The Imprint of Founders on Biotech Firms

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Abstract

This paper examines the profile of founders of Danish and Swedish biotech firms and the imprint they have left on their new firms. Drawing on unique data from the SCANBIT database at CBS, offering full coverage of all biotech firms in Scandinavia specialized in drug discovery (DDF), we examine the background of founders in terms of prior organizational affiliation with e.g. pharmaceutical firms, other biotech firms or universities. Similarly profiling is made of all members of the board of directors from the first year of the company and of all inventors behind the discoveries for which firms have filed patent applications.

A pattern is identified whereby university-dominated founder teams to a much higher extent mobilize university inventors for external R&D collaborations, as compared to industry-dominated founder teams. Swedish DDFs acquire their overall stronger academic affiliation through this *general* mechanism whereby university-dominated founder teams "clone" themselves unto the composition of inventors.

Using regression models we examine effects on the financial performance of firms of compositions of founders, boards and inventors, separately and in various configurations. The *composition of founder backgrounds* is found to have an enduring, significant effect on the performance of DDF, but in most cases only when appearing in specific *configurations* with inventor compositions. Elements of a best practice regarding the combination of founder and inventor attributes emerge from this analysis. It is also found that such best practice differs across DDFs distinguished by two distinct research strategies.

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1 Introduction

This paper examines the imprint of founders on the high-tech firms they establish. Understanding the strength and the qualities of this imprint has multiple practical implications for the management, governance and financing of firms, as well as for the design of policies aimed at generating and nurturing new high-tech firms. The role of founders and the experience they bring to new firms therefore is addressed in a growing literature (for an overview see e.g. (Klepper 2001)). The present study falls within an even smaller and more recent subset of that literature, taking the further step of examining *how* prior experience affects the performance of the new firms, and how this imprint *is brought about* (Baron & Hannan 2002;Beckman 2006;Beckman, Burton, & O'Reilly 2006;Feldman, Valentin, & Yoon 2007).

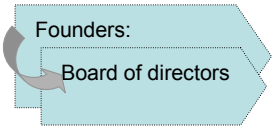
The present version of this paper, aimed at a broader audience taking an interest in Scandinavian biotechnology, largely omits further references to this academic literature. In a separate paper the authors will position the findings presented here in the context of current and previous literature.

Using unique data offering full coverage of start-ups of Drug-Discovery Firms (DDFs) in Denmark and Sweden this paper examines the following four sets of issues

I) Founders, initial boards and the instauration of firms

Founders, along with the board directing the firm through its first year, take decisions and establish structures which enable and constrain a broad range of subsequent routines producing what could be referred to as the *instauration* of the firm.

Figure 1: Founder and Board of directors' relation

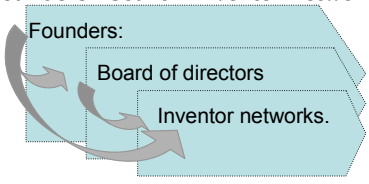


Less than one third of Danish and Swedish DDFs are established by single founders. We inquire into the composition of both *founder teams* and *boards* in terms of the prior experience they bring to bear on the new venture, and we examine if founders set up boards mirroring their own composition, or boards offering complementary compositions of experience. Original new data identifies all founders and first year board members in Danish and Swedish DFFs. This examination applies descriptive statistics only, presenting findings on founders in Section 3 and on boards in Section 4.

II) Organising innovation

The primary output of DDFs takes the form of advances in their drug candidates, based on research requiring integration of multiple fields of expertise (Pisano 2006). Part of this expertise is accessed from academic scientists, while other parts come out of the industrial R&D practise of the DDF itself or from other firms. Organising collaborative research so as to obtain effective composition of these diverse skills is a key challenge for the management of DDFs. The personal network of founders and boards play an important role in identifying external research partners and in shaping the balance in research orientation towards more open academic search vs. more targeted issues. Consequently the instauration of the firm, i.e. its founder team and initial board, expectedly affects the composition of inventors brought together in collaborative projects to push drug candidates into and through the pipeline of the company. Advances in R&D are reflected in patents, which offer also information allowing each contributing inventor to be identified.

Figure 2: The relation cascade of founders - board - inventor network



Having established this inventor identification for all the inventions patented by Danish and Swedish DDFs we may inquire into the imprint of founders and boards on the composition of

inventors. We examine the composition of inventor teams and the way it is affected by firm instauration. This examination applies descriptive statistics only and is presented in Section 5.

III) Research strategies

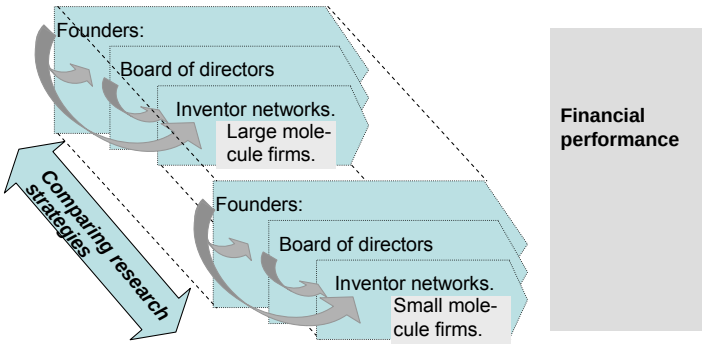
In drug discovery an important strategic bifurcation lies in the choice between a biopharmaceutical approaches based on large, complex molecules versus an approach based on small, chemically synthesised molecules. Their dissimilarities are described in the opening section of Section 2, which also explains why we should expect differences between the two research strategies regarding *successful configurations* of founders, boards and inventors. Reflecting the analytical significance we attribute to this distinction between research strategies (Valentin, Jensen, & Dahlgren 2007), findings on founders, boards and inventors throughout the paper are presented in a breakdown by research strategies (small vs. large molecule firms)

IV) Financial performance

The final argument of this paper builds on the notion that critical qualities of DDFs grow out the configurations formed by a) founders, b) boards and c) inventors. Therefore we identify dimensions in these configurations which by their variations affect the financial performance of firms. Put differently, we submit that configurations of levels a, b, and c reflect key dimensions in the ability of the DDF to move its R&D forwards towards commercialisation. The stronger these dimensions are present in the firms, the higher their financial performance, and vice versa. This argument can be summed up in the following two conjectures:

1) Dimensions in the configuration of founders, boards and inventors can be identified which drive, respectively impede the financial performance of DDFs. In other words, compositions of founders, boards and inventors may be aligned so as to systematically enhance performance, while absence of such alignment is financially penalised.

