are that (i) the workforce of startups is systematically assembled and that (ii) startup workforce members are systematically added as the business ages. Moreover, we show that (iii) startup workforces are statistically significantly less heterogeneous than under our simulated benchmark. We also show that (iv) startup workforces with university graduates tend to be somewhat more heterogeneous compared to startup workforces without university graduates while there is no difference between startup workforces from knowledge–based and non–knowledge–based sectors, and that (v) startup workforces become statistically significantly more heterogeneous in terms of member characteristics over time. They do, however, (vi) become less heterogeneous than if members were randomly added but become substantially

[3]In addition, Ruef et al. (2003) base their analysis on data on "nascent" entrepreneurship while we consider actual startups.

more heterogeneous than if founding workforce members hired people with skills identical to their own. Finally, (vii) startups from knowledge–based sectors become more heterogeneous over time compared to startups from other sectors while startups that involve university graduates become less heterogeneous relative to startups that did not involve university graduates. We discuss this discrepancy in Subsection 6.2.

Given that management theory tends to advocate team heterogeneity as beneficial to firm performance, our finding of comparatively little team heterogeneity may seem surprising. Our results indicate that the gloomy side of team heterogeneity such as increased communication costs and conflict may compensate the associated advantages in reality. Another related explanation of our findings is homophily. Social scientists explain homophily with the lack of access to individuals with characteristics different from their own (Aldrich and Kim 2007; Byrne 1971; Coleman 1988; Ruef et al. 2003) while Parker (2009) identifies cognitive biases in founders' belief as the key source of homophily.

Management theory that concerns itself with startup team assembly would therefore probably benefit from being integrated with theories of homophily rooted in sociology in order to become aligned with the empirical regularities we find in our representative data set. We hope to provide a solid empirical fundament for such theoretical endeavors.

The paper is organized as follows: We first review the existing management literature on team heterogeneity and team dynamics in Section 2. We describe our data in Section 3, define our measures of heterogeneity in Section 4, explain our "random matching" approach in Section 5 and discuss our empirical results in Section 6. Section 7 concludes.

2 Existing studies

In this section, we review the existing body of literature related to the (i) heterogeneity of teams with respect to education, age and prior wages and (ii) changes in team heterogeneity as startups mature. We first discuss team heterogeneity in general terms before turning to the specific team heterogeneity measures we adopt.

2.1 Affective and cognitive conflict

The main issue in the context of team heterogeneity discussed in the management literature is conflict. Conflict is seen both as a promoter of creativity and as a source for animosity and resentment (Ensley et al. 2002). It is more likely to occur if values and personal backgrounds of the acting individuals are different (Jehn 1994) and if joint social interaction norms are lacking (Amason and Sapienza 1997). Such interaction norms may be more different the more heterogenous the characteristics of the team members are.

The literature distinguishes between "cognitive conflict", the "sharing and developing of ideas through cognitive tug and pull" (Ensley and Pearce 2001 p. 146) which is "stimulated when top managers scrutinize one another's perspectives in an effort to extract and combine the best elements of each" (Amason and Schweiger 1994, p. 246) and "affective conflict" which is more emotive in nature and which is shown to harm the establishment of strategic consensus (Knight et al. 1999).

Cognitive conflict promotes organizational success (Amason and Sapienza 1997; Bunderson and Sutcliffe 2002; Hambrick et al. 1996; Hambrick and Mason 1984, Kilduff et al. 2000) as it avoids group think, induces people to reconsider their suggestions, generates a variety of perspectives (Miller et al. 1998; Simons et al. 1999), and leads to more creativity (Ensley et al. 2002; Smith et al. 1994).

Affective conflict is demonstrated to have negative consequences for organizational success. It is detrimental to strategic decision making and blocks strategic change (Knight et al. 1999; Lant et al. 1992; Wiersema and Bantel 1992).

One can, however, not stimulate cognitive conflict without simultaneously increasing affective conflict since they constitute the two sides of the same coin or, as Amason and Schweiger (1994, p. 246) phrase it, "cognitive conflict inadvertently produces affective conflict". Prior research has documented that the two types of conflict indeed often occur simultaneously (Baron 1988; Brehmer 1976; Cosier and Rose 1977; Ensley et al. 2002; Pelled 1996; Pelled et al. 1999; Tjosvold 1985) and that there are significant links between them (Amason 1996; Jehn 1995, 1997).

While management theory has not come to a unique verdict with regards to the mapping between team heterogeneity and firm performance, a comprehensive review and meta–analysis of the related empirical literature by Brouwers et al. (2000) shows that team heterogeneity does not have clear-cut effects on performance but that team heterogeneity appears to further performance for high–difficulty tasks. By contrast, heterogeneity does not matter for low–difficulty tasks. We hence speculate that team heterogeneity is larger in knowledge–based startups, as there are likely to be more high–difficulty than low–difficulty tasks to be performed, than in other startups. This essentially is the only hypothesis we are able to formulate given the contradictory results generated by existing empirical studies on team heterogeneity reviewed below.

Subsection 2.2 surveys existing empirical studies that investigate age and education heterogeneity in teams. It also discusses our new heterogeneity measure, wages. Subsection 6.2 reviews the existing literature on the dynamics of heterogeneity in teams.

