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EXECUTIVE SUMMARY

The objective of this study was to assess empirically whether economies of scale and scope exist at the research project level. The assumption underlying European Union research policy appears to be that such economies exist, hence the emphasis placed on the 'critical mass' of research and development (R&D) projects. Overall, the results of this analysis do not support a simple assumption that 'bigger is better' in the context of the European Framework Programmes (FPs). Thus, some of the basic assumptions underlying the change in the general orientation of the FPs towards larger projects should be reconsidered.

There are many factors that must be taken into account when determining the relation between scale, scope and performance (i.e. innovation impacts obtained by individual participants). That is why use was made of an elaborate conceptual framework:

- Three sets of factors mediate (sit between) the relation between project scale and performance: (a) the pool of available resources; (b) the learning process (absorptive capacity); and (c) the transaction costs.
- Three additional sets of factors moderate the relation between project scale and the mediating factors above (pool of resources, learning process, and transaction costs): (a) partner contribution to the project; (b) project characteristics; (such as scope) and (c) project management.
- The industry and market environment(s) in which the research project was positioned.

Performance, as assessed by individual participants, was measured along eight dimensions:

- Goal achievement – the degree to which the project achieved its scientific, technical and commercial objectives
- Knowledge outputs – publications, doctoral dissertations, etc.
- Technological outputs – tools and techniques, models, simulations, prototypes, etc.
- Network outputs – building relationships with other organisations
- Research capacity impacts – effects on the capacity of the partner to undertake research such as research staff, technological skills, critical mass

- Commercial outputs – increased turnover, profitability, competitiveness
- Product innovation – new or improved products or services
- Process innovation – new or improved production processes

A multi-layered statistical and econometric analysis sought to capture the effects of project scale on these eight dimensions of performance while controlling for the mediating and moderating sets of variables above. The data came from three sources: (i) the 'InnoImpact' survey (a previous survey carried out to identify the innovation performance of FP projects); (ii) a follow-up survey specifically devised and carried out for this project; and (iii) the Community Research and Development Information Service (CORDIS). The follow-up survey determined the final sample utilised in the study, consisting of responses from 1,172 organisations participating in a total of 676 research projects funded by the Fifth and Sixth Framework Programmes for Research (FP5, FP6).

The descriptive analysis did not indicate any absolute advantage of project size, when measured by the number of partners, on performance. On the contrary, larger projects appeared to add significantly to transaction costs. When measured by the average funding per partner, (relative) project size was more strongly related to a number of performance dimensions, namely knowledge output, technological output, and research capacity impact. Larger collaborative projects in terms of average funding seemingly allowed more sophisticated partners to undertake projects that were riskier, more complex, and of longer duration compared to those undertaken individually. Evidence suggests that it is not necessarily the absolute size but the relative size of a project (partner funding) that might be responsible for 'critical mass' effects.

The econometric analysis showed (up to a certain scale) increasing and then (beyond that scale) decreasing returns to scale for one of the performance dimensions, i.e. network outputs, when scale is measured by the number of partners in a consortium. When scale is measured through the project budget, the analyses suggest the exact opposite pattern: decreasing and then increasing returns for goal achievement. While similar results were obtained for the remaining performance dimensions, the statistical significance was low. Importantly, the size of the estimated threshold varies considerably across the five project performance dimensions examined with the full sample: network outputs, goal achievement, knowledge outputs, technological outputs, and research capacity impacts. Taken overall, the results from all steps of the econometric analysis indicate that increasing scale generally does not seem to improve project performance, with the notable exception of firms which seem to benefit from increasing scale in terms of their own funding, showing a positive effect mainly on commercial impacts.

To sum up, project scale affects performance in complex ways: mostly, its effects are transmitted through critical intervening variables, such as the complementarities of resources, learning conditions, and transaction costs. When the net effect is negative – which is most of the time – it is because increasing scale lowers the positive effect of resources and learning, and magnifies the negative effect of transaction costs. Conversely, when the net effect is positive – mainly for private enterprises – it is because increasing scale strengthens the positive effect of resources and learning, and diminishes the negative effect of transaction costs. The underlying explanation of positive or negative net effects must be sought basically in the characteristics of the R&D project.

In the context of European Research Framework Programmes, increasing scale does not improve project performance unequivocally. Firms may be an exception – they seem to benefit from increasing budgets, with a positive effect mainly on commercial impacts.

Several messages emerge for policymakers and FP programme managers:

- The basic assumption of 'bigger is better' in collaborative R&D projects is not supported by our analysis. In our view, the rationale for increasing project sizes in the Framework Programmes should be carefully reconsidered.
- Increasing the scale of collaborative R&D projects in the Framework Programmes without good knowledge about the 'optimal', or 'most appropriate', size should be resisted. It remains doubtful, however, whether such knowledge can be obtained ex-ante economically with our current level of understanding.
- A closer look must be taken at relative project size as reflected by average funding per partner, and especially with an eye on the participants belonging to the business sector, where size is indeed translated into positive effects on performance – at least in some instances.
- Given the importance of the issue for the European Research Area (ERA), and the diversity of underlying determinants, monitoring of the effects of R&D project scale and scope on performance of the main funding instruments for in the various broad technology areas should become an integral part of the monitoring and evaluation exercises of the Framework Programmes.

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CHAPTER 1 INTRODUCTION AND BACKGROUND

1.1 Background

This study was carried out at the request of the European Commission as part of a series of studies on 'Forward Visions on the European Research Area'.