Fig. 3 Key analytical relationships addressed in the paper



2) Successful configurations in important respects differ between small and large molecule DDFs, reflecting different challenges and contingencies in their respective research strategies. The configuration giving best results for small molecule DDFs is different, and in some important respect directly opposite from, the configuration working best for large molecule firms.

These latter issues are addressed in a series of regressions presented in Section 6. Furthermore previous studies on the same data from the ScanBit database has brought out that the DDF segments in Denmark and Sweden are similar in terms of size and growth patterns. But within this similarity quite notable differences appear in terms of structure, financing, university collaborations, and key outputs such as patent and projects (Valentin, Dahlgren, & Jensen 2006;Valentin & Jensen 2007). We therefore also report descriptive data in this report by systematically applying a breakdown by the two countries. Key inferences from this analysis are presented in Section 7.

2 Research strategies

In drug discovery an important strategic bifurcation lies in the choice between a biopharmaceutical approach based on large, complex molecules versus an approach based on small, chemically synthesised molecules (Smith 2004). Drug discovery based on trial-and-error synthesis and test of

small, chemical molecules was the backbone of the pharmaceutical industry prior to the emergence of modern biotechnology. Chemical synthesis and large scale testing are still the basis for the vast majority of drug development. As modern biopharmaceuticals emerged in the 1970-90s it was seen as a competence-destroying new technology, growing out of academic research (Zucker & Darby 2001), and it was believed to replace the chemistry regime of the incumbent pharmaceutical industry (Cockburn et al. 1999). However the two approaches increasingly have come to make use of the same research tools offered by molecular biology and genetics (Kresse 2001). Large dedicated biotechnology firms in the US, on their way to becoming FIPCOs, (Fully Integrated Pharmaceutical Companies) now incorporate both approaches (Jarvis 2006). Still, in the timeframe considered in this paper (1997-2004), the two approaches, translate into major differences in discovery strategies (Valentin, Jensen, & Dahlgren 2007), and firms pursue either one or the other, but never both. The two approaches diverge in the way they integrate experience from pharmaceutical R&D with the theoretical advances of molecular biology and genetics. Consequently we should expect differences between the two research strategies in terms of the skills and backgrounds required from founders and board members, along with differences in the skills brought together in inventor teams. Therefore differences in these respects between large and small molecule DDFs are examined.

In Denmark and Sweden 40% of all DDFs are small molecule firms, while 60% operate in large molecule discovery (Table 1). The breakdown is roughly the same within the two countries, Denmark having only a slightly larger share of large molecule firms (62%) than Sweden (58%).

Table 1: Shares of small and large molecule firms , separate for Denmark and Sweden

	DK		SE		Total	
Firms	**N**	**% of total**	**N**	**% of total**	**N**	**% of total**
Small molecule	20	37.74 %	19	42.22 %	39	39.79 %
Large molecule	33	62.26 %	26	57.78 %	59	60.20 %
Sum	53	100.00 %	45	100.00 %	98	100.00 %

3 Founders

The ScanBit database offers information on almost all founders of Danish and Swedish DDFs. These 98 firms were established by a total of 247 founders. The 59 large molecule firms on average were established by 2.64 founders. Small molecule firms have the slightly lower average of 2.33. Differences are more pronounced within those 30% of all firms which had one founder only, which is more frequently the case for large molecule firms. The most pronounced difference in this respect is found within the Danish segment, where single founders established 24% of small molecule firms, while they gave rise to no less than 40 % of large molecule firms (Appendix A, Table A.2).

For 96% of these founders we succeeded in establishing their organisational affiliation immediately prior to establishing the focal firm. Distributions of founders by prior organisations are presented in a breakdown by large and small molecule firms (Table 2) and by country (Table 3).

Founders from universities (defined as including also the limited occurrence of Government Research Institutes) constitute 54% of all inventors. They are also the largest single group in all break downs, but notable variations are found. Academic founders are more prevalent in large molecule firms (58%) than in small molecule firms (46%) (Table 2). But they are particularly more predominant in Swedish DDFs (70%) compared to Danish firms (40%) (Table 3). This difference is attributable to a much larger share of Danish founders from pharmaceutical firms (27% vs. 8% in SE) and founders from other biotech firms (18% in Dk. vs. 8% in SE). The latter distribution, in other words, also brings out than in Denmark the first generation of DDFs to a notable extent spawned founders of subsequent rounds of new firms.

4 Company boards

4.1 Board compositions

Data was collected on members of the boards over the first year after the company was established. We noted considerable changes in board membership over the first year, so coverage of the entire first year period was preferred over recording the composition boards only at the date of establishment. Unsuccessful detection of 21% of all board members gives us less complete information compared to what was achieved for founders.

The average number of board members for the 59 large molecule firms is 4.61 and 5.23 for the 39 small molecule firms.

Compared to recruitment of founders, Public Research Organisation contribute less in terms of board members. A total of 31% come from PROs. Lawyers and venture capitalist form a notable share of 26% of all board member, while "other firms" (predominantly pharma and other biotech firms) contribute 41%). This distribution is quite similar in small and in large molecule firms (Table 2). But PRO's in Sweden also in this respect play a much larger role. 40% of Swedish board members come from PROs (versus 21% in Denmark). "Other firms" conversely form a smaller share of Swedish board members (35% vs. 47% in Denmark).