2.2 Heterogeneity in education, age and prior wages

Research on educational heterogeneity and firm performance

Starting with existing studies dealing with heterogeneity in education and firm performance, Bantel (1993) claims that educational heterogeneity adds variety in perspectives, Wiersema and Bantel (1992) relate educational heterogeneity to diversity in cognitive perspectives and Tihany et al. (2000) find that educationally more diverse teams are better equipped to handle complex decision making situations for their sample of 126 US electronics industry firms. Zimmerman (2008) shows that diversity in terms of education significantly increases capital raised at IPO for a sample of 243 US software firms. Likewise, Amason et al. (2006) find that educational heterogeneity of startup teams is weakly positively related to firm performance in their sample of 174 "high potential" new ventures.

An influential study by Roure and Keeley (1990) analyzes the mapping between team heterogeneity in terms of prior experience and firm performance using a sample of 36 "high potential" new ventures, finding weak evidence for positive effects of that type of heterogeneity on financial performance. Beckman et al. (2007) come to similar conclusions for their sample of 161 Silicon Valley high technology startups and their success measure Initial Public Offering.

Coad and Timmermans (2012), who basically use the same data set as we do, study the relationship of alternative combinations of founding team member characteristics on the employment growth and survival of dyad (two–person) teams. They find that differences in age between the two team members improve startup performance.

These positive findings do contrast, however, with Ensley et al. (1998) who document negative effects of educational team heterogeneity on firm performance for a sample 88 fast growing US firms. Ensley et al. (2001) come to a similar conclusion for 70 Inc. 500 firms. They speculate that affective conflict frequently dominates cognitive conflict.

Most studies hence indicate that there exists a positive, albeit often statistically insignificant relationship between team heterogeneity.

It seems plausible to observe more heterogeneity in education for knowledge–based startups since cognitive conflict appears to be more important for such firms to solve problems that arise in the R&D process as well as in production and distribution of the final product. Cognitive conflict is more likely to dominate affective conflict in such a setting. Indeed, Bantel and Jackson (1989) show that educational heterogeneity is positively related to innovation in the banking sector. In a similar vein, Østergaard et al. (2011) use survey data for incumbent firms combined with Danish register data similar to ours to document a positive relationship between educational diversity and innovative performance.

Research on age heterogeneity and firm performance

Richard and Shelor (2002) use differences in team age as a proxy for differences in perspectives, belief systems and social networks which should all improve organizational performance. The intuition here is similar to Williams and O'Reilly (1998) who argue that age heterogeneity provides better access to sets of information and perspectives which enhances group decision making. The potential that these types of cognitive conflict entail is, however, countered by an increase in affective conflict since differences in age make communication and social integration more difficult. Kilduff et al. (2000), Richard and Shelor (2002) as well as Wiersema and Bantel (1992) find a positive correlation between age heterogeneity in teams and firm performance. Bantel (1993) does, however, find only little empirical support for age heterogeneity being positively related to strategic clarity and thus firm performance. Coad and Timmermans (2012) provide evidence for a positive relationship between age differences among team members and firm performance.

Age heterogeneity may be more important for knowledge–based startups since younger managers are associated with trying the new and risky (Boeker, 1988; Hambrick and Mason, 1984; Wiersema and Bantel, 1992) and since they are also better equipped to understand recent innovations as well as the associated opportunities and threats (Boeker 1988). At the same time, pulling off a new–technology–startup may require a substantial amount of industry experience (Shane and Stuart 2002). Combining both young and old workers, hence may improve firm performance in particular for knowledge–based firms, a claim that is empirically substantiated by Bantel and Jackson (1989). With these pieces of evidence and the results by Brouwers et al. (2000) in mind we expect team heterogeneity to increase more in knowledge–based startups than in other firm foundations.

Previous wages

Formal education and age only capture a fraction of the set of skills that determine an individuals' ability that is relevant for firm performance. Ever since Mincer (1958), researchers have related wages to observed worker characteristics like education and age — that we study separately — but also to other variables like tenure, labor market experience, gender, sector of employment etc. Wages hence combine a wealth of information and thus constitute a heterogeneity measure that takes into account the multi–dimensionality of worker characteristics. Moreover, when regressing observed worker characteristics on observed wages, a large fraction of the observed wages remains unexplained (Heckman et al. 2003). This fraction relates to unobserved characteristics of the workers which implies that considering wages as a team member demographic also accounts for skills that otherwise would go unnoticed.

Previous wages, or rather their standard deviation across team members, have not yet been used to measure team heterogeneity in startups before. Following the arguments in the beginning of this section, greater heterogeneity in prior wages will, however, increase both cognitive and affective conflict since they reflect differences in characteristics of team members. Affective conflict associated with differences in prior wages hence appears to dominates cognitive conflict which leads us to expect to observe that actual team heterogeneity is larger than our benchmark.

2.3 The dynamics of founding teams

The preceding paragraphs all dealt with founder heterogeneity at startup. However, startups evolve over time and may change team members and workforce. Our analysis to follow takes a "dynamic team perspective" (Vanaelst et al. 2006) that we subsequently take to the data. We find this issue particularly important since existing studies have underscored the importance of team additions on organizational performance

(Forbes et al. 2006) but have not analyzed dynamic teams beyond case studies.