DG Research of the European Commission is responsible for implementing the Seventh Framework Programme for RTD (FP7). This call for tender concerns the FP7 work programme within the area SSH-2007-7.1.1.2, under the topic of Scale and Scope as Drivers of the European Research Area (ERA).

After the approval by Council and Parliament of the Seventh Framework Programme for Research and Technological Development, the focus in European research policymaking has shifted back to the idea of the European Research Area. A Green Paper re-launching the debate on the issue has been published in 2007.

The idea of the European Research Area was first launched in the year 2000 via a Commission Communication on the issue. The concept was also referred to in the 2000 Lisbon European Council Presidency Conclusions, in which Europe was urged to turn itself into a knowledge-based economy through more and better investment in the knowledge triangle of research, education and innovation.

The idea of the European Research Area was launched in response to three perceived S&T weaknesses:

- insufficient funding of R&D,
- lack of an environment to stimulate research and exploit results,
- fragmented nature of activities and dispersal of resources.

In response, the European Research Area aimed for:

- the creation of an 'internal market' in research, an area of free movement of knowledge, researchers and technology, with the aim of increasing cooperation, stimulating competition and achieving better allocation of resources,
- a restructuring of the European research fabric, in particular by improved coordination of national research activities and policies, which account for most of the research carried out and financed in Europe,

- the development of a European research policy which not only addresses the funding of research activities, but also takes account of all relevant aspects of other EU and national policies.

One of the core assumptions underlying the ERA idea appears to be that economies of scale and scope are very important in research funding and execution, implying therefore that coordination and collaboration in research funding and execution are beneficial, while fragmentation and dispersal are inefficient.

Because of insufficient empirical foundation in the relevant literature, this assumption remains largely to be validated. The purpose of this series of studies is to start filling those gaps and obtain much better insight into when and where in research economies of scale and scope matter.

1.2 Objectives

The objective of this study was to assess whether economies of scale exist at the research project level. The assumption underlying European Union research policy is that such economies exist, hence the emphasis placed on the 'critical mass' of R&D projects. Yet till today and despite repeated rounds of policy discussions centred on this notion, critical mass remains a poorly defined notion. At the project level it tends to be interpreted mainly in terms of bringing together more and more players and pooling their resources.

The 2002 follow-up Commission Communication on ERA described how FP6 was specifically designed and formulated to help achieve the ERA, and how this had been done through, among other mechanisms, 'new support instruments which will make it possible to build up critical masses of resources (NoEs and IPs)'.

Some Framework Programme ex-post evaluation studies, based on anecdotal evidence however, have suggested that larger-scale projects under FP6 have not always had the expected impacts on efficiency and effectiveness. Hence, to arrive at a better understanding and to aid evidence-based policymaking in this field in the future, it is important to develop a structured, methodologically robust analysis of these issues. The concrete research questions to be answered in the context of this project were the following:

- Are larger research projects more productive in scientific and technological terms than smaller research projects, after taking account of a number of control variables into consideration? These control variables are:
    - o thematic priority, instrument, characteristics of the individual consortium participants (sector, public/private, size, resources/capabilities, internal organisation, objectives of the individual consortium participants, and type of actor such as firm, university, research institute),
    - o project type and objectives (e.g. clear/unclear project objective, radical/incremental, risky or not risky, product/process/technology oriented, generic/specific),

- other consortium characteristics (e.g. history of cooperation between consortium members, management issues, project-team dynamics such as type of prime contractor, levels of communication, of coordination, of cohesion, and of learning).

- In reference to the first question, why is this or is this not the case? What can be explanatory factors? In other words, under what conditions are larger research projects more/less productive than smaller research projects?

As measures of the size of a research project the project budget, or the number of partners participating in the project, or a combination of the two, is used. Scientific productivity of a research project means the number and the impact of the scientific publications it generates, and technological productivity means the number of patents, tools, techniques, models, simulations, prototypes, demonstrators, pilots, etc.

The services requested in this study essentially comprise three sequential components: (1) a literature overview, the development of a conceptual framework, and a sound approach to data collection, (2) the collection of data, and (3) the analysis of data.

1.3 Study approach and implementation

The study has been implemented in three phases:

- Preparatory analytical work: this phase included an extensive literature review followed by the construction of an analytical framework and the definition of a set of hypotheses. Intermediate results were presented in a workshop to the High Level Advisory Group (HLAG)[1]. The HLAG gave extensive feedback which was taken on board in the final versions of the framework and the literature review. Chapter 2 describes both the literature review and the analytical framework.

- Data collection: the existing data collected in the Innovation Impact study[2] were used as the basis for the selection of respondents and the optimisation of the response, as well as for reuse as far as the new variables of Erascope allowed it. An online questionnaire was implemented and respondents were contacted by mail to participate in the survey. Other data were collected from CORDIS and from EPO PATSTAT. The data were filtered and organised for the third phase. Chapter 3 describes the data collection process in more detail.

