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Composition of Collaborative Innovation Networks: An Investigation of Process Characteristics and Outcomes

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ABSTRACT

In this study we test how different ways of composing collaborative action networks influence food innovation. Networks have received considerable attention in the literature and are perceived to enhance the likelihood of innovation success by overcoming resource and capability deficiencies. While previous studies of collaborate innovation in the food sector have been mostly qualitative case studies of one or a few networks, we compare 96 networks which were all structured according to the same network template. After content-analysing archive data, we estimated a vector-generalised linear model with binomial response distributions and probit link functions; with network composition as the predictor and the innovation process charateristics and outcomes as response variables. Our findings show that differently composed manufacturer networks lead to different outcomes and different process characteristics. We find that strong management and coordination of activities are more important for heterogeneous manufacturer networks than for homogeneous manufacturer networks, and that vertically composed networks with suppliers contribute to efficiency gains to a higher extent than networks consisting solely of manufacturers.

Keywords: Collaborative innovation networks; composition; manufacturer; suppliers.

1 Introduction

Interaction with external actors has become an important topic in the innovation literature (see West and Bogers, 2014; Huizingh, 2011; Dahlander and Gann, 2010). Even though many authors champion the idea that external actors can somehow "catalyse" innovation processes, it is still not clear how different actor combinations in a collaborative network might influence the innovation process and which outcome will be most affected by their involvement.

Previous studies of collaborative networks within the food sector has pointed towards postiv effects for innovation. Devaux et al (2009) found that engaging small potato producers together with market agents and other service providers in collaborative networks (in this case the Papa Andina network in the Andes) generated commercial, technological and institutional innovations, empowered small farmers, reduced marketing costs, and increased efficiency in service delivery (Devaux et al. 2009). By establishing links between the small potato producers and the market agents, the collaborative network facilitated knowledge sharing, social learning, capacity building, which resulted in improved productivity and product quality. New market opportunities were identified that led to the development of new kinds of potatoes for which they could charge a higher price.

In another study of innovation co-production support initiatives in the Australian and Dutch dairy sector, Klerkx and Nettle found that these initiatives, which provided a platform for integrating scientists, farmers and service providers, stimulated collaboration and induced learning about innovation. But there where also some challenges. To attract a broad range of farmers, to get them all engaged in the same topic and to maintain commitment through out the whole process was difficult. How to effective broker and facilitate these networks is still an open question (Klerkx and Nettle, 2013).

In addition to the qualitative studies of collaborative food networks mentioned above, quantitative studies have been conducted outside the food sector. Most of these studies have compared the external relations of independently sampled firms in terms of simple structural characteristics, and then related differences in these characteristics to differences in innovation performance measured as number of patents (Noni, Orsi, Belussi 2018), ex-ante evaluation of innovation projects technical and business qualities (Lo and Li, 2018), and sales generated by new products per employee (Tsai, 2009). Gemünden, Ritter and Heydebreck (1996), for example, collected ratings of the perceived importance of contacts with customers, suppliers, universities and consultants from 321 German high-tech companies. From these ratings, the authors derived seven prototypical "network configurations", and compared groups of companies which they had classified as instances of such configurations in terms of their subjective self-assessments on four dimensions of innovation success: improvement of products, new product development, technical process innovation success and economic relevance of process innovations.

Another example is Nieto and Santamaría (2007), who used data from an existing panel of 1300 Spanish manufacturing companies. Over a period of five years, all the companies had reported subjective self-assessments as to whether they had developed (a) innovations with a relatively high degree of novelty and (b) incremental product innovations, both in a binary "yes" versus "no" format. In addition, all the companies had reported, in a forced-choice format, whether they had engaged in technological collaboration exclusively with customers, exclusively with suppliers, exclusively with research organisations, exclusively with competitors or with multiple external actors. Apart from collaboration with competitors, all types of technological collaboration had weak positive associations* with the likelihood that innovations of both types would occur.

In this paper, we investigate the effects of network composition in a set of collaborative innovation networks. We contribute to the innovation network literature by investigating a larger number of networks than previous qualititative studies, and by extending the simple structural characteristics most often correlated with innovation performance in previous quantitive studies. All the collaborative innovation networks were constructed ad hoc; not only was their composition under the control of a policy-maker, but all had the objective to stimulate the innovativeness of the participating actors by giving them access to other organisations, and thereby to knowledge and resources that would otherwise have been unavailable to them.

Möller, Rajala, and Svahn (2005) identify in a conceptual paper, three factors which play a core role in promoting understanding of the management of strategic nets: 1) value activities in the net, 2) outcome pursued through the net, and 3) the structure of the net. Before we set out to present our method and results, we will introduce how we conceptually distinguish between value activities in the net (what we call *process characteristics*) and outcome pursued through the net (here called *innovation outcomes*), and explain in some detail the particular aspect of the structure of the network composition on which we direct our attention.

1.1 Process characteristics and innovation outcomes

A process characteristic is defined here as a particular way to manage the collaborative action in a network, while an innovation outcome is defined as result obtained from the activities in a network. In the pertaining literature, several process characteristics are considered as important for temporarily constructed innovation networks. Among the most frequently identified are good coordination of the network (e.g., Ahlström-Söderling, 2003; Hanna and Walsh, 2002; Huggins, 2000; Ammenberg et al., 1999; Franke, 1999; Chaston, 1995), trust-building social activities (e.g., Elvekrok et al. 2018; Fuller-Love and Thomas, 2004), and facilitation of knowledge transfer between participants (e.g., Pittaway et al., 2004).

* Since Nieto and Santamaría (2007) do not report marginal effects for their bivariate probit models or estimates of the intercept terms from which the marginal effects could have been computed, it is difficult to judge the size of the effects. From the bivariate product-moment correlations reported in the paper, one would conclude that all types of external collaboration have negligible effects on innovations with a high degree of novelty (bivariate correlations between $r = .00$ and $r = .13$), and that only collaboration with multiple external actors has a substantial effect on incremental innovations ($r = .29$), whereas the effects of all exclusive forms of collaboration are negligible (bivariate correlations between $r = .00$ and $r = .06$).

In an earlier, qualitative study of some of the networks investigated in the present paper, Olsen, Elvekrok and Nilsen (2012) found that coordinators of time-limited, project-based networks perceived seven important process characteristics for the success of the networks. Four of these were largely under the control of the network coordinator (strong network management, stimulating social activities, strong coordination of activities, homework), two relied on resource allocation by the individual companies in the network (strong member contribution, support by company) and one was related to the development of trust and cooperation among the participants (stimulation of team spirit).