In work most closely related to our analysis, Vanaelst et al. (2006) analyze ten university spin-outs and find that new team members tend to have a background different from the background of the initial team members, i.e. team heterogeneity increases over time.

In other related work on team development over time Dahl and Klepper (2008) show that firms that later turn out to be successful consistently pay higher wages from the beginning, thereby attracting the most capable workers. This hiring policy leads to what Dahl and Klepper term "enduring firm capabilities" (p. 26). However, they do not make statements regarding team heterogeneity and its development over time.

Forbes (2005) describes adding team members as a process where resource–seeking aspects and interpersonal attraction are important. Interpersonal attraction is likely to dampen affective conflict while the resource–seeking aspect relates to complementary skills and knowledge that a new team member brings about. Any lack of complementary skills may become more apparent to the initial founding team as their startup gets closer to market and as it grows.

This is in contrast to Parker's (2009) theoretical model of Bayesian learning where cognitive biases prevents team members from adding new members with different skills. Teams therefore become more homogeneous as they grow older.

An alternative and more menial explanation for a possibly decreasing team heterogeneity may simply be that work becomes more routinized as startups become older so that cognitive conflict may no longer be of particular importance.

It appears to be difficult to a priori assess whether we should expect to observe stronger or weaker changes in team heterogeneity for knowledge–based startups. Knowledge–based startups may need to be founded by heterogeneous teams as the product or service as well as its marketing and logistics may need complementary skills (Colombo and Piva 2012). On the one hand, these startups may therefore be more heterogeneous right from the start and may not need to add further team members with characteristics different from the characteristics of the initial founders. On the other hand, these firms may need to learn about the complexity of their product or service over time and they may later realize gaps in their skills portfolio.

3 Data

While existing studies, in particular the stack of case studies, often can go into great depth, they are unable to make generalizable statements. This makes Vanaelst et al. (2006, p. 268) close their paper by writing that there "would appear to be scope for more large-scale testing of the insights generated in this article".

The data set we use does not only differ from existing studies in terms of size. It is also different in terms of representativity — our data constitute a population, all startups in a given year, while existing studies are based on samples.

The data is provided to us by Statistics Denmark, Denmark's federal statistical office. It constitutes register data and covers the whole population of firms set up in Denmark in 1998. These firms are tracked until the end of 2001.

We link the information on startups with an employee–level data set, the so–called "IDA" data, that contains information about the characteristics of the founders and the employees working in the startup. IDA, previously used i.a. by Bingley and Westergaard–Nielsen (2003), Dahl and Sorenson (forthcoming) as well as Dahl and Klepper (2008), covers a wide range of variables on the total Danish population from 1980 onwards. The time series dimension of the data allows us to track founders and employees over time. Timmermans (2010c) provides an excellent review of the IDA data.

Our full data set contains information on 14,171 startups, the founder(s) and the employees working in these startups. Following Timmermans (2010a, 2010b), we verify that our startups are actual startups by checking whether the corresponding firm identifiers existed in previous years. More importantly, we also discard firms for which we were able to find corresponding plant identifiers in previous years. We identify a total of 1,614 team foundations. These figures suggest that Gartner et al.'s (1994) claim that "the management of new ventures generally constitutes a shared effort" may actually not hold for more representative data sets as ours.

Table 1 displays descriptive statistics of our data set. It differentiates between startups that are knowledge–based and those that are not. We use four definitions for knowledge–based startups. The first is based on the startups' industrial classification. To define sectors of economic activity as knowledge–based we use a definition developed by the Centre for European Economic Research. According to this definition all sectors in which R&D, new knowledge and human capital play an important role are considered as knowledge–based. The Appendix provides a summary of our classification. Our second definition is that firms are knowledge–based if at least one founder holds a university degree. Third, we narrow this definition down by focusing on university graduates from a "relevant field", i.e. from technical or natural sciences, veterinary or agricultural sciences, and health sciences (except general practitioners and hospitals), following Kaiser et al. (2011). Since even graduates with a university degree in a relevant field may found a restaurant instead of a knowledge–based, high growth startup we finally, and similar to Timmermans (2010b), consider foundations of university graduates *and* in sectors that we identified as knowledge–based.[4]

Table 1 shows that team foundations constitute a small minority across all sectors and type of startup. Startups from consumer–oriented services and the construction sector are most often founded by teams. The respective share of team startups is 18 percent here. The lowest fraction of team foundations is in knowledge–intensive services (excluding non–technical consulting services). These differences in the share of team foundations may be due to differences in labor intensity and entry costs. There are no systematic differences between startups from knowledge–based and non knowledge–based sectors. Startups with university graduates and startups from knowledge–based sectors are at least, however, as often founded by teams as the average startup. Regarding the number of team members, we find that knowledge–based startups tend to be founded by more team members than the average startup.

4 Measurement

Our study involves various measurement issues that are related to the definition of our main heterogeneity variables that we discuss in the following.

Age and previous wages are continuous variables. To measure team heterogeneity we use the respective standard deviations across the team members, following Ensley and Pearce (1990).