- Analyses: the third stage of the study included two different analyses, a descriptive analysis and an econometric analysis. The HLAG reconvened to examine the analyses and provide recommendations based on the intermediate results. The

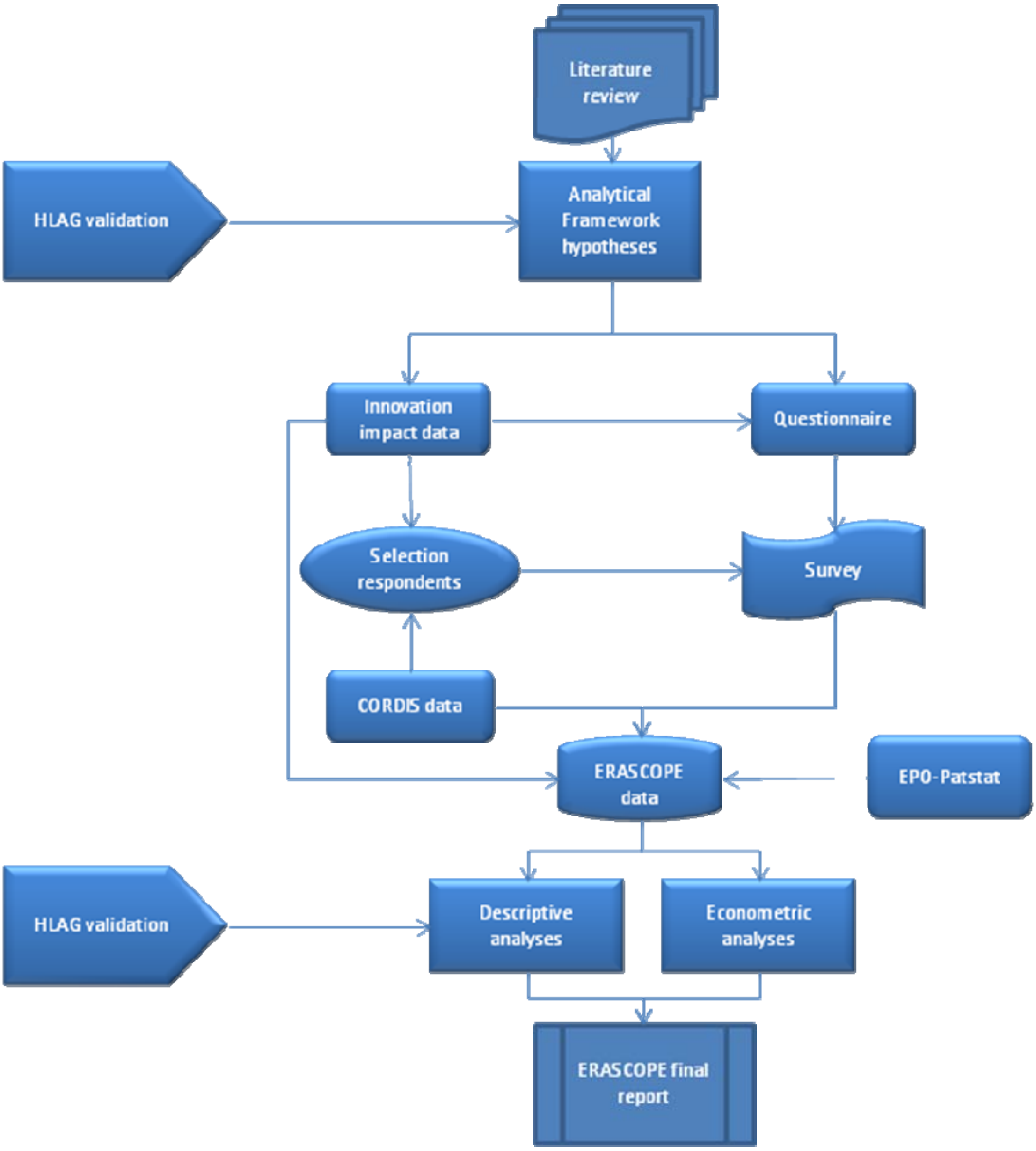
[1] See Annex 1 for the composition of the HLAG

[2] http://www.innovationimpact.org/joomla/result/innoimpact%20final%20report%20OPOCE%20NBNA23100ENC.pdf

feedback and comments were taken on board in the final round of analyses. Chapter 4 explores the analyses in detail.

Figure 1: Erascope implementation provides a graphical overview of the implementation of the study (following page).

Figure 1: Erascope implementation



CHAPTER 2 LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

The main aim of the literature overview was to shed light on rationales for public funding of research and development (R&D), and collaborative R&D in particular, and on the factors influencing R&D project performance. It provided a synthesised overview of the existing literature on:

- The role of collaborative R&D within the broader concept of innovation and competitiveness and the distinct rationales for public funding of collaborative R&D in particular,
- a definition of R&D project performance and conceptualisations, as well as measurements of returns to R&D,
- the relevance of scale and scope in research,
- identification of factors influencing project performance including scale and scope.

The literature review thereby contributed to the development of the conceptual framework and the empirical work performed in this study. It took into account the specific role of the European Union Framework Programmes and their underlying objectives.

2.1 Collaborative Research and Development (R&D)

Collaborative R&D occupies a central role within the broader concept of innovation and competitiveness. This is because technological inter-firm alliances constitute a prominent vehicle for the creation and exploitation of new knowledge, a process upon which economic and social development is based. Since the mid 1980s, the number of R&D alliances has grown rapidly, and so has the academic and policy interest in the phenomenon.

Vast theoretical and empirical literature on R&D collaboration has emerged over the past three decades that attempts to explain why firms enter into research partnerships and what the results of such partnerships are for the partners, industry, and society as a whole

(Hemphill and Vonortas, 2003; Malerba and Vonortas, 2009; Caloghirou et al., 2004; Vonortas, 1997).

According to Hagedoorn et al. (2000) there are two distinct but complementary strands in the extant literature. On the one hand management theorists, in line with the resource-based view of the firm perspective, focus on the firm and R&D projects as their unit of analysis, viewing partnerships as a mechanism to bundle resources, build up capabilities, and create future technological and market opportunities. On the other hand, economists utilising the theoretical apparatus of industrial organisation and transaction-cost theories are mainly interested in the impacts of firms' actions on industrial structure, economic efficiency, and social welfare.