Table 2: Distribution of founders by prior organisation and board members by organisational affiliation while serving on board, separately for large and for small moleculre firms

R&D Strategy	**Large molecules**		**Small molecules**				**Large molecules**		**Small molecules**	
Founders	**N**	**% of total**	**N**	**% of total**		***Board***	**N**	**% of total**	**N**	**% of total**
*PRO**	88	58.28%	40	45.98%		*PRO*	73	31.74%	50	30.49%
DBF	18	11.92%	13	14.94%		*Financier*	30	13.04%	12	7.32%
Pharma	27	17.88%	18	20.69%		*Lawyer*	31	13.48%	32	19.51%
VC	5	3.31%	2	2.30%		*Other firm¤*	94	40.87%	66	40.24%
Other firm	13	8.61%	14	16.09%		*Other org*	2	0.87%	4	2.44%
SUM§	151	100.00%	87	100.00%		***SUM§***	230	100.00%	164	100.00%
Not identified	5	n	4			*Not identified*	42		40	

§) Included is multiple presents of founders

*) Acronym for Public Research Organisation, which in addition to universities also include also two founders from Government Research Institutions. We therefore also refer to this group as Academic

¤) This group includes both Pharmaceutical firms and drug discovery firms

Table 3: Distribution of founders by prior organisation and board members by organisational affiliation while serving on the board, separately for Denmark and Sweden.

	DK		**SE**				**DK**		**SE**	
Founders	**N**	**% of total**	**N**	**% of total**		**Board**	**N**	**% of total**	**N**	**% of total**
PRO	53	40.46%	75	70.09%		*PRO*	40	21.39%	83	40.10%
DBF	24	18.32%	7	6.54%		*Financier*	24	12.83%	18	8.70%
Pharma	36	27.48%	9	8.41%		*Lawyer*	30	16.04%	33	15.94%
VC	3	2.29%	4	3.74%		*Other firm¤*	87	46.52%	73	35.27%
Other firm	15	11.45%	12	11.21%		*Other organisation*	6	3.21%	0	0.00%
SUM§	131	100.00%	107	100.00%		***SUM§***	187	100.00%	207	100.00%
Not identified	7		2			*Not identified*	30		52	

§) Included is multiple presents of founders

¤) This group includes both Pharmaceutical firms and drug discovery firms

4.2 The imprint of founders on board composition

To study the imprint of founders on boards we distinguish between industry- and PRO-predominance. Industry-dominated founder teams and boards are defined as having a share of industry-affiliated members at or above the overall average for all firms. PRO predominance, conversely, is defined as being below the same overall average.

Tables 4 and 5 give cross tabulations of founder and board compositions, separate for small and large molecule DBFs. Turning first to small molecule firms their founder compositions consistently show an industry-dominated pattern (Table 4). 27 out of 39 small molecule firms (69%) have industry-dominated founder teams. Both industry- and PRO dominated founder teams have remarkably similar propensities for industry-dominated boards, found in 70-75% of the cases. That means that among small molecule DDFs, industry-dominated founder teams "clone" themselves with industry dominated boards. By composing their boards with similar industrial pre-dominance, pro-dominated founders in fact do the opposite. I.e. they pursue *complementarity* by composing boards offering the industrial experience they lack.

In this respect large molecule firms form an interesting mixed case (Table 5). Again, industry-dominated founders build industry-dominated boards. The key difference lies with PRO-dominated founders, who in much fewer cases pursue industrial complementarity in the composition of boards. In fact 45% of these firms "clone" themselves with PRO-dominated boards.

Table 4: Founder and board configuration, industry domination for firms with a small molecule R&D strategy

		Board configurations					
		Industry dominated		PRO dominated		Total	
Small molecules		N	% of total	N	% of total	N	% of total
Founder configurations	*Industry dominated*	19	70,37%	8	29,63%	27	100,00%
	PRO dominated	9	75,00%	3	25,00%	12	100,00%
	Total	28	71,79%	11	28,21%	39	100,00%

Table 5: Founder and board configuration, company domination for firms with a biopharmaceutical R&D strategy

		Board configurations					
		Industry dominated		PRO dominated		Total	
Biopharmaceuticals		N	% of total	N	% of total	N	% of total
Founder configurations	*Industry dominated*	32	82,05%	7	17,95%	39	100,00%
	PRO dominated	11	55,00%	9	45,00%	20	100,00%
	Total	43	72,88%	16	27,12%	59	100,00%

5 Inventors

5.1 Inventor compositions

Data on the inventors behind the discoveries made by DDFs is constructed for the ScanBit database in a multi-stage process, beginning by recording the names of inventors behind each patent assigned to each company. On the patent front page inventors are identified by name and address only. In a strongly science-based field such as biotechnology inventors leave a number of papyrophilic traces, allowing us to build on the simple information of inventor names. E.g. publications of inventors are often cited in the patent to which they have contributed. We used this and similar information as a point of departure for search in various bibliometric sources, to establish the organisational

affiliation of inventors at the time of invention (defined as the application date of the patent)[1]. Patents based on bio-scientific research often involves multiple inventors, and each inventor team now may be characterised by the composition of organisations collaborating in specific inventions, e.g. by shares of inventors coming from academia or from industry. While this methodology for enriching patent-based inventor data is time consuming, it offers considerable advantages for systematic observation and analysis. Entire technology areas, or countries, may be characterised by their inventor compositions. For an example see (Valentin & Jensen 2004)

In the period studied in this paper Danish and Swedish DDFs filed a total of 1095 patents, comprising no less than 3356 inventor participations. Identification of host organisation at the time of invention was achieved for 3046 inventors (90.76% of the total of total of 3356.

Large molecule inventions rely to higher extent on university scientists as inventors. The constitute 38% of inventors, compared to 24% for small molecule inventions (Table 5).
Differences are even more pronounced in the break down by country presented in Table 6. In Swedish DDF 42% of inventors come from universities, compared to 21% in Danish firms.