For the categorial variable education a calculation of standard deviations is not meaningful which is why we, consistent with Clarysse and Moray (2001), Teachman (1980) Ucbasaran et al. (2003), Vanaelst et

[4]Restricting attention to university graduates *in relevant fields* and in sectors that we identified as knowledge–based did lead to a substantial decrease in the number of teams which is why we discard a separate analysis.

al. (2006) as well as Wiersema and Bantel (1992), use the Blau-index instead. The Blau-index is calculated as one minus the sum of the squared shares of team members with education k, s_k: $B = 1 - \sum_{k=1}^{n} s_k^2$, where the summation over the squared shares constitutes the Hirschman-Herfindahl concentration index that is frequently used in Industrial Organization and n defines the number of team members. The more homogeneous teams are, the closer the Blau-index gets to $1/n$ and it approaches 1 the more heterogeneous teams are.

An important measurement issue relates to the values of the Blau-index being dependent on the number of individuals in the team. For two team members, the index either takes on the values one or $\frac{1}{2}$. For three team members the set of possible values is 1, $\frac{5}{9}$ and $\frac{1}{3}$. To correct for team size, we scale the Blau index as follows:

$$B^{tr} = \frac{n}{n-1}(1 - \sum_{k=1}^{n} s_k^2) \quad \in [0, 1]. \tag{1}$$

The transformed Blau-index takes on the value zero if all team members have the same education and is one if each individual attained a different education.

5 Random matching

Blau-indices and standard deviations do not per se provide much information about the degree of heterogeneity in the teams. The reason is that there is no natural reference level providing a basis to decide whether a particular value of the measures means that the heterogeneity is low, high, or average. We therefore construct a reference by using simulation methods. We test whether the observed degrees of heterogeneity are statistically significantly different from the degree of heterogeneity in a situation where teams are randomly assembled. Thus, our benchmark is a situation where founders do not systematically look for teammates. This allows us to gather information about both whether the search for teammates occurs systematically and in which direction the search is carried out (similar/more homogeneous or dissimilar/more heterogeneous). If individuals systematically look for team mates, the observed team heterogeneity is statistically significantly different from the randomly generated team heterogeneity. If the observed heterogeneity is statistically significantly larger than the simulated heterogeneity, teams systematically add individuals who are are different from themselves.

To generate a random distribution of team characteristics we first select all individuals of a given sector and randomly assign them to firms, thereby maintaining the actually observed team size of firms. Thus, we generate sector–specific and team size–specific random teams. We subsequently calculate our measures of team heterogeneity, average them to the sector and team size level and store the corresponding heterogeneity measures. This procedure is carried out 1,000 times in total which generates a random distribution of team heterogeneity. We term this benchmark "random matching" and compare it to the actual distribution of team heterogeneity we observe in our data.

To analyze the dynamics of team heterogeneity we compare teams before and after individuals joined or left a startup. We calculate the differences in heterogeneity before and after the team composition changed. We also compare it to an identical situation where team members are added or subtracted in a sector–specific and team size–specific random way.

The random assignment of new team members to firms mimics a situation where firms do not at all search systematically for individuals and hence constitutes an extreme case. At the other extreme, firms may systematically search for teammates but focus on individuals which are identical to themselves, i.e. they try "cloning" themselves with respect to education, age or wages. We consider this situation of "random cloning" as a second benchmark that we also compare to the changes in team heterogeneity we observe in our data.

6 Results

Our results fall into two parts. The first relates to team heterogeneity at startup while the second is concerned with the dynamics of team heterogeneity.

6.1 Team heterogeneity at startup

Table 2 displays actual observed and simulated team heterogeneities at startup. It differentiates between knowledge–based and non–knowledge–based startups as discussed in Section 3.

Table 2 shows that team founders both systematically look for team members — the observed team heterogeneity is statistically significantly different compared to the benchmark — and that team heterogeneity is statistically significantly *lower* than if teams were randomly assembled. This is at odds with management theory that advocates team heterogeneity.

The quantitative differences between actual heterogeneity and our benchmark are most substantial for team age where actual and simulated standard deviations differ by as much as 28.2 percent. It is less pronounced for education and wages the difference is around twelve percent.

Knowledge–based manufacturing startups are unsurprisingly among the most heterogeneous in terms of education, wages and age which is fully consistent with our prior put forward in Subsection 2.1. This is partly also true for startups that involve university graduates where, however, age heterogeneity is fairly low. We speculate that this observation may be explained by cohorts of university graduates founding a startup, probably after the idea behind the new firm was incepted at university. In fact, for university graduates in relevant fields we actually find no differences in terms of wages between observed and random team assembly.

Startups from construction are among the firms with the lowest heterogeneity in general. This results coincides very well with the meta–analysis provided by Brouwers et al. (2000).

In Table 3 we show the results of tests that directly contrast the degree of heterogeneity between knowledge–based and non-knowledge–based start-ups. One problem in such analyzes is that the distribution of the measures of heterogeneity under the null hypothesis can only be analytically derived for a given team size.[5] We therefore separately consider firms with two team members (upper part of Table 3) and for firms with more than three team members (lower part of Table 3).[6]

While Table 3 generally shows that knowledge–based startups are more heterogeneous than non-knowledge–based startups, these differences are statistically insignificant in most cases. There are a few exceptions: for two-person-teams we find statistically significantly differences in the degree of heterogeneity with respect to wages between startups with and without university graduates. For three-person-teams we tend to find more heterogeneity in terms of education for knowledge–based startups. However, for the heterogeneity with respect to age we find a significantly *lower* degree of heterogeneity in knowledge–based startups in three-person teams.