The distinctive character of these two research traditions is perhaps most apparent in their attempt to answer the basic question of motives: why do firms form R&D collaborations in the first place? In the economics literature, cooperative R&D is seen as a means to set cost-sharing and/or output-sharing rules for the participants in a project in order to correct for market failures which would otherwise prevent firms from conducting the socially optimum level of R&D. Within this line of reasoning, motives for participating in cooperative R&D principally relate to the possibility of enhancing R&D productivity through cooperation on relevant inputs, as well as to the ability to change the appropriability conditions concerning R&D outputs (Katz, 1993; Geroski, 1993). Other motives include improved market access through partners, risk sharing, and securing government subsidies (Sakakibara, 2002).

From a management perspective, cooperative R&D is seen as a vehicle whereby firms overcome their resource constraints through mutual learning (Westney, 1988; Kogut and Zander, 1992) and sharing of specialised resources and capabilities with partners (Sinha and Cusumano, 1991). Cooperative R&D is therefore considered as a means to share, combine and internalise complementary resources and knowledge to achieve synergies, avoid duplication of efforts and overcome problems related to technological and market-related risks and uncertainties (Hagedoorn, 1993; Hagedoorn et al., 2000; Hemphill and Vonortas, 2003; Malerba and Vonortas, 2009).

To summarise, frequently mentioned advantages of research partnerships to private sector partners include:

- research and development (R&D) cost sharing,
- reduction of R&D duplication, research synergies,
- risk sharing, uncertainty reduction,
- knowledge spillover internalisation,
- easier access to finance,
- access of complementary resources and skills,
- more effective deployment of extant resources and further development of resource base,

- strategic flexibility, market access, and the creation of investment 'options',
- promotion of technical standards,
- market power, i.e. co-opting competition.

2.2 Government intervention in Collaborative R&D

Public support for science, technology and innovation has been justified on the basis of market failures and system failures. Market failure requires that the social returns on research investment exceed the private returns tfor the individual organisation undertaking the investment. The principal causes of the discrepancy are said to be imperfect appropriability – leading to knowledge spillovers – and uncertainty. The expected underinvestment by the private sector arguably raises the need for public investment to achieve a socially optimal level of research effort. Governments may choose to support collaborative research so that the private sector engages. Moreover, as long as not all relevant parties join the collaboration there is still the potential for an externality flow beyond the collaborative project which provides additional incentives for public sponsorship of collaborative R&D activities.

System failures may be the result of the complexity of scientific and technological advancements and innovation. For example, one can argue for the existence of 'lock-in' in some technological trajectory, even though an alternative path of technological development might be more efficient. Public intervention may be necessary to make the transition. Alternatively, government intervention may be proposed based on institutional constraints on the utilisation and dissemination of knowledge. As a result of the systemic nature of innovation, there are many feedback loops between the various stages of the innovation process. Government intervention may be justified to avoid coordination and institutional failures. Also, government intervention may be necessary in order to facilitate/optimise the transition between successive technology lifecycles. Finally, the government also plays an important role in providing the necessary investments in human capital and in mechanisms to intensify the flows and absorption of knowledge.

The rationale for governments funding private R&D and collaborative R&D may take both system and market failures into account, which then are transformed into more actionable policy objectives such as a) harnessing the talents of university staff and graduates for national benefit, b) underwriting collaborative interaction of firms and academia, c) upgrading the country's international competitiveness in existing areas, and d) developing new areas of international strength (see Grimaldi and Tunzelmann, 2002). Kuhlmann (2002) identifies a shift from 'mechanistic' to 'reflexive' research and innovation policymaking, which puts stronger emphasis on systemic failures as:

- Strategy targets have moved from excellence of individual researchers respectively to competitiveness of single companies to the modernisation of institutes, corporations, sectors, regions, and (national, regional, sectoral) 'innovation systems'[3].

- Policy means have moved from direct R&D subsidies to adoption and dissemination-oriented policies of new technologies, to liaison/brokerage services, to network or 'cluster' stimulation, to continuing education, to regulatory policies (e.g. IPR).
- The scope of potential impacts and benefits has moved from clear-cut R&D results to developing innovative products and processes, fostering the knowledge base and increasing absorptive capacities.

Policy thinking regarding research in the European Union has arguably progressed from the traditional market failure arguments towards concepts of systemic failure and related scale and scope effects. This may be manifested by the increasing attention paid not only to collaborative R&D but also to the broader concept of the ERA and its vision for increasing coordination among national and regional research policies, as well as between research and regional development policies. It also seemingly underlies the philosophy of the Framework Programmes for Research. The justification of the first three or four Framework Programmes primarily reflected market failure arguments based on the need to support pre-competitive research of generic applicability across the Community. The main funding instrument was focused on cooperative research projects of limited time duration. The thinking underlying more recent Framework Programmes, however, has moved visibly towards the arguments of systemic failure. This trend started somewhat shyly with the Fifth and moved forward visibly with the Sixth and Seventh Framework Programmes that have endorsed new funding instruments in research such as integrated projects, networks of excellence, and joint technology initiatives to advance whole technology platforms.

2.3 Economies of scale and scope in R&D

Vonortas (2009) discusses in detail the economies of scale and scope in research. Scale effects may be present at several levels: the research project, the organisation, the group of organisations (if cooperative project) and the geographical area (country, region). The concept of returns to scale is used to describe what happens to output when all inputs are increased together (by the same proportion) when a specific technique is in place. An increase in all inputs resulting in a more than proportional increase in research output indicates increasing returns to scale. Increases of the same proportion means constant returns to scale. Research output which increases by a smaller proportion than all of the research inputs results in decreasing returns to scale.