Table 5: Inventor affiliations separate for large and small moldecule DDFs

R&D Strategy	Large molecule		Small molecules		All firms	
Inventors	**N**	**% of total**	**N**	**% of total**	**N**	**% of total**
University	582	38.44%	369	24.09%	951	31.22%
GRI	46	3.04%	92	6.01%	138	4.53%
Company	886	58.52%	1071	69.91%	1957	64.25%
SUM*	1514	100.00%	1532	100.00%	3046	100.00%
Not identified	182		128		310	

**) Included is multiple presents of the inventors*

Table 6 : Inventor affiliation separate for DDFs in DK and SE

Country	DK		SE	
Inventors	**N**	**% of total**	**N**	**% of total**
University	311	20.51%	640	41.83%
GRI	73	4.82%	65	4.25%
Company	1132	74.67%	825	53.92%
SUM*	1516	100.00%	1530	100.00%
Not identified	174		136	

**) Included is multiple presents of the inventors*

Figure 4: Average share pr year of company

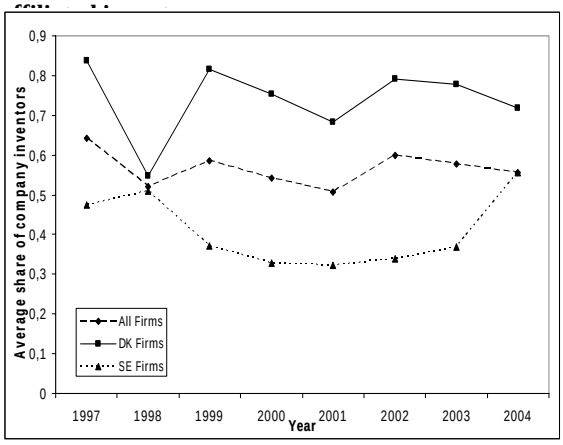


Fig. 5 shows Danish-Swedish differences across time, indicating some turbulence in the pattern in the late 1990s while the volume of patenting was still comparatively small. From 1999 until 2003 a fairly stable, considerable difference is seen between their involvement of inventors from industry. Towards the end of the period a convergence appears, based particularly on an increase in the Swedish involvement of industrial scientists.

[1] In previous studies of biotech patents the authors applied this procedure and obtained identification of 85 – 90% of inventors. Subsequent validation, based on direct confirmation from inventors, revealed identification errors for less that 5% of inventors.

5.2 The imprint of founders on inventor composition

To what extent are compositions of inventors shaped by the composition of founders? That question is addressed in Table 7, which breaks down companies by the three dimensions of country, research strategy, and composition of founders. The latter is a dichotomy of industry- vs. pro-dominated founder teams, defined as in section 4.2. For each cell in this 8-fold classification we calculate the share of university inventors as a share of all inventors falling in the same category. I.e. Danish small molecule firms with industry-dominated founder teams in their patents filed between 1997 and 2004 drew on a total of 584 inventors, 73 of which came from universities, producing for that category the share of 12.48%, given in the first upper-left cell in Table 7. Percentages, in other words neither horizontally nor vertically add up to 100%. In the interpretation of Table 7 it is useful to keep in mind the country variation observed in Table 3 of PRO founders as a share of all founders: 40% in Denmark and 70% in Sweden, indicating also a much larger share of PRO dominated founder teams in Sweden.

Table 7: Share of university scientists among inventors for companies with different founder configurations, separate for small and large molecule firms and for Denmark and Sweden.

Founder configuration	Small molecule firms				Large molecule firms				All firms			
	DK		SE		DK		SE		DK		SE	
	PRO inventors		PRO inventors		PRO inventors		PRO inventors		PRO inventors		PRO inventors	
	N	% of total	N	% of total	N	% of total	N	% of total	N	% of total	N	% of total
Industry dominated	73	12.48%	100	29.85%	159	25.44%	85	25.22%	232	19.17%	185	27.53%
PRO dominated	120	58.82%	163	41.37%	29	32.22%	255	77.98%	149	50.68%	418	57.98%
Total	193	24.46%	263	36.08%	188	25.97%	340	51.20%	381	25.33%	603	44.73%

The aggregation of all firms to the right in Table 7 shows Sweden having higher PRO-inventor shares for both industry- and PRO-dominated founder teams. However country differences for both Industry- and PRO-dominated firms are merely about 7%. In the same aggregation of all firms the large difference comes from founder compositions, PRO founder-dominated firms having a share of PRO inventors 2-3 times higher than their Industry dominated counterpart. This difference between compositions of founder teams appears throughout Table 7, consistently within small and large molecule firms and within each country. It is particularly pronounced for Danish small molecule firms and for Swedish large molecule firms.

To summarise, founder composition strongly affects the composition of inventors contributing to the inventions of DDFs. The much higher overall involvement of PRO-inventors in Sweden primarily reflects the much larger Swedish prevalence of PRO-dominated founder teams. The most notable specific country-effect in this overall pattern appears within Pro-dominated large molecule firms, where 78% of all Swedish inventors come from public research organisations, as compared to 32% in similar Danish firms.

6 Modelling effects on financial performance

6.1 What relationships are modelled?

In the introduction we argued that founders, along with the first-year-board of directors, in the early stages of the firm take decisions and establish structures, which enable and constrain a broad range of subsequent routines, establishing fir the firm what could be referred to as its *instauration*.

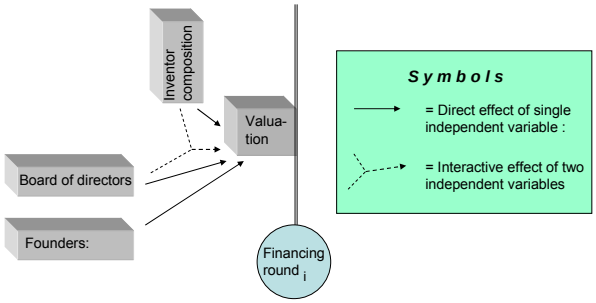
Using descriptive statistics the previous sections have brought out the imprint left on firms of this instauration, particularly regarding the effects of founder composition on the type of inventors mobilised by the firm for its research projects. Inventor composition as an example of imprinting

was highlighted because of the importance of research outcomes for the development of DDFs. We therefore expect inventor compositions to matter for *the financial performance* of firms. At the same time this performance in many other ways is influenced by the imprints of founders and initial boards on the firm.

Using multiple regressions the present section examines how these different factors separately and jointly affect the ability of firms to build value. This ability is revealed in the injections of new venture capital required for the financing of firms until they become profitable. For Danish and Swedish DDFs these financing rounds on average occur every 1.8 years, and are recorded in ways allowing us to transform them into an indicator of the total value of the firm. It is variations in firm valuation we are out to explain, i.e. defining it as the dependent variable in regression models.