In the same study, Olsen et al. (2012) identified twelve types of potential outcomes accruing to the individual firms participating in such networks. These outcomes were either related to products (new products, new ideas), processes (solution of problems, efficiency gains), marketing (access to new markets), organisation (improved cooperation with business partners, increased understanding of business partners, enlarged business network), knowledge (knowledge transfer, new publications) or motivation (increased self-confidence, increased optimism). Innovation outcomes related to products, processes, organisation and marketing align well with standard innovation metrics (see OECD and EUROSTAT, 2005). Outcomes related to knowledge and motivation have an intermediary status and can be regarded as enablers of the more concrete innovation outcomes captured by standard metrics (e.g., Powell, Koput and Smith-Doerr, 1996). An interesting question is how the importance of particular process characteristics and the likelihood of achieving different innovation outcomes vary as a function of the composition of the network.

1.2 Network composition

In this study, we compare three types of networks: homogeneous manufacturer networks (composed of manufacturers from the same business sector), heterogeneous manufacturer networks (composed of manufacturers from different business sectors) and vertical collaboration networks (composed of manufacturers, suppliers and/ or customers).

Network process characteristics have previously been deemed important for innovation. The ability to identify common goals and the capacity to handle inter-organizational relationships are important for the network outcomes (Hülsheger, Anderson, and Salgado, 2009; Dhanaraj and Parkhe, 2006; Ritter and Gemünden, 2003). However, whilst professional management is important for all networks, it is probably most crucial for networks composed of partners competing in the same market. Belderbos et al. (2004) found that firms engaged in partnerships with competitors face greater risk of information leakage, which influences the communication flow negatively. Building trust, hindering freeriding and reducing concerns among the partners about undesirable knowledge spill-over may therefore be especially important in homogeneous manufacturer networks (Olsen and Gausdal, 2014). Accordingly, we hypothesise that network process characteristics such as strong network management, stimulating social activities, strong coordination of activities, homework, strong member contribution, support by company and stimulation of team spirit are more relevant for homogeneous manufacturing networks than for heterogeneous manufacturer networks and vertical collaboration networks.

Homogeneous manufacturer networks, consisting of partners with similar industry experience and overlapping product knowledge and skills, have higher group similarity than heterogeneous manufacturer networks and vertical collaboration networks. A common finding in the organisational behaviour literature is that collaboration with similar others produces smoother and more harmonious group processes, improves willingness to share information and gives homogeneous groups an advantage over heterogeneous groups (Evans and Dion, 2012; Sivasubramaniam, Liebrowitz and Lackman, 2012; Mesner-Magnus and DeChurch, 2009). Combining relevant, partly overlapping knowledge may also be important when solving technological challenges. In a study of UK manufacturing firms, Laursen and Salter (2006) found that, in some cases, firms can gain more by drawing deeply from a small number of key sources instead of searching widely among many different actors. The authors argue that this can be the case in the early stages of technology development, when only few actors have relevant knowledge within a field. We hypothesise that collaboration among the same type of partners in a network will give access to a deeper understanding and thereby help resolve specific problems.

According to a meta-analysis by Mesmer-Magnus and DeChurch (2009), similar teams may indeed share more information, but it is only the sharing of unique information that has a significant positive effect on team performance. Sharing information not commonly held by all the network members builds the available knowledge stock and improves the network outcome. Although two other meta-analyses of studies of team-level antecedents of innovation report large differences between the original studies, overall job-related diversity had a positive relationship with innovation (Van Dijk, van Engen and van Knippenberg, 2012; Hülsheger et al., 2009). Job-related diversity within a team means that the participants have access to a broader technical and social information base than participants in more homogeneous teams (Owens and Neale, 2000). Diversified teams can stimulate divergent thinking (creativity) and give access to fresher ideas and more unique information (see Stam, Arzlanian, Elfring 2014's meta-study of entrepreneurs' personal network and small firm performance). Since we expect the diversity of knowledge to be larger in heterogeneous manufacturer networks and in vertical collaboration networks than in homogeneous manufacturer networks, we also expect these networks to contribute most to new ideas and new products.

Not only network diversity, but also network partner composition matters. In a recent meta-analysis of how strategic supply chain integration affects performance, Mackelprang et al. (2014) found that this effect is by no means universal across different performance outcomes. Furthermore, they concluded that supplier integration leads to different outcomes than customer integration, internal integration or full integration. This aligns well with Belderbos et al. (2004), who found that determinants of R&D cooperation with competitors, customers, suppliers or institutions differed significantly across cooperation types. In previous studies investigating the impact of collaborating with suppliers, positive contributions emerge in terms of cost reduction, improvement of product development processes and reduced time to market for new products (Sun, Yau, Suen, 2010; Amara and Landry, 2005). Whilst collaboration with suppliers seems to improve the efficiency of innovation processes in manufacturing firms, collaboration with customers has been shown to improve responsiveness to customer needs (von Hippel and Katz, 2002). A recent meta-analysis of the relationship between strategic supply chain integration and performance showed that both supplier integration and customer integration influence market performance and new product flexibility (Mackelprang et al., 2014). Based on previous findings, we hypothesise that vertical collaboration networks are more likely to lead to efficiency gains and improved market access than homogeneous and heterogeneous manufacturer networks.

For network results related to organisation (improved cooperation with business partners, increased understanding of business partners, enlarged business network), knowledge (knowledge transfer, new publications) or motivation (increased self-confidence, increased optimism) we do not expect any significant differences between the three networks investigated. These results are likely outcomes of all networks.

2 Method

2.1 Data

A network program for food innovation and technology transfer was funded by the Ministry of Agriculture in Norway in 1994. From the first pilot network started up in March 1995 and until the end of the program in December 2011, 96 networks were successfully completed. The Ministry of Agriculture and later Innovation Norway - the Norwegian Government's most important instrument for innovation and development of Norwegian enterprises - devised guidelines for the goals, the topics and the prioritised target groups for the networks, while Nofima (a Norwegian food research institute governed by the Ministry of Agriculture) managed and coordinated the network program. The total funding from 1995 to 2011 was 96.6 million NOK (approximately €12 million).

The networks were adapted to the participating companies, their needs and resources and the allocation of companies to networks was based on a common interest in topics. Examples of topics covered were: new product development, internationalization, grocery trade of niche products, opportunity identification for specific sectors, innovation in practice, technical production improvements and solving of operational problems. 36 of the networks were homogeneous manufacturer networks (37.50%), 30 were heterogeneous manufacturer networks (31.25%) and 30 were vertical collaboration networks (31.25%). All the networks were temporary, with a timeframe of one to two years, consisting of five to ten companies (with Norwegian food companies, be it cereal, fish, meat, vegetable or processed food companies. as the central node), and the network participants met three to four times a year (for more information, see Olsen et al., 2012 and Gundersen, 2003).