Economic theory offers three possible reasons for increasing returns to scale: specialisation, dimensional effects and indivisibilities. Specialisation implies a finer

[3] Notice that a counter-shift in EU policymaking can be witnessed by the introduction of the European Research Council (FP7-IDEAS), which exclusively targets individual researchers.

division of labour as the research project grows larger. Dimensional effects refer to the case where a larger unit of capital produces disproportionately more than a smaller unit. Indivisibilities exist when certain inputs are available only in certain minimum sizes: larger research scales may utilise such inputs more efficiently. For instance, professional management or large physical infrastructure could be such an input. On the other hand, the prevailing reason for decreasing returns is the coordination and control complications of large size operations.

Under the assumption that all inputs are in perfectly elastic supply to the organisation, then the scale effects above translate into cost effects: increasing returns are reflected in economies of scale – decreasing long-term average cost – whereas decreasing returns to scale are reflected into diseconomies of scale – increasing long-term average cost.

On the other hand, economies of scope are present when the same one research operation deals with several subjects because of cost advantages. Economies of scope in research may result in situations where several research projects involve at least some of the same management and S&T knowledge, skills and capital equipment, thus allowing for cross-fertilisation and productive exchange. In research projects, economies of scope may arise due to the increasing complexity of the research endeavour and the formation of an interdisciplinary team with complementary knowledge assets.

While scale and scope effects may be theoretically discussed separately, in practice they frequently occur simultaneously and are difficult to distinguish empirically. Aspects of research management practice and technique across different sectors further complicate the picture. Difficulties include:

- Research output differentiation: The cost disadvantages of a smaller scale research enterprise may be offset by differentiation of the research outputs in ways that achieve much higher prices for them – for instance, high value-added niche markets. This gives rise to the coexistence in the same technology areas of research enterprises of very different sizes.
- Differences between sectors and technology areas: In the presence of significant economies of scale in research one would expect the size of the competing research enterprises to grow and competition to be of a classic oligopolistic nature. Such a strategy could, however, prove fatal in the presence of new techniques coming outside of the narrow confines of the industry in question. A case in point is the pharmaceutical industry and the biotechnology revolution.
- Different inputs and techniques: Only rarely, if ever, would a large research enterprise resemble – in terms of inputs, structure, and techniques – a much smaller research operation. Therefore, the concept of capital-labour ratios requiring uniform capital and labour units becomes questionable. Equipment and labour skills are usually commensurate with particular scales of the research operation.
- Broad ranges of efficient research output: In the presence of constant returns to scale in research, the long-term average cost curves are flat rather than U-shaped

as required by economies and diseconomies of scale. The shape and position of short-term cost curves will then be the result of managerial decisions and the influence of particular characteristics of the research operation/project in question.

- Imbalances among different stages of research: Imbalances among the different stages of the research enterprise may be the result of deliberate managerial decisions rather than indivisibilities in capital equipment. Excess capacity may be built into the design of a research operation due to anticipated needs. For instance, it is well understood that the cost of successive stages of research – from more basic to applied, on to development and prototyping – increases in a geometric progression. Research managers may build excess capacity in the earlier (less costly) stages of research and tolerate the cost of parallel projects in competing approaches in order to eliminate as much uncertainty as possible before moving closer to market.
- Research output mix: The concept of economies of scope does not take into consideration the demand side, that is, the possibility that a research enterprise is set up to respond to different kinds of research output mixes. This requires some flexibility built into the system which may make it appear less cost efficient than what it could be if it were to serve exclusively the current research output mix.
- Pre-emptive investment in research scale: Occasionally, an organisation or group of organisations may invest in a level of research capacity beyond what is currently needed. The reason is dynamic and strategy related: competitors, current and prospective, may be discouraged by the existence of idle excess capacity that can be used quickly when the opportunity arises. They may thus decide to abandon plans for expansion of existing, or establishment of new, research operations.
- Scale and technological change: Efficient scale requirements drastically change over time according to the features of existing technology. This works at two levels. On the one hand, there are very extensive differences across sectors and technological areas. There is, for instance, hardly any resemblance of scale and structure among research operations in the chemical industry and mobile telephony. Even within the same broad sector, there are quite significant differences – see bulk and specialty chemicals. On the other hand, minimum efficient scales of research will change dramatically within the same sector at different stages of the sector's evolution, typically getting larger as the sector matures, products become more standardised and research opportunities decrease.
- Scope and technological change: Opportunities of economies of scope and complementarity will also differ across technology areas and will change over time on the basis of technology evolution, complexity of research and required interdisciplinarity to solve problems. This creates significant room for managerial intervention and strategic considerations.

Overall, it should be noted that empirical findings regarding the influence of scale economies on R&D performance are mixed (Cohen and Levin, 1989; Patel and Pavitt, 1995). Some researchers note that these inconsistent findings result from the difficulty to separate in practice scale and scope and to do so in different industrial/technological environments. While the two concepts are conceptually distinct, there is a lack of sufficiently detailed data to distinguish between various measures of scale and scope and empirically test the effect on R&D project performance (Henderson and Cockburn, 1996).