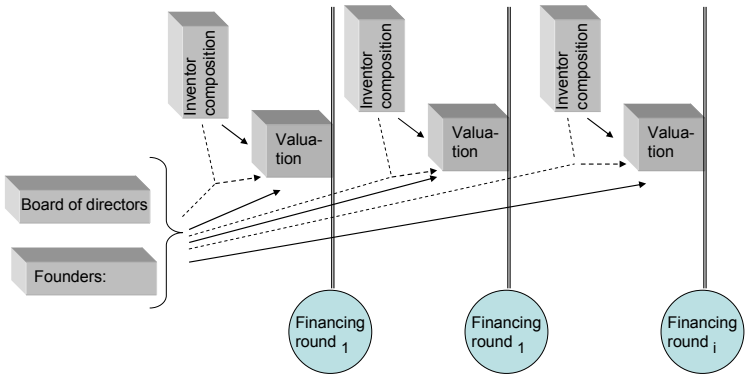
For each financing round we build the data architecture visualised in Fig. 5. Effects on a specific financing round of the compositions of founders, first-year-boards and inventors are examined separately (full line arrows) and jointly (dotted arrows). Founder and board compositions define an initial state of the firm, of course remaining unaltered across consecutive financing rounds. Inventor compositions, on the other hand, change from one invention to the next. The previous sections showed clear propensities on part of firms to compose inventor teams in divergent directions. We try to catch this pattern by aggregating, for each firm, all inventor participations appearing in all its patents filed in the interval since the previous financing round, up until the next round at which point we calculate the valuation of the firm. In other words, independent variables referring to the instauration of the firms are fixed across time, whereas inventor compositions may vary from one interval between financing rounds to the next, as do also firm valuations revealed in these rounds. This sequential architecture is visualised in Fig. 6.

Fig. 5 Visualisation of key relationships in regression models



Finally, recognising the quite persistent differences between large vs. small molecule firms observed above, we expect the key relationship presented in Fig. 6 to vary across the two types of firms. We therefore build models targeted at bringing out characteristic relation-ships *within* each type of firm, hence ending up with two quite different models. Of course we present results of both models for both types of firm, which allows us to identify how they differ.

Fig. 6 Visualisation of key relationships in regression models



6.2 Data

Using data extracted from ScanBit the analysis covers a total of 98 Danish and Swedish companies in the time span from 1997 to 2004.

6.2.1 Dependent variable: Post Money Value

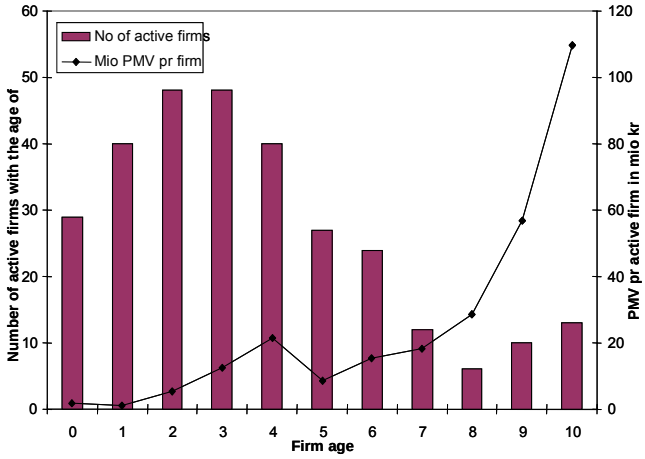
The DDFs in pharmaceutical discovery examined in this paper are financed primarily by venture capital and in most cases are not yet profitable. DDFs typically build value for years while operating without profits, and sometimes also without revenues, rendering conventional financial metrics inadequate. That is particularly so for firms in their early years (Hand 2005), which pertains to the larger part of the firms in our dataset. To obtain a financial performance measure we use in stead the total value of the firm (PMV), which for unlisted firms may be calculated from their financing rounds.

For firms listed on the stock exchange, the value per share is available on a daily basis. The share value for a given year is calculated as the average daily closing price per share for each firm, which reduces fluctuations during the year in the market assessment of firm values. For non-listed firms share values are based on the total amount invested in each round divided by the number of new shares committed. Only rounds involving new issued shares and capital increases with share premium are taken into account, to reduce the risk of biased and internal determination of share prices, resulting from converting debts or warrants exercised into share capital. New investments are assumed to better mirror a market assessment of the firm.

The *Post Money Value* (PMV) refers to the total value of a firm. For listed firms, PMV is the market capitalization value, calculated as the average daily closing price in each year for a given firm multiplied with the number of stocks committed. PMV for non-listed firms is calculated as share value multiplied by the total number of shares committed as per each round of capital inflow. This value corresponds to the amount an investor has to invest to acquire the whole firm if buying at the price resulting from the latest round.

The histogram plot of PMV in Fig. 7 shows heavily right-skewness and non-normal distribution but by taking the natural algorithm of the adjusted PMV we obtain a dependent variable with a normal distribution.

Figure 7: PMV per firm in mio DK kr



6.2.2 Independent variables

Data on founders, first-year-boards and inventors are identical to those introduced for the descriptive statistics in the previous sections.

6.2.3 Controls

Number of Employees:
To control for firms size we use the average number of employees in the year of the financing round from which the dependent variable is extracted.

Number of patents per employee:
As a control for the overall level of inventiveness of the firms we use the total number of patents accumulated by each firm up until an investment round. This number is normalised by firm's total employment in the year prior to the financing round. We suggest that this ratio should be read not primarily as an indicator of project "productivity", since the mere number of inventions neither by DDF management nor by investors would be considered as a performance indicator. Rather this

ratio indicates efforts directed at getting value outof patents, e.g. by pushing patented inventions further forwards in the pipeline of the company.

Number of active clinical projects:
The number of clinical projects of a DDF reflects both its future and present value (because these projects already may have been the source of significant revenues though alliances formed with pharmaceutical firms). The value of a drug candidate increases as it progresses through Clinical Phases I-II-III, due to the gradual reduction in remaining risk.