[5] This is another reason why we apply simulation methods to evaluate the degree of heterogeneity.

[6] By applying simple t-tests we treat the measures of heterogeneity as continuous variables implying that we assume the test statistics follow t-distribution under the null hypothesis.

We hence find very little evidence for actual team heterogeneity being larger than under our benchmark. We do, however, find weak support for our hypothesis that knowledge–based startups employ a more heterogeneous workforce than startups that are not knowledge–based.

6.2 The dynamics of team heterogeneity

Table 4 displays changes in workforce heterogeneity before and after a new workforce member was added. The key finding of that table is that team heterogeneity increases over time. Compared to team heterogeneity before new team members joined the firm all heterogeneity measures we consider increase by around 50 percent. Note that this is not an artifact caused by the fact that some startups may have grown considerably after foundation. This is so since our benchmark indeed compares apples and apples, namely teams that add/substract the exact same amount of team members.[7]

How do these observed changes compare to our two hypothetical situations where additional team members are randomly matched (column "With random assignment") or where they constitute clones of the existing team members ("With random cloning")? The table shows that the observed changes in team heterogeneity are substantially and statistically significantly larger than under the hypothetical situation of random cloning. The observed changes are, however, statistically significantly smaller than if team members were randomly added. This means that individuals actually look for other individuals with characteristics different from their own, but compared to a situation of random assignment they tend to systematically choose additions with similar characteristics.

We again find quite substantial relative differences between startups from knowledge–based and non knowledge–based sectors. Startups in knowledge–based sectors are among those where heterogeneity increases the most, with knowledge–based service firms being the main drivers behind this pattern. Other business related services constitutes an exception from this rule.

While we document that team heterogeneity among startups in knowledge–based sectors has increased more than among non–knowledge–based startups, we come to a somewhat different conclusion for startups with and without university graduates. In both startups types team heterogeneity substantially increases. However, this increase is considerably smaller for startups that involve university graduates which seems

[7] In addition, even if our benchmark did not take differences in net team additions into account, our figures would still be meaningful since these additions could both increase or decrease team heterogeneity.

to contrasts with our result that startups from knowledge–based sectors increase team heterogeneity more than startups from other sectors. This is also true for startups that involve university graduates from relevant fields in knowledge–intensive sectors. Colombo and Piva (2012) provide a theoretical explanation for our finding. Their graphical model predicts that academic technology–based startups rather add team members with technical than with commercial skills compared to academic non-technology–based startups. This in turn implies that heterogeneity in education increases to a lesser degree for academic compared to non–academic startups, an implication that both our study and Colombo and Piva's (2012) own empirical analysis on Italian technology–based startups support.

The absolute differences between knowledge–based and non–knowledge–based firms along with tests for statistical significance of those differences are shown in Table 5. These tests are based on observed changes and indicate that the differences between knowledge–based sector firms and other firms are also statistically highly significant for education and wages. Differences in age heterogeneity are statistically insignificant. The table also shows that the differences in changes in observed heterogeneity are statistically significant for all heterogeneity measures for startups with university graduates.

7 Conclusions and implications

Existing management theory advocates that startups are to be founded by individuals with heterogeneous skills, arguing that varieties in perspectives enable teams to take decisions that foster startup performance. However, team heterogeneity may go along with "affective conflict", i.e. destructive conflict, that may arise because individuals who need to reach a joint decision have different characteristics. These negative effects may lead founders to associate with individuals of similar characteristics rather than with individuals with individuals of different characteristics which leads to team "homophily" rather than team heterogeneity.

While existing studies of team heterogeneity are generally based on highly selective samples, we provide evidence for an entire *population* of startups. We identify 1,614 team foundations across all sectors in Denmark in 1998. We trace those startups until 2001 which enables us to team dynamics as well. We use education, age and previous wages as indicators of team heterogeneity. Our use of previous wages is novel. It combines a wealth of information on an individual's characteristics like education, experience or tenure in a single measure.

In order to be able to assess if team heterogeneity is large or small we compare observed team heterogeneity to a benchmark which is the random distribution of possible team assemblies based on characteristics of the team members.

We find that observed heterogeneity differs statistically significantly from the heterogeneity we generate in our benchmark situation. This means that founders systematically look for fellow team members. They do, however, tend to look for individuals who have similar characteristics as themselves — the degree of heterogeneity is statistically significantly smaller compared to our benchmark. These first two findings hold for both knowledge–based and non–knowledge–based startups. However, knowledge–based startups tend to be more heterogeneous in characteristics than other startups.

The findings contrast with management theory's view that more team heterogeneity is better — if that indeed was the case, we should observe more heterogeneity in our data.

Our results are, however, consistent with Parker's (2009) learning model where homogeneous founders bound together because they are overoptimistic and possess self–serving attributes — individuals sharing similar beliefs are taken on board since founders believe that they thereby improve firm performance, a cognitive bias that is reinforced by self–serving attributes. Parker (2009) also finds that "informed outsiders" may have a positive impact on founders' decision to establish a heterogeneous venture team, thereby improving the startups' future performance.

Another explanation for our finding of relative homogeneity may be found in social network theory which identifies limited access to co–founders as the main source of homogeneity (Aldrich and Kim 2007; Coleman 1988; Ruef et al. 2003).