The sources of data for this study were the reports written by the managers of the individual collaborative action networks. The reports were based on standardized evaluation forms, handed in by all the participants. In addition to the account of activities and achievements, the network managers reflect in writing on the development of the network: what went well and what failed to work out. The reports, varying in size from one to four pages were imported to ATLAS.ti, version 6.0, where all the information was coded and categorised. During the coding, the categories were developed inductively by two researchers independently of each other (see Table 1); a subsequent comparison of their coding showed satisfactory consistency. A cross-case synthesising analysis (Yin, 2009) was then performed: data from all the networks were categorised according to how they were constructed (homogeneous, heterogeneous and vertical collaboration), as well as quantified according to the process characteristics and the outcome reported, and finally analysed. Communalities across as many cases as possible were searched for. As a final quality measure, the results of the analysis were presented to previous network coordinators. Their verification of the findings also supports the validity of the study.

Table 1.
Description of the variables

Category	Variable	Description
Network composition	Homogeneous manufacturer network	A network solely composed of manufacturers from the same sector
	Heterogeneous manufacturer network	A network composed of manufacturers from different sectors
	Vertical collaboration network	A network composed of manufacturers collaborating with their customers and/or suppliers.
Importance of process characteristics	Strong network management	A central coordinator manages the network. A good network manager clarifies expectations up front, designs the network, and organizes the meetings.
	Stimulating social activities	Allowing sufficient time for interaction and discussion, and facilitating socializing during the organized meetings
	Strong coordination of activities	Strong coordination of activities means strict policy for handing in homework before the deadline and efficient time management of the meetings.
	Stimulation of team spirit	Stimulating trust and willingness to share information, skills and resources. Emphasizing the team spirit and the attitude of the participants
	Homework	Network participants work on relevant practical cases in between the organized network meetings.
	Strong member contribution	Network members are strongly committed and appear honest and reliable.
	Strong support by company	The participants receive strong support from their company and have time and resources earmarked for the necessary work in the network.
Achievement of network outcomes	Increased optimism	Network participation creates optimism and gives niche producers renewed belief in the probability of survival
	Increased self-confidence	Network participation increases the partners' self-confidence ("If they can, we can")
	Increased understanding of business partners	Network participation leads to increased understanding of technical and commercial challenges in other industries
	Improved cooperation with business partners	Network participation increases cooperation between the participants after the network ends
	Enlarged business network	Network participation builds wider personal network
	Knowledge transfer	Network participation contributes to the dissemination of knowledge. Knowledge is transferred from external experts to the companies, from the companies to the experts, between the companies, and is diffused within the companies.
	New publications	Network participation makes researchers aware of problems and stimulates to new research ideas resulting in new publications
	New ideas	Network participation generates new ideas by inspiring innovative thinking.
	Problems solved	Network participation contributes to solving technical and product-related problems
	Efficiency gains	Network participation contributes to efficiency gains by disseminating new cost saving and workload-reducing procedures
	New products	Network participation contributes to the development of new products
	Access to new markets	Network participation provides access to new markets.

Table 2.
Model variables

Variable group	Variable	Observed frequencies No (0)	Observed frequencies Yes (1)	*M*	*SD*
Network composition	Heterogeneous manufacturer networks	66	30	.313	.464
	Vertical collaboration networks	66	30	.313	.464
Importance of process characteristics	Strong network management	38	58	.604	.489
	Stimulating social activities	65	31	.323	.468
	Strong coordination of activities	44	52	.542	.498
	Stimulation of team spirit	77	19	.198	.398
	Homework	55	41	.427	.495
	Strong member contribution	73	23	.240	.427
	Strong support by company	87	9	.094	.291
Achievement of network outcomes	Increased optimism	88	8	.083	.276
	Increased self-confidence	90	6	.063	.242
	Increased understanding of business partners	13	83	.865	.342
	Improved cooperation with business partners	71	25	.260	.439
	Enlarged business network	69	27	.281	.450
	Knowledge transfer	6	90	.938	.242
	New publications	73	23	.240	.427
	New ideas	81	15	.156	.363
	Problems solved	14	82	.854	.353
	Efficiency gains	49	47	.490	.500
	New products	62	34	.354	.478
	Access to new markets	83	13	.135	.342

Reliability

To assess the reliability of the coding system, a random selection of 20 projects were coded by a second rater. Aggregated over the 19 binary coding axes, the agreement between the first and second rater was 72%. Cohen's κ was .27. The theoretical maximum of κ, given the marginal distributions of the codes assigned by the two raters, would be .33 in the present case (e.g., see von Eye and von Eye, 2008). Hence, the observed κ was 81% of its theoretical maximum, which can be regarded as satisfactory.

3 Analysis and results

3.1 Model specification and estimation

We specified a vector-generalised linear model (VGLM; Yee and Hastie, 2003) with binomial response distributions and probit link functions, equivalent to a multivariate binary probit model. The values on the response variables Y_j (j = 1, …, 19) were the binary codes (1: present, 0: absent) assigned to the 96 networks on the 19 coding axes (strong network management, stimulating social activities, strong coordination of activities, stimulation of team spirit, homework, strong member contribution, strong support by company, increased optimism, increased self-confidence, increased understanding of business partners, improved cooperation with business partners, enlarged business network, knowledge transfer, new publications, new ideas, problems solved, efficiency gains, new products, access to new markets). Base rates for all response variables are shown in Figure 1.

The linear predictor η_j for each response variable contained a constant term and two indicator variables X_1 and X_2 (1: present, 0: absent) for heterogeneous manufacturer networks and vertical collaboration networks, respectively. Homogeneous manufacturer networks were the reference level (with values of 0 on both indicator variables). Thus, the model had the form

$$\mathrm{E}(Y_j) = \mathbf{\Phi}(\eta_j), \tag{1}$$

$$\eta_j = \mathbf{X}\boldsymbol{\beta}_j, \tag{2}$$

where $\mathbf{\Phi}$ is the cumulative distribution function of the standard normal distribution. The parameters $\boldsymbol{\beta}_j$ were estimated by penalised maximum likelihood, using iteratively reweighted least squares (Green, 1984) with Fisher scoring and small-sample bias reduction (Kosmidis and Firth, 2009). Compared to a baseline model involving only constant terms, the model showed significantly improved fit to the data (LR χ^2 = 64.44, df = 38, p < .01). Parameter estimates are shown in Appendix 1. Predicted probabilities are shown in Appendix 2.