Table 8: Variable definitions

Status in model	Role in hypothesis	Indicator	Variable acronym
Dependent Variable	The value of the firm by each round of investment	(Log) Post money value	Ln(PMV)
Independent variables	Founder	The number of founders that has a professional background in a DDF or a Pharmaceutical company	F_Biotech
		The number of founders with a professional background in university	F_University
	Board	The number of board members that has a professional background in a DDF or a Pharmaceutical company	B_Firm
	Inventor	The number of inventors affiliated with a company	Inv_Comp
Control variables	Firm size	The number of employees	Empl
	Inventiveness	The number of patents filed until focal capital round	Acc_Pat
	Output variable	The number of active clinical project in the year of investment	Pro_Act
	Use of resource variable	Accumulated number of patents divide by the number of employees	Pat/Empl
	Output variable	Number of active project divided by the number of patents filed in the same year	Proj/Pat

6.3 Methodology

The firm data extracted from ScanBit on a total of 98 DDFs from 1997 to 2004 form an unbalanced panel dataset, since we include also late entries and early exits. Unobserved effects should be expected since we observe same firm across time. These unobserved effects cannot be addressed through a fixed effects approach since some of the key independent variables (founders and first-year-boards) are fixed over time. To solve this problem a random effect model could be applied, but initial regressions, along with xt-test0 and Hausman tests, show that the most appropriate model would be an ordinary least square estimation.

For the model on small molecule firms the xt-test0 of Breusch and Pagan Lagrangian multiplier test for random effects give significant difference between a random effect model and an ordinary OLS (Prob > chi2 = 0.0078). The xt-text0 for large molecule firms shows that there is no significant difference between a random effect model and an OLS model, the Chi2 of the t-test equal to Prob > chi2 = 0.1195.

For both groups of firms a Hausman test comparing a fixed effect model and a random effect model returns a significant difference, indicating the need to take account of fixed effects. We therefore specify regressions to take into account that observations from same firm are related by using the cluster option in STATA. Furthermore year dummies are applied in the model to capture the time specific effects on firm valuations.

To cope with potential multicolinearity problems the founder and inventor variables in models for large molecule firms (Models 1A +B) are centred by the mean. All final models are tested negative for multicolinearity and the white correction of standard errors is performed by the robust heteroscedastic correction in STATA.

Table 9: Descriptive statistics

Model 1					
Variables	**N**	**Mean**	**Std dev**	**Minimum**	**Maximum**
Ln(PMV)	172	17.268	2.0827	11.178	22.846
PMV (mio. Kr)	172	341.574	1097.494	0.072	8352.000
F_Biotech	105	-0.233	1.174	-0.988	4.012
B_Firm	166	1.735	1.285	0.000	4.000
Inv_Comp	105	4.829	8.035	0.000	61.000
Pat_Acc	169	5.586	7.906	0.000	65.000
Empl	169	20.183	34.823	0.000	381.000
Proj_Act	169	1.953	3.304	0.000	16.000
Proj/Pat	105	0.966	1.459	0.000	8.000
Pat/Empl	165	0.673	1.203	0.000	9.000
Model 2					
Ln(PMV)	127	18.291	2.661	11.972	23.939
PMV (mio. Kr)	127	1374.912	3711.018	0.158	24920.000
F_University	127	0.803	1.155	0.000	5.000
B_Firm	127	1.929	1.844	0.000	7.000
Inv_Comp	75	11.720	15.528	0.000	69.000
Proj/Pat	81	1.253	2.063	0.000	9.000
Pat/Empl	120	0.839	1.158	0.000	7.000

6.4 Results

Results are presented in Tables 10 and 11. Model 1A in Table 10 was fitted to the data on large molecule firms. Model 1B is presented only to show the outcome of applying exactly the same model to small molecule firms. Similarly in Table 11, Model 2B was fitted to data on small molecule firms, and in this case the model on large molecule firms (2A) is presented merely for comparison. Each of the four models is presented in three versions, the first being the base-model including only control variables, the second omitting the interaction term, which plays a critical role in the argument, and the third including this interaction term.

Turning first to model Model 1A on large molecule firms, a negative, significant estimate is found for Inv-Comp. I.e. negative effects on firm valuations are associated with an increasing number of inventors from industry, meaning primarily inventors from the internal staff of researchers from the focal firm. This relationships is only weakly significant (at the 10% level) in the first of the two versions of model 1A, and becomes stronger when the interaction term is included in the second version.

A non-significant estimate is obtained for F-biotech. I.e. although founders coming from pharma firms and from DDFs are by far the most frequent founders with an industrial legacy (compare Table 2), the number of founders with this background *in itself* has no effects on the valuation of firms.

The key finding in Model 1A is that the interactive term of F-Biotech*Inv_Comp is positive and significant. Increasing the number of *both* industry founders and industry inventors positively affects the valuation of firms, although the first term in the interaction by itself is inconsequential,

and the second term by itself has negative effects. A non-significant estimate is obtained for the number of board-members coming from pharma and from biotech firms (B_Firm).

Among the controls the total number of patents filed up until each capital round (Acc_pat) positively affects valuation, as does the number of clinical projects (Pro_Act). Pat/Empl is negative and significant, indicating that employment increases disproportionably above increases in the firm's patents portfolio is penalised in subsequent valuations.

Applying the same statistical model to small molecule firms (Model 1B, Table 10) shows that the independent variables affecting valuations in large molecule firms turn inconsequential for small molecule firms. For the latter the number of board members from pharma firms and from other DBFs is strongly significant and positive, whereas it has no effects on large molecule firms. The control variables have similar effects in the two models, with the exception of Pro-Act, which had strong positive effects in large molecule firms, but which has no effects for small molecule firm (at least with all the other factors controlled for).

Turning next to the model fitted to small molecule firms (Model 2B in Table 11) the number of inventors from industry (Inv.Comp) positively affects firm valuations, and this holds for the two full versions of 2B, i.e. both with and without the interaction term.

The number of founders from universities (F_University), negatively affect firm valuations when entered as a single term. The relationship is weaker in the model without the interaction term, and grows strongly significant only when the interaction term in included.

The interaction term multiplies numbers of academic founders (F-University) with the number of inventors from industry (Inv-Comp). Its strongly significant, positive effect means that the more these two attributes are found *together* in small molecule firms, the better their financial performance. Small molecule firms specifically lacking this combination draw a negative effect from having multiple university founders (negative effects from this variable intensifies when the interaction term is introduced).

The number of board members from pharmaceutical firms and from other DBFs positively affects firm valuations.

As for the controls, the ability to generate an increasing number of project out of the firm's patent portfolio (Proj/Pat) is positive (but significant at the 10% level only). Again a penalty is put on employment when it grows disproportionably, relative to the size of the firm's patent portfolio.