2.4 Economies of scale and scope in Collaborative R&D

An important limitation of the classic discussion on scale and scope effects in research for today's environment is the concentration on individual organisations. This contrasts with one of the most striking features of industrial innovation today, namely that only a small minority of firms can innovate alone. Adapting to an environment of high risks, global competition, increasing complexity of technological advances, and rapid generation and diffusion of technical knowledge and know-how, a large number of firms have opted for cooperative relations. In the presence of technological development that involves a greater array of product and process systems, subsystems, and components, no single firm can deploy all of the requisite capabilities and assets at a reasonable cost. In this context, a network can serve as a locus for innovation because, for any network member, it provides timely access to external knowledge and resources that are otherwise unavailable, while also testing internal expertise and learning abilities (Powell et al., 1996). Linkages within innovation networks are very complex, involving not only diverse kinds of formal contracts, but also informal exchanges of knowledge, thus increasing opportunities for knowledge transmission.

To the extent that the relevant unit of analysis has shifted from the individual organisation to the consortium or the network, the conceptualisations of scale and scope in the economic literature must be recast. The relevant research resources, capabilities and strategies are no longer those of the individual organisation but those of the group. The research question then becomes whether the incremental benefits obtained by a larger and more inclusive network through the leveraging of larger pools of resources and capabilities overcome the incremental cost of increased coordination needs and ebbing motivation.

At the project level, a large consortium or a large budget would, in principle, be associated with improved performance. In terms of both scientific and technological outputs, the efforts and skills of multiple partners in an R&D project would lead to a larger pool of resources and expertise and hence would, ceteris paribus, increase the likelihood for success (Schilling, 2005). Equally important, a large consortium, composed of carefully chosen participants, would increase the heterogeneity of resources pooled together for project use. Increased heterogeneity in skills and experiences among project participants may foster creative problem solving, promote learning and new knowledge creation, and may thus increase the likelihood of project success.

Unfortunately, large consortia also have a negative side: the administrative and coordination costs of running the project also increase with size. In addition, large numbers of participants may bring a greater likelihood of social loafing and free riding, thereby decreasing the extent of learning (Gibson & Vermeulen, 2003; Wong, 2004) and hence the likelihood of project success. For example, Stuart (1998) argued that the most successful alliances are those between firms with similar technological foci and/or operating in similar markets, whereas in contrast, distant firms find it difficult to cooperate effectively.

The trade-off between these effects will have a direct bearing on the consortium's absorptive capacity (ACAP), that is the set of capabilities relevant to the acquisition, assimilation, transformation, and exploitation of knowledge to finally produce marketable, innovative results.[4] This trade-off, in conjunction with the notion of research exploration-exploitation (March, 1991), underlines the core analytical framework in this study.

In the context of the Framework programmes, seeking larger sizes of R&D projects aims at economies of both scale and scope: the larger the consortium or the project budget, the better are considered to be the chances to reap the benefits of partner specialisation by allowing them to bring in the complementary resources they are best able to deliver, to achieve minimum efficient scales in equipment or team size, or to strive for a multitude of outputs from the same project (publications, patents, direct innovation outputs). A large consortium, composed of carefully chosen participants, would increase the pool of resources available for project implementation, as well as the heterogeneity of resources pooled together for project use. Interestingly, heterogeneity connects with the notion of technological cognitive distance among project participants (Nooteboom et et al., 2007). Increased heterogeneity in skills and experiences would foster creative problem solving, would promote learning and new knowledge creation, and thus would, ceteris paribus, increase the likelihood of project success.

The research question then becomes whether the incremental benefits obtained by a larger and more inclusive network through the leveraging of larger pools of resources and capabilities overcome the incremental cost of increased coordination needs and ebbing motivation.

2.5 Factors affecting R&D Project Performance

Determining the performance of an R&D project is a subtle matter because such projects are often complex and involve several interdependent phases. The relevant literature strongly suggests that no single, reliable, objective measure of project performance exists. Performance indicators need to be linked to the specific goals of the project. The conclusion of a survey of R&D project success factors and product innovation (Balachandra and Friar, 1997) was that while there is an abundance of success factors presented in the literature, their relevance to different contexts is varying. A more precise

[4] Zahra and George (2002) building on the work of Cohen and Levinthal (1990).

framework to position R&D projects and related success factors is lacking, and may not even be possible to construct.

The project management literature sets performance within the classical triangle of achievement of objectives in terms of time, contents, and budget (Zöllner, 2003). Therefore, it is important to distinguish between project success as achieving the goals of the project and successful project management which refers to issues such as staying within the foreseen budget, keeping the timeline, and assuring proper use of quality assurance mechanisms. The distinction between project success and successful project management allows differentiating between content criteria, which relate to the achievement of certain outputs, effects and impacts of projects, and process criteria – which mainly relate to the successful implementation of certain management procedures.

For the purposes of this study, project performance has been conceptualised to comprise eight dimensions: a) project goal achievement, b) knowledge outputs, c) technological outputs, d) network outputs, e) research capacity impacts, f) commercial impacts, g) product (goods/services) innovation, and h) process innovation.

- Goal achievement: degree to which the project achieved its scientific, technical and commercial objectives,
- Knowledge outputs: significance of outputs such as publications, doctoral dissertations, reports, conference proceedings,
- Technological outputs: significance of technical outputs such as tools and techniques, models and simulations, and prototypes,
- Network outputs: significance of networking results, such as links with research organisations and other businesses,
- Research capacity impacts: effect on the ability of the partner to carry on research activities (increased number of research staff, enhanced technological skills, critical mass of research, etc),
- Commercial outputs: exploitation outputs of the project in question such as increased turnover, profitability, enhanced competitiveness,
- Product innovation: new or improved goods/services as a result of the project,
- Process innovation: new or improved production processes as a result of the project.