The model proposed by Parker (2009) also predicts that homogeneity is state–dependent: founders do not learn from their initial allegedly suboptimal startup team composition. They update information regarding firm performance in a self–serving manner and add team members in a way that generates ever more homogeneous teams. Our empirical findings do not subscribe to this model prediction as our data suggest that while team heterogeneity initially is comparatively low, we do observe a fairly substantial increase in team heterogeneity over time. Team heterogeneity in terms of education, previous wages and age increases by around 50 percent. It does, however, increase statistically significantly less than if team members were randomly added. At the same team, team heterogeneity increases substantially (and statistically significantly) more compared to a situation where added team members had exactly the same characteristics as the initial founding team members. Thus, founders both systematically add team members and add individuals that possess somewhat different characteristics than themselves. They hence appear to indeed learn from their initially — and according to management theory — “poor” team composition.

While team heterogeneity increases in all types of startups over time we find that in startups from knowledge–based sectors, like knowledge–based manufacturing or technology-intensive services, team heterogeneity increases statistically significantly more than in startups from non–knowledge–intensive sectors. We come to opposite conclusions for startups that involve university graduates, even if they start a firm in a knowledge–intensive sector. This is consistent with Colombo and Piva (2012) whose model predicts that these types of startups rather add team members with technical than with commercial skills.

Our paper shows that teams are founded by individuals with comparatively similar observable characteristics. Possible explanations for our results are put forward by cognitive biases affecting team selection and by network theory. It remains to be unresolved which theory more accurately predicts the empirical regularities we find in our large and representative data set. If it is indeed network theory, the inability of individuals to find partners with different characteristics this would provide scope for “entrepreneurial matching markets” where potential entrepreneurs with different skills would, for example, be brought together at startups camps organized by universities or government agencies.

Integrating existing management theory on team heterogeneity with network theory, which is rooted in sociology, and theories of cognitive bias, would probably generate theoretical evidence that may be able to explain the empirical regularities we find. We hope that our paper constitutes an empirically firm foundation for such theory building.

The present paper sought to generate stylized facts on team heterogeneity and the dynamics of team heterogeneity. Studying the performance effects of team heterogeneity using a representative data set like ours appears as an attractive subject of future research.

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Table 1: Descriptive statistics

	Number of firms	**Share of teams (in %)**	**Average team size in startup year**
All firms	14,608	11.4	4.3
Firms in knowledge–intensive sectors			
High-tech manufacturing	137	14.6	5.6
Technology-intensive services	1,881	5.2	3.6
Knowledge–intensive services	946	5.5	3.9
Firms in non–knowledge–intensive sectors			
Non-high-tech manufacturing (non-technical consulting services)	754	14.7	6.4
Other business oriented services	2,167	6.1	4.6
Consumer-oriented services	2,579	17.8	4.5
Construction	1,720	18.4	4.0
Wholesale and retail trade	4,424	10.7	3.8
Firms with university graduates	2,569	11.7	5.5
Firms w/o university graduates	11,495	10.6	3.8
Firms w/ university graduates in relevant fields	957	13.6	6.2
Firms w/o university graduates in relevant fields	13,097	10.5	4.0
Firms w/ university graduates in knowledge–intensive sectors	1,157	9.0	4.4
Firms w/o university graduates in knowledge–intensive sectors,2[1]	12,907	10.9	4.2

Table 1 displays basic descriptive statistics of our data. Differences in the total number of firms are due to missing information in the education variable.

Table 2: Heterogeneity in startup year

	Education		**Age**		**Wages**	
	Observed	With random assignm.	Observed	With random assignm.	Observed	With random assignm.
	(1)	(2)	(3)	(4)	(5)	(6)
All team startups	0.855	0.953***	8.409	10.167***	0.273	0.309***
Firms in knowledge–intensive sectors	0.861	0.961***	7.838	9.377***	0.281	0.312***
High-tech manufacturing	0.905	0.964*	10.628	11.298	0.303	0.380***
Technology-oriented services	0.859	0.974***	7.091	8.086***	0.270	0.291
Knowledge–intensive services	0.849	0.936***	8.174	11.072***	0.294	0.326*
Firms in non-knowledge–intensive sectors	0.855	0.952***	8.475	10.258***	0.272	0.309***
Non-high-tech manufacturing	0.874	0.946***	9.607	11.961***	0.275	0.313***
Other business oriented services	0.921	0.965***	8.495	9.800***	0.309	0.336**
Consumer-oriented services	0.860	0.949***	8.235	9.954***	0.277	0.331***
Construction	0.771	0.939***	8.194	9.971***	0.235	0.278***
Trade	0.883	0.960***	8.624	10.475***	0.280	0.301***
W/ univ. grad.	0.912	0.975***	8.072	10.477***	0.298	0.317***
W/o univ. grad.	0.839	0.946***	8.381	10.082***	0.263	0.307***
W/ univ. grad. in rel. field	0.890	0.977***	8.098	10.265***	0.296	0.319**
W/o univ. grad. in rel. field	0.849	0.950***	8.356	10.156***	0.267	0.308***
W/ univ. grad. in knowl.–intens. sectors	0.885	0.976***	7.407	9.197***	0.295	0.303
W/o univ. grad. in knowl.–intens. sectors	0.851	0.951***	8.387	10.272***	0.268	0.310***

Table 2 displays our heterogeneity measures for education, previous wages and age in the year the startup was founded. It contrasts observed heterogeneity with our benchmark, heterogeneity under random assignment. The asteriks "***", "**" and "*" indicate if the observed heterogeneity is statistically significantly different from the benchmark at the one, five and ten percent marginal significance level.