When the exact same model is applied to Large molecule firms (Model 2A in Table 11) the only variable maintaining significant effect is Proj/Pat.

Table 10: Comparison of the effect board, founder and inventor data has on large versus small molecule firms

Model 1A. Large molecule firms

	Model 1	Model 2	Model 3
Acc_Pat	0.072***	0.083***	0.091***
	[0.022]	[0.020]	[0.021]
Empl	-0.002	0.006	0.008
	[0.004]	[0.007]	[0.006]
Pro_Acc	0.180**	0.214***	0.211***
	[0.069]	[0.057]	[0.051]
Proj/Pat	0.326*	0.117	0.090
	[0.177]	[0.150]	[0.142]
Pat/Empl	-0.331**	-0.331**	-0.350***
	[0.139]	[0.127]	[0.123]
F_Biotech		0.224*	0.200
		[0.119]	[0.133]
Inv_Comp (a1)		-0.070*	-0.089**
		[0.039]	[0.035]
B_Firm		-0.023	0.015
		[0.156]	[0.144]
F_Biotech*Inv_Comp (a2)			0.048**
			[0.025]
Constant	18.683***	18.229***	18.246***
	[0.613]	[0.720]	[0.675]
Year fixed effects	Yes	Yes	Yes
No of Observations	104	97	97
No of Firms	34	34	34
R-squared	0.562	0.576	0.587

Model 1B Small molecules firms

	Model 1	Model 2	Model 3
Acc_Pat	0.043**	0.044***	0.044**
	[0.021]	[0.015]	[0.016]
Empl	0.011***	0.008***	0.008***
	[0.003]	[0.002]	[0.002]
Pro_Acc	-0.143	-0.043	-0.045
	[0.160]	[0.106]	[0.105]
Proj/Pat	0.235	0.143	0.156
	[0.146]	[0.094]	[0.104]
Pat/Empl	-0.763***	-1.061***	-0.995***
	[0.153]	[0.321]	[0.307]
F_Biotech		-0.401	-0.239
		[0.297]	[0.398]
Inv_Comp		0.015	0.029
		[0.013]	[0.018]
B_Firm		0.308***	0.254**
		[0.096]	[0.100]
F_Biotech*Inv_Comp			-0.006
			[0.005]
Constant	19.773***	19.429***	19.411***
	[0.697]	[0.691]	[0.587]
Year fixed effects	Yes	Yes	Yes
No of Observations	78	67	67
No of Firms	14	14	24
R-squared	0.651	0.683	0.683

- * p<0.1, ** p<0.05, *** p<0.01
- Robust standard errors are given in brackets

Table 11: Comparison of the effect board, founder and inventor data has on large versus small molecule firms

Model 2A. Large molecule firms			
	Model 1	Model 2	Model 3
Proj/Pat	0.847***	0.821***	0.805***
	[0.139]	[0.134]	[0.142]
Pat/Empl	-0.285*	-0.230	-0.223
	[0.153]	[0.160]	[0.172]
F_University		-0.019	-0.033
		[0.105]	[0.107]
Inv_Comp		0.040*	0.035
		[0.021]	[0.026]
B_Firm		0.076	0.090
		[0.199]	[0.203]
F_University*Inv_Comp			0.010
			[0.019]
Constant	19.125***	18.594***	18.530***
	[0.692]	[0.994]	[1.064]
Year fixed effects	Yes	Yes	Yes
No of Observations	104	97	97
No of Firms	34	34	34
R-squared	0.416	0.421	0.415

Model 2B Small molecules firms			
	Model 1	Model 2	Model 3
Proj/Pat	0.175	0.212	0.265*
	[0.204]	[0.173]	[0.129]
Pat/Empl	-1.000***	-1.296***	-1.243***
	[0.256]	[0.390]	[0.364]
F_University (a1)		-0.370	-0.608**
		[0.276]	[0.217]
Inv_Comp (a2)		0.053***	0.041***
		[0.012]	[0.009]
B_Firm		0.387*	0.338**
		[0.198]	[0.151]
F_University*Inv_Comp (a3)			0.056***
			[0.018]
Constant	22.111***	19.513***	19.882***
	[0.343]	[0.948]	[0.699]
Year fixed effects	Yes	Yes	Yes
No of Observations	78	67	67
No of Firms	24	24	24
R-squared	0.342	0.562	0.586

- * p<0.1, ** p<0.05, *** p<0.01
- Robust standard errors are given in brackets

Table 12 shows the results of Wald tests used to evaluate the combined effects of the variables and the interaction effect. The first half of the table tests the estimates found table 10 for model 1a in which we consider large molecules and the biotech founders. Adding the inventor composition parameter to the estimate of the interaction term provides an insignificant combined estimate. This suggests that a biotech founder compensates for the negative effect of the inventor composition on PMV.

The second part of table 12 holds Wald tests indicating the combined effects of inventor composition and university founders for small biotech firms. The estimates used are drawn from model 2b in table 11. We test the combined effect of the founder, inventor and the interaction variable. The Wald test reveals the estimate to be significantly negative suggesting that one additional company inventor is insufficient to compensate for the negative effect of the academic founder. Assuming the parameter estimates of the interaction term and the inventor composition term is even across the entire range of quantiles, the table also reveals that the compensation rate between inventor composition and a university founder is three to one. The firm needs three additional company inventors to compensate for a university founder with respect to PMV.

Table 12: Wald test for differences in parameters and parameter compositions using model 2 in table 10 and model 4 in table11.

Large molecule firms

Variables	Parameter equation	Value	Chi-Square
F_Biotech*Inv_Comp minus Inv_Comp	a2+a1 = 0	-0.041	1.41

Small molecule firms

Variables	Parameter equation	Value	Chi-Square
F_University minus (Inv_Comp plus F_University*Inv_Comp)	a1+a2+a3 = 0	-0.499	5.58**
F_University minus 3(Inv_Comp plus F_University*Inv_Comp)	a1+3(a2+a3) = 0	-0.317	2.12

7 Inferences

7.1 Understanding the imprint of founders on new firms

At the most general level the models demonstrate that the *composition of founder backgrounds* has an enduring, significant effect on the performance of DDFs. For large molecule firms this effect appears and remains significant regardless of its combinations with inventor attributes. For small molecule firms founder background matters only in combination with a particular profile of inventors

The composition of inventors matters particularly in terms of the number of industrial vs. academic scientists mobilised internally and externally in the R&D efforts of the firm. Again, in some cases this inventor profile significantly affects firm performance regardless of other factors, in other cases its significance appears only in combination with other firm characteristics, specific founder backgrounds in particular.