3.2 Effects of network structure on process characteristics and network outcomes

The importance of four process characteristics (strong network management, stimulating social activities, strong coordination of activities and homework; see Figure 2) differed significantly between networks with different structures. For three of these, the pattern was the same: project managers were most likely to see strong network management, stimulating social activities and homework as important when the networks were heterogeneous manufacturer networks, while when the networks were homogeneous manufacturer networks (with vertical collaboration networks in between), project managers were least likely to attach importance to the same characteristics. Stimulating social activities, on the other hand, were most likely to be deemed important for vertical collaboration networks, and least likely for homogeneous manufacturer networks (with heterogeneous manufacturer networks in between).

Furthermore, one network outcome (access to new markets) was significantly affected by the structure of the networks, while one was marginally significantly affected (efficiency gains; see Figure 2). Access to new markets was more likely to be achieved in heterogeneous manufacturer networks than in homogeneous manufacturer networks or vertical collaboration networks. Efficiency gains, on the other hand, were more likely to be achieved by vertical collaboration networks than by homogeneous or heterogeneous manufacturer networks.

3.3 Residual analysis

Correlations of the probit residuals $\mathbf{\Phi}^{-1}(e_{ij})$ = $\mathbf{\Phi}^{-1}(y_{ij} - \mathbf{\Phi}[\eta_{ij}])$ of the response variables are shown in Appendix 3. To examine their structure and screen for omitted variable bias, the probit residuals were subjected to maximum likelihood factor analysis. Four latent factors were sufficient to explain their covariation (goodness-of-fit χ^2 = 119.52, df = 101, p = .10). The first factor (11.4% of the variance) captured the residual covariation between strong network management (which had a varimax-rotated standardised factor loading of λ = .93) and strong coordination of activities (λ = .80). The second factor (8.1% of the variance) captured the residual covariation between strong member contribution (λ = .78) and stimulation of team spirit (λ = .61). The third factor (also 8.1% of the variance) captured the residual covariation between increased optimism (λ = .75), increased self-confidence (λ = .56), enlarged business network (λ = .44) and new ideas (λ = .42). The fourth factor (6.9% of the variance) captured the residual covariation between problems solved (λ = -.61), access to new markets (λ = .53) and increased understanding of business partners (λ = -.41). All the other loadings were below .40.

The residual covariation captured by the first three factors can be regarded as unproblematic. The response variables whose residuals loaded on these factors were so close in meaning that they can be seen as alternative, partially redundant measures of the same underlying constructs. Factor 1 could, for example, be interpreted as the stringency of network management, Factor 2 as the intensity of network interaction and Factor 3 as increases in self-efficacy. In light of this redundancy, it is not surprising that the network structure indicators in the linear predictors of the VGLM could not completely explain the covariation among the response variables whose residuals loaded on these three factors.

The residual covariation captured by the fourth factor, on the other hand, is more problematic and may indicate the omission of a predictor variable from the model that simultaneously affected several of the response variables. There is good reason to suspect that this omitted variable is the *objective* which the respective network was mainly intended to address. For example, there were several networks in our database which were set up with the specific objective to improve export marketing opportunities for the participating manufacturers. Other networks were set up to solve particular types of operational problems, for example risks of cross-contamination between different processing steps. It is immediately evident that objectives as disparate as the improvement of export marketing and the reduction of cross-contamination risk are rather unlikely to ever be addressed by the same network. In light of this, the negative correlation of the residuals of problems solved and access to new markets, captured by the fourth factor, would not be as problematic as it might initially appear.

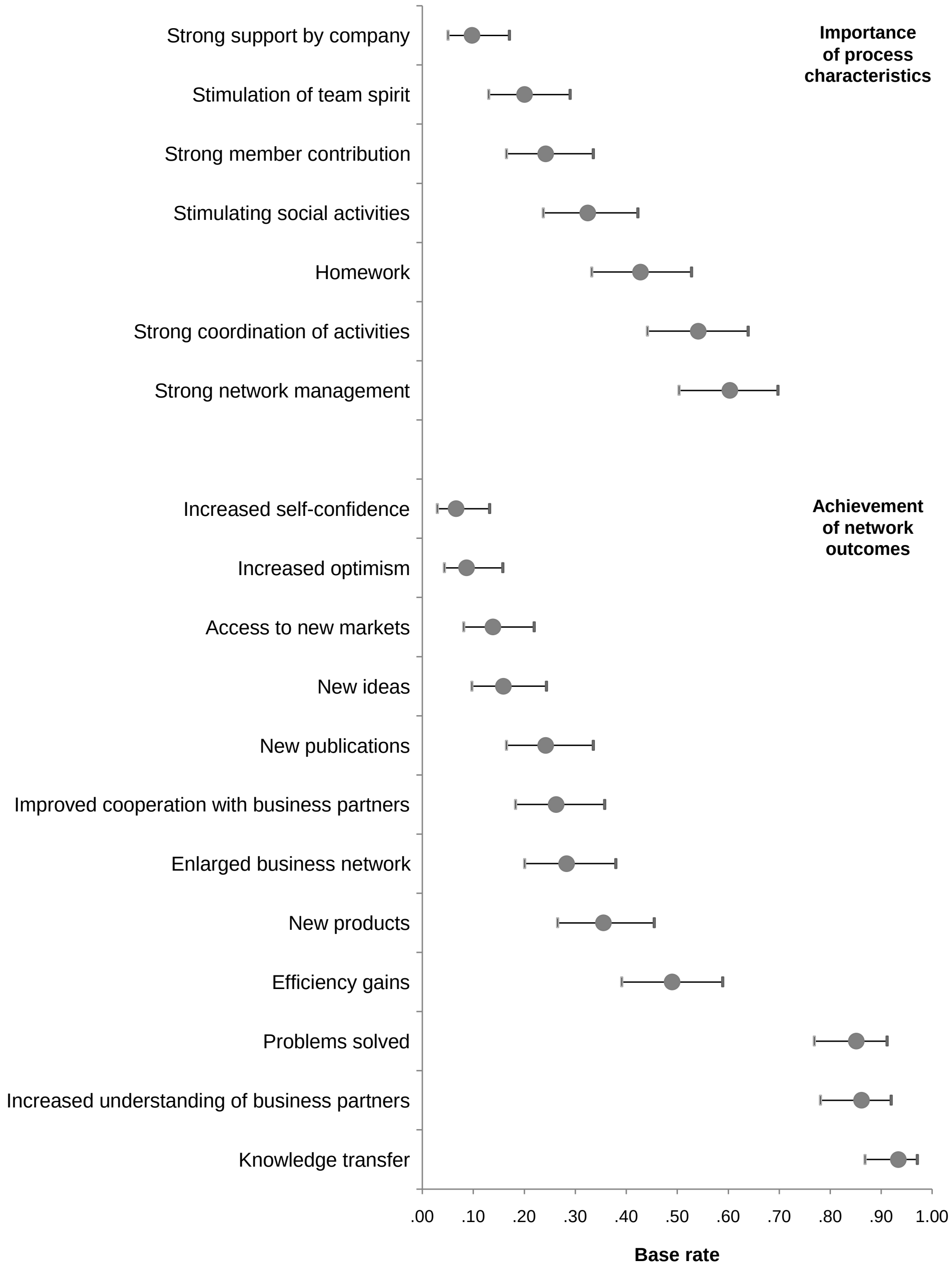

Figure 1. Base rates of dependent variables (error bars represent 95% confidence intervals)