Table 3: Differences in heterogeneity between knowledge–based and non–knowledge–based firms in startup year

Teamsize of two						
		Firms in knowledge–intensive sectors	Firms in non–knowledge–intensive sectors	Pearson's $\chi^2(1)$	t-value	p-value
Education	Blau-Index = 0	0.153	0.212	1.392		0.238
	Blau-Index = 1	0.847	0.787			
Age	Standard deviation	7.267	7.533		-0.325	0.745
Wages	Standard deviation	0.273	0.249		0.866	0.387
		Firms w/ university graduates	Firms w/o university graduates	Pearson's $\chi^2(1)$	t-value	p-value
Education	Blau-Index = 0	0.105	0.165	2.054		0.152
	Blau-Index = 1	0.895	0.835			
Age	Standard deviation	6.898	7.555		-0.866	0.807
Wages	Standard deviation	0.296	0.245		1.938	0.053
		Firms w/ university graduates in relevant fields	Firms w/o university graduates in relevant fields	Pearson's $\chi^2(1)$	t-value	p-value
Education	Blau-Index = 0	0.162	0.156	0.008		0.928
	Blau-Index = 1	0.838	0.843			
Age	Standard deviation	7.071	7.490		-0.378	0.647
Wages	Standard deviation	0.272	0.250		0.579	0.563
		Firms w/ university graduates in knowl.-intens. sectors	Firms w/o university graduates in knowl.-intens. sectors	Pearson's $\chi^2(1)$	t-value	p-value
Education	Blau-Index = 0	0.135	0.158	0.141		0.708
	Blau-Index = 1	0.865	0.842			
Age	Standard deviation	6.937	7.499		-0.506	0.613
Wages	Standard deviation	0.298	0.249		1.324	0.186
Teamsize larger than three						
		Firms in knowledge–intensive sectors	Firms in non–knowledge–intensive sectors	Pearson's $\chi^2(1)$	t-value	p-value
Education	Blau-Index	0.843	0.870		-1.324	0.186
Age	Standard deviation	8.567	9.823		-2.086	0.037
Wages	Standard deviation	0.308	0.302		-0.329	0.742
		Firms w/ university graduates	Firms w/o university graduates		t-value	p-value
Education	Blau-Index	0.910	0.850		4.105	0.000
Age	Standard deviation	8.894	9.821		-2.224	0.027
Wages	Standard deviation	0.308	0.293		1.176	0.240
		Firms w/ university graduates in relevant fields	Firms w/o university graduates in relevant fields		t-value	p-value
Education	Blau-Index	0.905	0.858		2.433	0.015
Age	Standard deviation	8.946	9.714		-1.365	0.173
Wages	Standard deviation	0.309	0.296		0.779	0.437
		Firms w/ university graduates in knowl.-intens. sectors	Firms w/o university graduates in knowl.-intens. sectors		t-value	p-value
Education	Blau-Index	0.886	0.864		0.911	0.363
Age	Standard deviation	7.793	9.730		-2.859	0.004
Wages	Standard deviation	0.305	0.296		0.415	0.678

Table 3 displays tests for statistically significant differences in founder heterogeneity between knowledge–based firms and other firms. It differentiates between firms with two and more than three founders. Our heterogeneity measure for education can only take on the values 0 or 1/2 for teams of size two which is why we apply Pearson χ^2 tests here. The p–values refer to two–sided tests for identity of the respective heterogeneity measures for knowledge–based and non–knowledge based startups.