Whilst there exists a rich set of arguments, and associated empirical evidence, concerning the motives underlying the formation of R&D consortia, the choice of governance structures under different conditions (Hagedoorn et al., 2000), and the scope of R&D collaboration (Oxley and Sampson, 2004), the empirical appraisal of R&D performance in general, and of the impacts of publicly-funded collaborative R&D in particular, remains relatively spotty. This is primarily a result of (a) difficulties in measuring the dependent variable (performance) in a consistent and appropriate manner (Caloghirou et al., 2003) and (b) of the heavy demands in collecting the rich data necessary to assess performance (Gulati, 1998).

In addition to the inherent ambiguity in conceptualising and operationalising R&D performance in general (Ruegg and Feller, 2003), any attempt to seriously investigate the factors affecting the impacts of publicly-funded collaborative R&D would need to build on the distinction between exploration and exploitation. March (1991) defined exploration as 'experimentation with new alternatives' having returns that 'are uncertain, distant, and often negative' and exploitation as 'the refinement and extension of existing competencies, technologies, and paradigms' exhibiting returns that 'are positive, proximate, and predictable.' Later, Levinthal and March (1993: 105) defined exploration as 'the pursuit of knowledge, of things that might come to be known' and exploitation as 'the use and development of things already known'.

The conceptual distinction between exploration and exploitation is important. It may explain why some consortia prove to be inefficient in leveraging their exploration potential, and are therefore unable to successfully commercialise their R&D output. For example, Rothaermel and Deeds (2004) in their study of R&D alliances suggested that exploration-focused collaborations lead to products-in-development (i.e. R&D output in terms of a prototype or a patent), while by contrast, consortia with an exploitation orientation tend to result in commercialised products. The exploration-exploitation distinction also allows for different learning processes as well as for different mechanisms determining their efficiency and effectiveness (e.g. Nooteboom, 2000).

Turning back to antecedents of project success, a recent report to the Commission[5] identified the following categories of factors affecting collaborative R&D performance:

- Partners' resources and capabilities (i.e. prior experiences, complementarity of assets, capability to manage consortia, cultural diversity, and partners' network structure – Lane & Lubatkin, 1998; Lane et al., 2001), and broader organisational factors such as firm strategy and objectives,
- Management aspects of the R&D consortium (i.e. social and behavioural dynamics of the consortium, such as communication, coordination and control mechanisms, and team leadership roles – Hirst & Mann, 2004; Hoegl et al., 2004),
- Perceived characteristics of the research result (i.e. complexity, trialability, relative advantage, usefulness and ease of use),
- R&D protection mechanisms (i.e. appropriability regimes – Zahra & George, 2002),
- Market conditions (i.e. technological shifts, government regulations, market structure, size and uncertainty – Katila & Shane, 2005; Schilling, 2005).

[5] 'Innovation Impact: An Analysis of the Impact of Publicly Funded FP5 and FP6 Projects on Innovation', DG Enterprise, European Commission, 2008.

2.6 Analytical Framework and Hypotheses

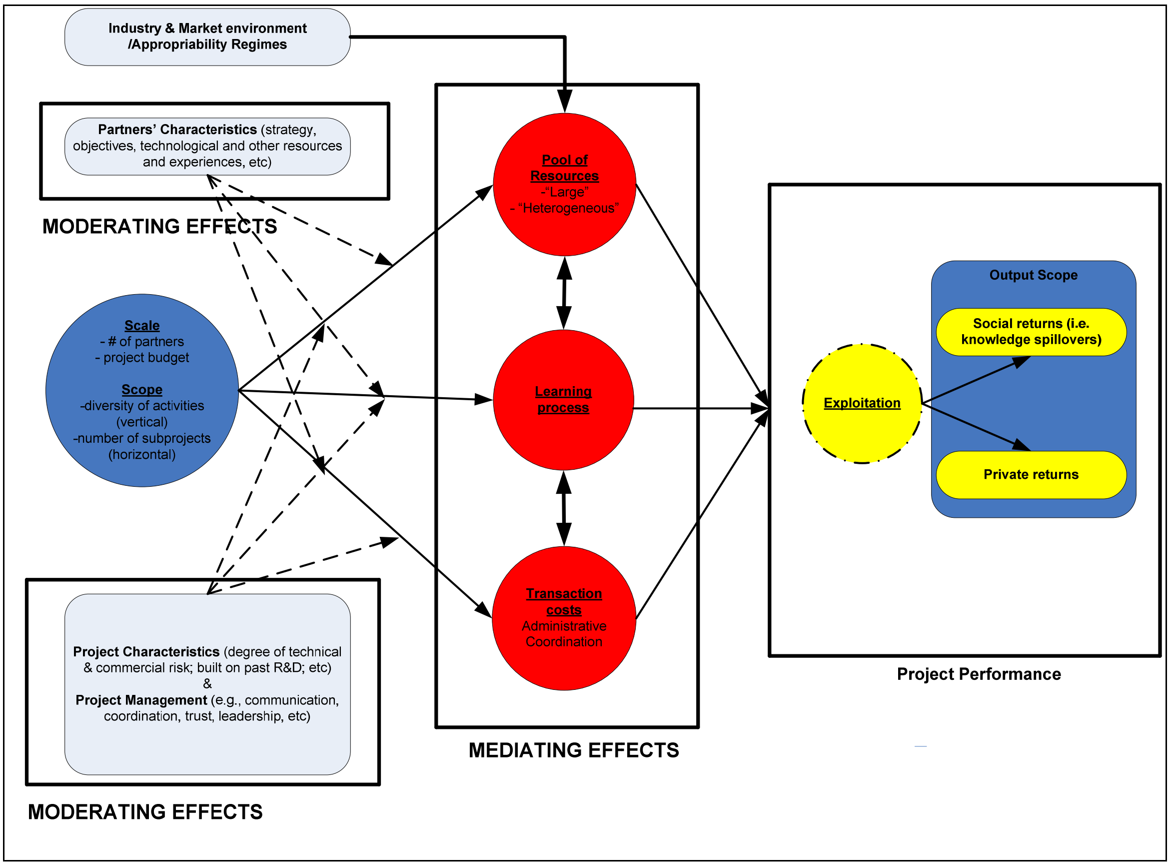
Figure 2 shows the conceptual framework guiding this study. This framework depicts project performance as being affected by project scale and scope via their effects on three mediating variables: the pool of resources committed to the project, the learning process (absorptive capacity, AC) and the transaction costs. It further supposes that these relations are influenced by certain classes of moderating variables that condition the effect of scale and scope on the mediating variables. These variables include partner's characteristics (specifically the 'quantity' of resources devoted by the partners), project characteristics, and project management mechanisms. In addition, market environment is included in the model as a 'control' to eliminate or reduce the bias from confounding effects.