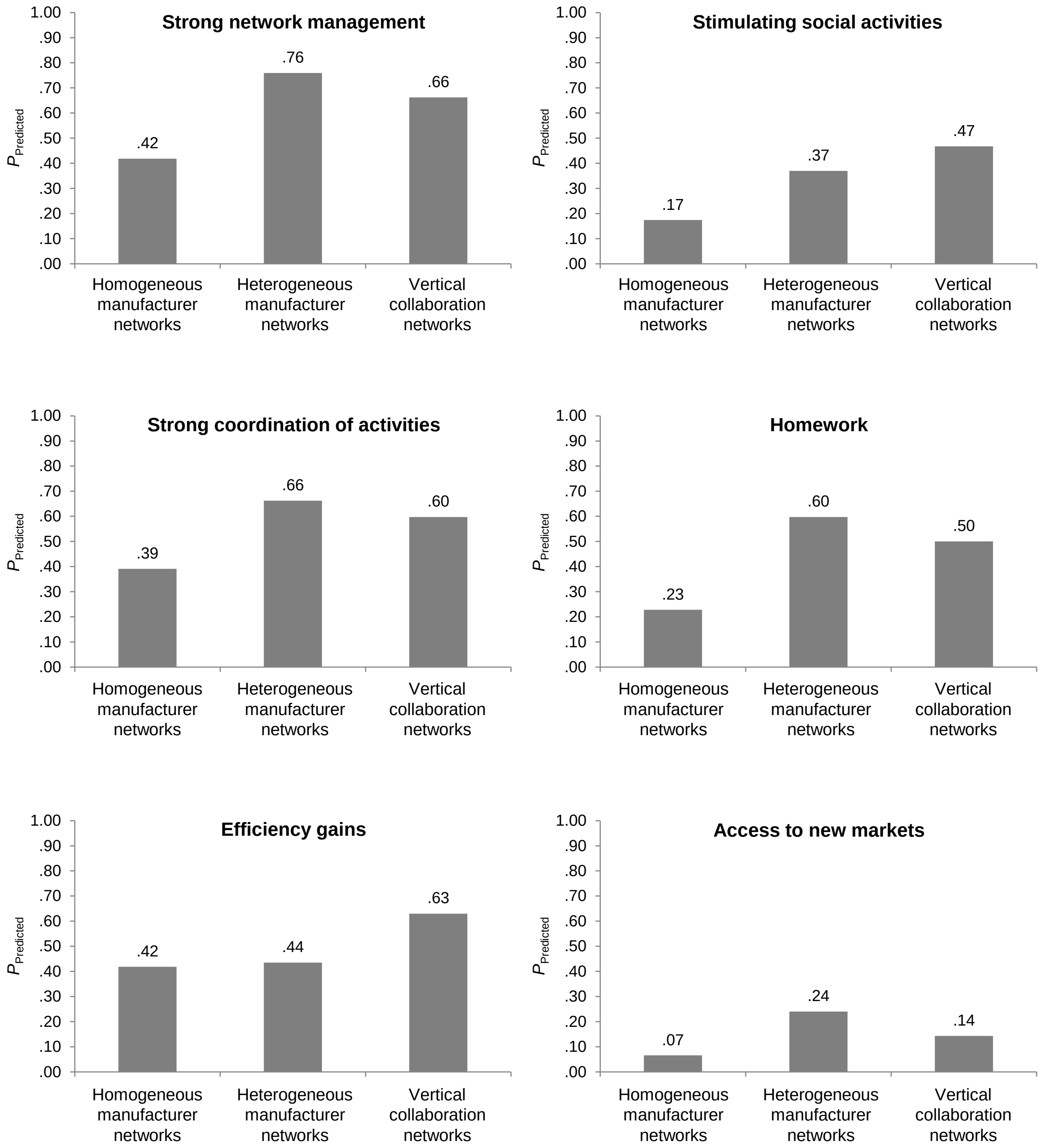

Figure 2. Importance of process characteristics and achievement of network outcomes as a function of network composition (only the significant effects are shown)

3.4 Robustness checks

Generalised linear models for binary variables (logit and probit models alike) are known to suffer from two biases. The first is related to the merely asymptotic unbiasedness of the usual estimators. In small samples (N < 200), the bias becomes so substantial that corrections are recommended. In the analysis reported above, we used the correction suggested by Kosmidis and Firth (2009). Hence, our results should no longer be strongly affected by small-sample bias. The second bias is related to the distribution of the response variable. Unlike in linear models, where a shift in the mean of a response variable only affects the constant, in generalised linear models all coefficients are strongly affected. The consequence in models for binary responses is that the more unbalanced the marginal distribution of the response variable, the more likely it becomes that the estimation will lead to "degenerate" coefficients which, when used for classification, will simply assign all observations to the majority class (e.g., see King and

Zeng, 2001).

To examine the degree to which our results suffered from such rare-event bias, we estimated 19 univariate GLMs, again with binomial response distributions and probit link functions, but regularised the estimation by weighting the observations in such a way that the weighted marginal distribution of all response variables was balanced. Goodness-of-fit and classification accuracy measures based on the unregularised and regularised model are shown in Appendix 4. The comparison clearly shows that the unregularised models were strongly affected by rare-event bias—so strongly, in fact, that even small imbalances in the marginal distribution of the response variables (base rates lower than .35 or higher than .65) led to degenerate coefficient estimates. This was the case for 15 out of 19 response variables. When used for classification employing the standard cut-off (i.e., $\hat{y}_{ij} = 1$ if $\mathbf{\Phi}[\eta_{ij}] > .50$ and $\hat{y}_{ij} = 0$ otherwise), the models had either zero sensitivity and precision or zero specificity, resulting in lift ratios of zero or one, which indicates classification performance no better than the base rate of the respective response variable.