Table 4: Changes in team heterogeneity due to new individuals entering the firm

	Education				**Age**				**Wages**			
	Observed	Observed (in %)	With random assignm.	With random cloning	Observed	Observed (in %)	With random assignm.	With random cloning	Observed	Observed (in %)	With random assignm.	With random cloning
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
All team startups	0.264	47.7	0.351***	-0.155***	2.574	45.1	4.372***	-1.189***	0.101	52.2	0.137***	-0.040***
Firms in knowledge–intensive sectors	0.302	60.2	0.387***	-0.138***	2.457	50.4	4.422***	-0.998***	0.129	69.4	0.154***	-0.037***
High-tech manufacturing	0.206	30.0	0.262***	-0.142***	2.253	29.8	3.599***	-1.133***	0.079	33.6	0.114***	-0.036***
Technology-oriented services	0.327	68.5	0.422***	-0.131***	2.356	60.6	4.384***	-0.882***	0.142	87.8	0.168***	-0.033***
Knowledge-intensive services	0.285	50.0	0.363***	-0.154***	2.787	46.6	4.882***	-1.212***	0.121	55.3	0.143**	-0.044***
Firms in non–knowledge–intensive sectors	0.261	46.7	0.346***	-0.157***	2.588	44.5	4.366***	-1.212***	0.098	50.2	0.135***	-0.041***
Non-high-tech manufacturing	0.192	30.6	0.274***	-0.147***	2.152	29.9	4.182***	-1.184***	0.073	34.2	0.124***	-0.034***
Other business oriented services	0.340	63.6	0.382***	-0.152***	3.060	57.4	4.539***	-1.094***	0.110	56.7	0.132***	-0.040***
Consumer-oriented services	0.246	43.4	0.328***	-0.154***	2.322	40.5	4.452***	-1.191***	0.098	46.5	0.158***	-0.043***
Construction	0.260	51.4	0.404***	-0.144***	2.871	49.2	3.898***	-1.174***	0.099	57.8	0.123***	-0.037***
Trade	0.257	44.0	0.317***	-0.176***	2.497	43.8	4.692***	-1.320***	0.098	49.7	0.129***	-0.045***
W/ univ. grad.	0.170	24.5	0.224***	-0.161***	1.769	26.0	3.778***	-1.151***	0.075	30.0	0.099***	-0.042***
W/o univ. grad.	0.292	55.9	0.374***	-0.154***	2.803	52.6	4.480***	-1.196***	0.110	61.8	0.144***	-0.040***
W/ univ. grad. in rel. fields	0.174	25.0	0.230***	-0.156***	1.893	27.4	3.591***	-1.096***	0.071	29.1	0.100***	-0.040***
W/o univ. grad. in rel. fields	0.281	51.5	0.360***	-0.155***	2.704	49.5	4.431***	-1.196***	0.106	57.7	0.140***	-0.040***
W/ univ. grad. in knowl.–intens. sectors	0.197	29.8	0.272***	-0.153***	1.950	33.7	3.893***	-1.006***	0.086	36.8	0.116***	-0.040***
W/o univ. grad. in knowl.–intens. sectors	0.276	50.9	0.355***	-0.155***	2.675	48.1	4.400***	-1.199***	0.105	56.3	0.138***	-0.040***

Table 4 displays the absolute and relative changes in our heterogeneity measures due to new individuals entering the firm. It contrasts the observed changes with our two benchmarks: changes according to "random assignment" and changes according to "random cloning". The table also contains if the difference between observed and hypothetical changes are statistically different. The corresponding marginal levels of significance of those two–sided tests are denoted by the asterisks "***", "**" and "*" which refer to statistical significant differences at the one, five and ten percent level.

Table 5: Differences in the changes in team heterogeneity due to new individuals entering the firm between knowledge–based and non–knowledge–based startups

	Firms in knowledge–intensive sectors	Firms in non–knowledge–intensive sectors	t-value	p-value
ΔBlau-Index (mean)	0.302	0.292	1.924	0.054
ΔStandard deviation of age (mean)	2.457	2.588	-0.505	0.614
ΔStandard deviation of wages (mean)	0.129	0.099	3.201	0.001
	Firms w/ university graduates	Firms w/o university graduates	t-value	p-value
Δ Blau-Index (mean)	0.170	0.292	-6.511	0.000
ΔStandard deviation of age (mean)	1.769	2.803	-4.637	0.000
ΔStandard deviation of wages (mean)	0.075	0.110	-4.085	0.000
	Firms w/ university graduates in relevant fields	Firms w/o university graduates in relevant fields	t-value	p-value
ΔBlau-Index (mean)	0.174	0.281	-4.026	0.000
ΔStandard deviation of age (mean)	1.893	2.704	2.573	0.010
ΔStandard deviation of wages (mean)	0.071	0.106	-2.955	0.003
	Firms w/ university graduates in knowl.-intens. sectors	Firms w/o university graduates in knowl.-intens. sectors	t-value	p-value
ΔBlau-Index (mean)	0.197	0.276	-2.668	0.008
ΔStandard deviation of age (mean)	1.950	2.675	-2.050	0.040
ΔStandard deviation of wages (mean)	0.086	0.105	-1.412	0.158

Table 5 displays tests for statistically significant differences in the changes in founder heterogeneity between knowledge–based firms and other firms. The *p*–values refer to two–sided tests for identity of the respective heterogeneity measures for knowledge–based and non–knowledge–based startups.

Appendix: Definition of knowledge based industries

	Sector	NACE revision 1
	Knowledge–intensive sectors	
1	High-tech manufacturing	23.30, 22.33, 24.11, 24.12, 24.13, 24.14, 24.17, 24.20, 24.30, 24.41, 24.42, 24.61, 24.62, 24.63, 24.64, 24.66, 29.11, 29.12, 29.13, 29.14, 29.31, 29.32, 29.40, 29.52, 29.53, 29.54, 29.55, 29.56, 29.60, 30.01, 30.02, 31.10, 31.40, 31.50, 31.62, 32.10, 32.20, 33.20, 32.30, 33.10, 33.30, 33.40, 34.10, 34.30, 35.20, 35.30
2	Technology-intensive services	64.2, 72, 73.1, 74.2, 74.3
3	Knowledge-intensive services (non-technical consulting services)	73.2, 74.11-74.14, 74.4
	Non–knowledge–intensive sectors	
4	Non-high-tech manufacturing	15-37 (without sector 1)
5	Other business oriented services	60.3, 61, 62, 63.1, 63.2, 63.4, 64.1, 71.1-71.3, 74.5-74.8, 90
6	Consumer-oriented services	55, 60.1, 60.2, 63.3, 70, 71.4, 80.4, 85, 92-93
7	Construction	45
8	Wholesale and retail trade	50-52