Combinations of founder backgrounds and inventor profiles, in specific combinations, significantly matter for the performance of DDFs. Arguably they do so because founders leave their imprint on many different aspects of their new firms. One of these aspects was clearly brought out in Table 7, showing the strong tendency of PRO-dominated founder teams to “clone” themselves onto PRO-dominated *inventor* teams.

Undoubtedly founder backgrounds leave profound imprints on many *other* fundamental attributes of their new firms. These other imprints appear in our models only as latent dimensions of the founder variables. With our current data we cannot tease out these latent dimensions, but the significant interactive terms in the models are probably best interpreted as indications of their critical role.

As an example, for small molecule firms (Model 2B), increasing number of university founders positively affects performance only when combined with increasing number of inventors from industry. This finding strongly indicates *complementarity* between academic and industrial science. What academic founders bring to this complementarity is not primarily remnants from their own academic research background. More likely it is their ability, based on their experience, to shape the broader research agenda of the firm in ways allowing scientists from industry to contribute to more valuable inventions. This shaping of the firm's research agenda is one highly likely candidate for the latent dimensions in variables covering founder attributes. The implication is that whereas many different aspects of the new firms are affected by such founder imprints, they enhance firm performance only when appearing in *certain configurations*. This is well illustrated by the above point that university-dominated founder teams boost performance when combined with industry dominated inventor teams,- and have the opposite effect without this combination. This finding, of course, is made all the more interesting by the observation in Table 7, that this combination is not the foremost preference of university dominated founder teams.

7.2 "Best combinations" differ across research strategies

The second important inference from the above regression results is that profound differences must be acknowledged between different types of DDFs in terms of direct and indirect founder effects on performance. The distinction between small vs. large molecule DDFs represents one such important differentiation. Founder attributes beneficial for small molecule firms in most cases are inconsequential large molecule firms. The same logic holds for effects of combinations. E.g. increasing reliance on industrial inventors, when combined with founders from industry, comes out as a best practice for enhancing the performance of large molecule DDFs. The exact same combination remains inconsequential in small molecule DDFs.

In a recently published paper the authors suggest a conceptualization of DDFs as research-based, problem-solving agents. By implication, DDFs are organized principally around their architecture of problem-solving, by which we refer to the patterns by which opportunities arise and the ways in which solutions are searched for. Large and small molecule firms, we argue, differ profoundly in these respects (Valentin, Jensen, & Dahlgren 2007). It seems obvious, therefore, to relate the above divergence regarding best practice in research organization to differences between large and small molecule firms in their patterns of search and problem-solving. As an example, the complementarity of university founders and industry inventors could well be argued to fit into the particular problem-solving architecture of small molecule firms. This combination is indeed what comes out of the regressions as a best practice for building value in small molecule firms,- but not in large molecule DDFs.

In closing, rather than pursuing these theoretical implications further, we emphasise in stead a key managerial implication: Best practice in composing founder teams and in combining them with other subsequent attributes of the firm differ across firms with different research strategies. There are of course some common elements contributing to best practice across all firms. But regarding many key issues in developing a DDF, in stead of assuming a best practice generally applicable to all firms, it seems more defensible to consider best practices separately for small and large molecule firms.

8 Apppendix

Table A1: Number of active firms' pr R&D strategy pr year

R&D Strategy	1997	1998	1999	2000	2001	2002	2003	2004
Biopharmaceuticals	17	29	35	44	53	56	57	55
Small molecules	15	20	22	27	33	36	38	37
Total	32	49	57	71	86	92	95	92

Table A.2: Founder team size divided on small and large molecule firms and on Danish and Swedish DDF's.

	Small molecule firms				Large molecule firms				All firms	
	SE		DK		SE		DK		SE & DK	
Founder team size	No of firms	% of total	No of firms	% of total	No of firms	% of total	No of firms	% of total	No of firms	% of total
1	6	35,29%	8	40,00%	7	33,33%	8	24,24%	29	29,59%
2	7	41,18%	5	25,00%	5	23,81%	13	39,39%	30	30,61%
3	1	5,88%	1	5,00%	1	4,76%	5	15,15%	8	8,16%
4	1	5,88%	2	10,00%	5	23,81%	4	12,12%	12	12,24%
5	0	0,00%	3	15,00%	0	0,00%	0	0,00%	3	3,06%
6	1	5,88%	0	0,00%	2	9,52%	1	3,03%	2	2,04%
7	1	5,88%	1	5,00%	0	0,00%	1	3,03%	5	5,10%
8	0	0,00%	0	0,00%	0	0,00%	1	3,03%	1	1,02%
9	0	0,00%	0	0,00%	0	0,00%	0	0,00%	0	0,00%
10	0	0,00%	0	0,00%	1	4,76%	0	0,00%	1	1,02%
SUM	17	100,00%	20	100,00%	21	100,00%	33	100,00%	98	100,00%
Not identified	2		0		5		0		7	

Table A.3: Founder and board configuration, team heterogeneity for firms with a biopharmaceutical R&D strategy

		Board configurations					
		High HHidx		Low HHidx		Total	
Biopharmaceuticals		N	% of total	N	% of total	N	% of total
Founder configurations	*High HHidx*	16	59,26%	11	40,74%	27	100,00%
	Low HHidx	19	59,38%	13	40,63%	32	100,00%
	Total	35	59,32%	24	40,68%	59	100,00%

Table A.4: Founder and board configuration, team heterogeneity for firms with a small molecule R&D strategy

		Board configurations					
		High HHidx		Low HHidx		Total	
Small molecules		N	% of total	N	% of total	N	% of total
Founder configurations	*High HHidx*	11	73,33%	4	26,67%	15	100,00%
	Low HHidx	15	62,50%	9	37,50%	24	100,00%
	Total	26	66,67%	13	33,33%	39	100,00%

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