The regularised estimates of the model parameters are shown in Appendix 5. Although the unregularised estimates (Appendix 1) can be seen as the best description of the present data set, we recommend that the regularised parameters should be used for generalising to new cases. Fortunately, all the effects that were significant in the unregularised model (Figure 2) were still significant after regularisation. In addition, the regularised estimates suggest that, if the base rates of one process characteristic (strong support by company) and two network outcomes (increased optimism, increased self-confidence) had been closer to .50, significant differences might have been observed on these variables too: strong support by the company may be more important for the success of homogeneous and heterogeneous manufacturer networks than for vertical collaboration networks, and homogeneous and heterogeneous manufacturer networks may be more likely to lead to increases in optimism and self-confidence among the participants than vertical collaboration networks.

4 Discussion

The aim of this study was to investigate how different ways of composing collaborative networks influence innovation. There is no direct evidence of the effect of different network compositions in the literature; on the contrary, more research is advocated (Klerkx and Nettle, 2013; Pittaway et al, 2004). Our findings show that differently composed manufacturer networks (homogeneous, heterogeneous and vertical) lead to different outcomes and different processes characteristics. We find that network managers perceive 1) controllable management activities to be most important for heterogeneous manufacturer networks and vertical collaboration networks, and 2) different composition of network to influence both efficiency gains and access to markets. These findings contribute to the existing literature by showing that the way networks are constructed influence both the innovation outcome of the network and how the network should be managed.

Contrary to what we expected, homogeneous manufacturer networks seem to be easier to manage than heterogeneous and vertical collaboration networks. We assumed that homogeneous networks, often consisting of competitors, would be harder to manage than networks consisting of non-competing partners. We thought competitors would be less willing to share information and more concerned of freeriding. However, the results indicate that - according to network managers - strong management and coordination of activities were the most important factors for heterogeneous networks, and that also trust-building activities (stimulation of social activities) and homework activities were significantly less important for homogeneous networks. How can we explain this? One possible reason may be that heterogeneity between the partners in a network demands more management work than networks consisting of homogeneous, but competing partners. In homogeneous manufacturer networks the partners are similar, come from the same sector, work with the same type of products and have in general a good understanding of each other. They are probably also aware of possible competitors and will take their precautions accordingly. This aligns with what Gnyawali and Park (2012) found in a case study of the co-opetition (simultaneous pursuit of collaboration and competition) between Sony and Samsung. In this alliance, the firms seem to prepare themselves for the consequences of the competition, to be able to collaborate and thereby develop advanced technologies. Conversely, heterogeneous and vertical integrated networks consist of partners with different background and knowledge; they may also lack a common frame of reference. The network literature points out that even though diversity is important for innovation it is also problematic, and if innovation is to take place in a network, the group members must share a common frame of reference (Owens and Neale, 2000; Jehn, Northcraft and Neale, 1999). Our results indicate that networks composed of heterogeneous partners lacking a common understanding gain more from management. The fact that process characteristics largely under the control of the network coordinator are perceived to be more important for vertical collaboration networks and heterogeneous manufacturer networks than for homogeneous manufacturer networks support Boschma's (2005) argument that the cognitive proximity between the actors in a network is important for a successful outcome.

Our hypotheses that homogeneous manufacturer networks would contribute more to resolve specific problems, and that heterogeneous manufacturer networks and vertical collaboration networks would create a greater amount of new ideas and new products were not supported. Previous studies have shown that access to external expertise can result in new-to-the market innovations and help resolve technical problems (Hagedoorn, 2002; Gnyawali and Park, 2011; Owens and Neale, 2000). However, in this study we observed no significant differences between the different networks' ability to result in new products, new ideas or to solve problems. Almost all the networks, independent of composition, contributed to problem solving and approximately 1/3 resulted in new products (see Figure 1). These findings may be directly connected with the nature of the networks investigated here, which often was to solve common product or production-specific problems.

Our hypotheses for vertical collaboration networks were only partly supported. Leaning on previous studies investigating the impact of collaborating with suppliers for innovation (Mackelprang et al. 2014), we expected vertical collaboration networks to contribute more to cost reduction and to product development process improvements than homogeneous and heterogeneous manufacturer networks. Suppliers collaborate with many partners and are perceived to be important disseminators of process-relevant knowledge. According to our study, network managers perceive vertical integration with suppliers in networks to contribute more to efficiency gains than the other networks investigated. These findings support our hypothesis. Conversely, our assumption that vertical collaboration networks would lead to greater market access than the other networks was not supported. Based on previous studies, we expected that collaboration with customers would facilitate market acceptance and lead to improved marked access (Gemünden et al., 1996; von Hippel and Katz, 2002). Our results show that network managers perceive vertical collaboration networks to lead to greater market access than homogeneous manufacturer network, but not as often as heterogeneous manufacturer networks. We still advocate that collaborating with customers in networks will contribute to manufacturers' access to new markets, and we believe that the reason why heterogeneous networks came out as the "winners" here has to do with the scarce number of vertical collaboration networks including customers (only 8). The fact that heterogeneous manufacturer networks lead to market access significantly more often than homogeneous manufacturer networks can probably be explained by the lack of competition between the actors. Lack of competition improves the manufacturers' willingness to introduce other manufacturers to their customers and to share relevant market information with the other partners in the network.

5 Conclusion

We conclude that composition of collaborative innovation networks appear to constitute a significant indication of both network outcome and network management. By investigating the effects of network composition on process characteristics and innovation outcomes, we were able to observe how these three core network factors, first identified by Möller, Rajala, and Svahn (2005), interact.

One of our key findings is that strong management and coordination of activities are more important for heterogeneous manufacturer networks than for homogeneous manufacturer network. Competitors seem to take their precautions enabling them to collaborate, while heterogeneous networks demand more management work due to a lack of a common understanding. These proposed explanations for our findings need to be explicitly tested in future studies. As expected, we find that vertically composed networks with suppliers contribute to efficiency gains to a higher extent than networks consisting of only manufacturers. Since our hypothesis for how network composition influences the outcome (access to new markets, problem solving and development of new products) was not supported - and we claim that this might be due to the nature of the networks investigated - we recommend that future studies replicate our study among other networks.

In this study, we have compared networks that were designed from the outside; our results indicate that governments can promote networks as an institutional policy mechanism to enhance innovation through public support systems. We believe that the existing literature suffers from a fundamental methodological problem. In theoretical terms, network composition is usually understood as an institutional mechanism (Pittaway et al., 2004) that can be designed, and is therefore exogenous with respect to the network's history. In other words, the composition of a network is understood as a variable that can be set to a particular new value by intervening in the system, causally isolating all future states of the network from the antecedent conditions that may have led to a particular composition. From this perspective, crosssectional investigations of existing networks cannot lead to valid causal conclusions because their composition - although it is typically treated as a fixed effect in regression analyses - will always be endogenous with respect to the histories of the networks.

The aim of this paper wass to investigate the effects of network composition in a set of collaborative networks that do not suffer from such endogeneity problems. All the networks were constructed ad hoc; not only was their composition under the control of a policy-maker, but all had the objective to stimulate the innovativeness of the participating actors by giving them access to other organisations, and thereby to knowledge and resources that would otherwise have been unavailable to them. Although the aim of this study was to eliminate the endogeneity problem often observed in other studies, it might be that the overall objective of the collaborative networks could affect the composition, as well as the process and the outcome, and thereby create another endogeneity problem. Future studies should therefore control for the objective of the projects when investigating the effect of network composition.

Knowledge of how to construct networks from the outside will be of value for all innovation policy support systems, but might be especially important for stimulation of innovation among small and medium size enterprises (SMEs) without internal R&D. Many SME's are actually micro enterprises with less than 10 employees (in Norway 38% of the food companies have less than 4 employees, www.matogdrikke.no), and the potential for innovation in these firms can therefore be hindered by a shortage of qualified personnel and limited resources (Blackburn and Jarvis, 2010). On the basis of our literature review, we argue that network research in general has been scarcely preoccupied with how networks are composed. This paper represents a valuable contribution to this scarcity.

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Appendix 1.

Parameter estimates (vector generalised linear model with binomial response distribution and probit link function)

		Term in linear predictor											
		Intercept				Heterogeneous manufacturer networks				Vertical collaboration networks			
Variable group	Response variable	*b*	SE(*b*)	*Z*	*p*	*b*	SE(*b*)	*Z*	*p*	*b*	SE(*b*)	*Z*	*p*
Importance of process characteristics	Strong network management	-.206	.211	-.978	.328	.911	.327	2.784	.005	.625	.316	1.975	.048
	Stimulating social activities	-.939	.246	-3.815	.000	.607	.339	1.790	.074	.857	.336	2.550	.011
	Strong coordination of activities	-.276	.212	-1.303	.193	.695	.317	2.190	.028	.523	.314	1.667	.096
	Stimulation of team spirit	-.838	.238	-3.522	.000	-.229	.370	-.620	.535	.233	.341	.683	.495
	Homework	-.745	.231	-3.219	.001	.991	.327	3.030	.002	.745	.325	2.288	.022
	Strong member contribution	-.421	.216	-1.951	.051	-.393	.337	-1.167	.243	-.512	.345	-1.485	.137
	Strong support by company	-1.176	.271	-4.342	.000	.109	.392	.279	.780	-.508	.480	-1.058	.290
Achievement of network outcomes	Increased optimism	-1.509	.323	-4.671	.000	.576	.420	1.370	.171	-.175	.511	-.342	.733
	Increased self-confidence	-1.325	.291	-4.548	.000	.101	.421	.241	.810	-.868	.666	-1.304	.192
	Increased understanding of business partners	1.325	.291	4.548	.000	-.258	.406	-.634	.526	-.511	.390	-1.311	.190
	Improved cooperation with business partners	-.658	.226	-2.908	.004	.148	.330	.449	.654	-.048	.338	-.142	.887
	Enlarged business network	-.658	.226	-2.908	.004	.148	.330	.449	.654	.148	.330	.449	.654
	Knowledge transfer	1.325	.291	4.548	.000	.092	.444	.207	.836	.359	.492	.731	.465
	New publications	-.939	.246	-3.815	.000	.429	.344	1.248	.212	.334	.347	.962	.336
	New ideas	-1.050	.257	-4.092	.000	.236	.364	.648	.517	-.017	.382	-.044	.965
	Problems solved	.939	.246	3.815	.000	-.006	.365	-.015	.988	.285	.391	.729	.466
	Efficiency gains	-.206	.211	-.978	.328	.042	.312	.136	.892	.538	.314	1.710	.087
	New products	-.658	.226	-2.908	.004	.494	.323	1.532	.126	.411	.324	1.270	.204
	Access to new markets	-1.509	.323	-4.671	.000	.804	.409	1.965	.049	.442	.430	1.030	.303

Appendix 2.
Predicted probabilities

Variable group	Response variable	Value of linear predictor (η)			Predicted probability (probit[η])		
		Homogeneous manufacturer networks	Heterogeneous manufacturer networks	Vertical collaboration networks	Homogeneous manufacturer networks	Heterogeneous manufacturer networks	Vertical collaboration networks
Importance of process characteristics	Strong network management	-.206	.706	.419	.418	.760	.662
	Stimulating social activities	-.939	-.332	-.082	.174	.370	.468
	Strong coordination of activities	-.276	.419	.247	.391	.662	.597
	Stimulation of team spirit	-.838	-1.067	-.605	.201	.143	.273
	Homework	-.745	.247	.000	.228	.597	.500
	Strong member contribution	-.421	-.814	-.933	.337	.208	.175
	Strong support by company	-1.176	-1.067	-1.684	.120	.143	.046
Achievement of network outcomes	Increased optimism	-1.509	-.933	-1.684	.066	.175	.046
	Increased self-confidence	-1.325	-1.223	-2.193	.093	.111	.014
	Increased understanding of business partners	1.325	1.067	.814	.907	.857	.792
	Improved cooperation with business partners	-.658	-.510	-.706	.255	.305	.240
	Enlarged business network	-.658	-.510	-.510	.255	.305	.305
	Knowledge transfer	1.325	1.416	1.684	.907	.922	.954
	New publications	-.939	-.510	-.605	.174	.305	.273
	New ideas	-1.050	-.814	-1.067	.147	.208	.143
	Problems solved	.939	.933	1.223	.826	.825	.889
	Efficiency gains	-.206	-.164	.332	.418	.435	.630
	New products	-.658	-.164	-.247	.255	.435	.403
	Access to new markets	-1.509	-.706	-1.067	.066	.240	.143

Appendix 3.

Correlations of probit residuals

No.	Residual	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	probit(*e*[Strong network management])	1.000																		
2	probit(*e*[Stimulating social activities])	.421	1.000																	
3	probit(*e*[Strong coordination of activities])	.824	.333	1.000																
4	probit(*e*[Stimulation of team spirit])	.157	.268	.260	1.000															
5	probit(*e*[Homework])	.336	.301	.295	.070	1.000														
6	probit(*e*[Strong member contribution])	.255	.200	.272	.488	.172	1.000													
7	probit(*e*[Strong support by company])	.062	.034	.037	.160	-.076	.416	1.000												
8	probit(*e*[Increased optimism])	.069	-.022	.106	.076	.081	.062	.247	1.000											
9	probit(*e*[Increased self-confidence])	.139	.059	.167	.253	.173	.238	.160	.435	1.000										
10	probit(*e*[Increased understanding of business partners])	-.031	-.204	-.029	-.105	.138	-.082	.114	.105	.093	1.000									
11	probit(*e*[Improved cooperation with business partners])	.085	.057	.113	.183	-.072	.144	.095	.136	.123	-.045	1.000								
12	probit(*e*[Enlarged business network])	.264	.241	.340	.139	-.019	.077	.147	.339	.254	-.008	.217	1.000							
13	probit(*e*[Knowledge transfer])	.330	-.020	.278	.031	.137	.071	.079	.071	.072	.282	.001	.072	1.000						
14	probit(*e*[New publications])	.236	-.001	.203	.091	.054	-.007	-.110	.167	.121	.154	.102	.032	.139	1.000					
15	probit(*e*[New ideas])	.168	.023	.221	.080	.227	.073	.029	.322	.256	.093	.050	.226	.108	.089	1.000				
16	probit(*e*[Problems solved])	-.105	-.209	-.033	-.179	.112	-.106	.054	-.071	-.234	.203	-.150	-.266	.209	-.040	-.016	1.000			
17	probit(*e*[Efficiency gains])	-.049	-.078	-.086	-.152	.066	-.073	-.178	.056	-.130	.082	-.002	.083	.172	.027	-.041	-.035	1.000		
18	probit(*e*[New products])	.243	.028	.217	-.084	.222	-.042	-.092	.114	.035	-.175	-.007	-.081	-.100	.258	.077	.109	.146	1.000	
19	probit(*e*[Access to new markets])	.111	-.013	.120	-.112	-.263	-.145	.001	.038	-.013	-.192	.171	.170	-.082	.031	.094	-.308	.087	-.082	1.000

Appendix 4.

Goodness of fit and classification performance of unregularised versus regularised models

	Unregularised					Regularised				
Response variable	R^2_G	Sensitivity	Specificity	Precision	Lift	R^2_G	Sensitivity	Specificity	Precision	Lift
Strong network management	.091	.741	.553	.717	1.186	.095	.741	.553	.717	1.186
Stimulating social activities	.075	.000	1.000	.000	.000	.086	.806	.462	.417	1.290
Strong coordination of activities	.058	.731	.500	.633	1.169	.058	.731	.500	.633	1.169
Stimulation of team spirit	.017	.000	1.000	.000	.000	.028	.421	.714	.267	1.347
Homework	.108	.439	.782	.600	1.405	.110	.805	.509	.550	1.288
Strong member contribution	.029	.000	1.000	.000	.000	.039	.522	.671	.333	1.391
Strong support by company	.022	.000	1.000	.000	.000	.073	.889	.333	.121	1.293
Increased optimism	.037	.000	1.000	.000	.000	.120	.625	.716	.167	2.000
Increased self-confidence	.039	.000	1.000	.000	.000	.227	1.000	.333	.091	1.455
Increased understanding of business partners	.019	1.000	.000	.865	1.000	.041	.711	.462	.894	1.034
Improved cooperation with business partners	.004	.000	1.000	.000	.000	.005	.360	.704	.300	1.152
Enlarged business network	.003	.000	1.000	.000	.000	.004	.667	.391	.300	1.067
Knowledge transfer	.006	1.000	.000	.938	1.000	.035	.322	.833	.967	1.031
New publications	.019	.000	1.000	.000	.000	.026	.739	.411	.283	1.183
New ideas	.006	.000	1.000	.000	.000	.012	.400	.704	.200	1.280
Problems solved	.007	1.000	.000	.854	1.000	.017	.329	.786	.900	1.054
Efficiency gains	.037	.404	.776	.633	1.294	.037	.404	.776	.633	1.294
New products	.029	.000	1.000	.000	.000	.032	.735	.435	.417	1.176
Access to new markets	.045	.000	1.000	.000	.000	.098	.538	.723	.233	1.723

Appendix 5.

Parameter estimates, regularised (generalised linear models with binomial response distributions and probit link functions; observations weighted in such a way as to balance the marginal distributions of the response variables)

		Term in linear predictor											
		Intercept				Heterogeneous manufacturer networks				Vertical collaboration networks			
Variable group	Response variable	*b*	SE(*b*)	*Z*	*p*	*b*	SE(*b*)	*Z*	*p*	*b*	SE(*b*)	*Z*	*P*
Importance of process characteristics	Strong network management	-.461	.209	-2.208	.027	.922	.323	2.854	.004	.626	.313	1.999	.046
	Stimulating social activities	-.523	.235	-2.226	.026	.641	.326	1.970	.049	.892	.323	2.759	.006
	Strong coordination of activities	-.377	.212	-1.780	.075	.696	.317	2.198	.028	.522	.313	1.667	.095
	Stimulation of team spirit	-.014	.210	-.064	.949	-.273	.325	-.839	.401	.250	.302	.829	.407
	Homework	-.576	.229	-2.516	.012	1.000	.325	3.075	.002	.756	.323	2.339	.019
	Strong member contribution	.283	.199	1.420	.155	-.424	.309	-1.371	.171	-.558	.316	-1.768	.077
	Strong support by company	.116	.201	.577	.564	.126	.292	.432	.665	-.763	.355	-2.145	.032
Achievement of network outcomes	Increased optimism	-.265	.230	-1.153	.249	.744	.303	2.455	.014	-.309	.366	-.845	.398
	Increased self-confidence	.190	.196	.973	.330	.122	.284	.428	.668	-2.142	.692	-3.095	.002
	Increased understanding of business partners	.330	.233	1.418	.156	-.319	.327	-.976	.329	-.616	.315	-1.956	.051
	Improved cooperation with business partners	-.034	.210	-.160	.873	.154	.307	.500	.617	-.055	.314	-.176	.860
	Enlarged business network	-.098	.213	-.461	.645	.154	.311	.495	.621	.154	.311	.495	.621
	Knowledge transfer	-.190	.196	-.973	.330	.148	.298	.497	.619	.586	.330	1.774	.076
	New publications	-.277	.224	-1.237	.216	.465	.314	1.478	.140	.364	.317	1.149	.251
	New ideas	-.085	.214	-.395	.693	.268	.306	.877	.381	-.028	.319	-.089	.929
	Problems solved	-.097	.203	-.478	.633	.000	.302	.001	.999	.357	.321	1.113	.266
	Efficiency gains	-.180	.210	-.857	.391	.042	.312	.136	.892	.537	.314	1.709	.088
	New products	-.303	.220	-1.379	.168	.506	.315	1.609	.108	.423	.315	1.340	.180
	Access to new markets	-.584	.257	-2.277	.023	.989	.329	3.003	.003	.573	.344	1.665	.096