Essentially, our framework posits that whatever outputs/results are produced from an R&D project are directly determined by what 'is happening inside the project'. What is happening relates to (a) the pool of resources available for project implementation, (b) the effectiveness of learning[6] taking place among project participants, and (c) the transaction costs incurred during project implementation. Effectively, we hypothesise that the pool of resources and learning affects performance positively and transaction costs affect performance negatively. Whatever effects scale has on project performance must be 'transmitted' through these three classes of intervening variables.

The notion of 'pool of resources' encompasses two distinct yet closely related concepts: (a) complementarity and (b) diversity (heterogeneity) of resources. Complementarity refers to the extent to which the resources provided by the partners supplement and enhance one another, acting synergistically towards project objectives. In this connection, it is important to note that the management literature on strategic alliances puts forward the notion of complementarity of resources as the key factor driving alliance formation. Diversity, in our context, is best understood as the extent to which the 'portfolio' of distinct resources provided by the partners is wide enough to cover the entire array of the skills necessary to achieve project objectives.

[6] Henceforth, we use the terms 'learning' and 'absorptive capacity' interchangeably.

Figure 2: Analytical framework



The two concepts are (intuitively) closely related, but not necessarily identical. One can easily think of a situation where partners provide complementary resources, which nevertheless do not cover the entire spectrum of requisite skills for successful project implementation.

Absorptive capacity according to Cohen and Levinthal (1990) refers to a firm's capacity to value external information, assimilate and apply it to commercial ends. The concept was taken up by a number of researchers and used in a variety of empirical settings, including the study of strategic alliances. The basic rationale is that the effectiveness of any inter-organisational arrangement (such as collaborative R&D) is basically a function of the quality of learning taking place among the partners. In our context, this means that since R&D projects are essentially striving to create new knowledge, success is inherently dependent on the effectiveness of learning within the consortium (i.e. the degree to which partners are capable of acquiring knowledge from one another and from external sources, to assimilate, and combine it in order to create new knowledge).

Transaction costs refer to the (inevitable) problems encountered by the partners during project implementation. The quid pro quo among partners inevitably brings with it problems in the coordination of activities, resulting from possible hidden agendas, a reluctance to reveal valuable information, potentially contradictory objectives, and so forth. Obviously, these problems work in the direction of making project success more difficult to achieve.

It is clear that these three classes of intervening variables are not independent from one another. In fact, it would be reasonable to argue that the pool of resources and the transaction costs influence directly, and in opposing directions, the effectiveness of learning in the consortium. Specifically, it seems reasonable to expect that the higher the complementarity and diversity of resources, the more effective the absorptive capacity of the consortium, as partners will have more and a wider array of skills to share and synthesise in their quest to produce new knowledge. A possible counter-argument here could be that as diversity (but not complementarity) increases, the more difficult it is for partners to assimilate knowhow from one another, and consequently the more difficult it is for them to synthesise the bits and pieces into new knowledge. Even though this is a serious point, one could argue that 'excessive' diversity among partners would adversely affect learning through higher transaction costs. In other words, any negative effects of diversity on learning would result from transaction costs incurred precisely because of excessive diversity. It is only logical to assume that high diversity, produced for example from widely different skills and experiences among partners, will result in more difficulties in coordination, in disparate objectives, etc. and hence in higher transaction costs. As for the latter, there would be little doubt that the higher the transaction costs incurred by the partners, the less likely the successful production of new knowledge.

In our conceptual framework, however, we do not model such effects among the mediating variables. Doing so would complicate considerably the empirical analyses in an already complicated framework, since we would need to estimate an even more complex set of relations among the variables of interest. Instead, and given that our primary interest is in the effects of scale, we prefer to make the simplifying assumption that the three 'mediators' are correlated, without paying explicit attention to the structural effects governing their inter-relations. Note however that we hypothesise differential effects of scale on performance transmitted through the mediators, as explained below.

Our primary interest is in estimating the effects of scale, which are assumed to pass through the intervening variables. We expect that scale will affect all three types of mediating variables positively (in a statistical sense). Put differently, we build our conceptual framework on the premise that as scale becomes larger, this will, ceteris paribus, (a) increase the complementarity and diversity of resources, (b) will increase learning, and (c) will increase transaction costs. Points (a) and (c) seem reasonable to hypothesise. There is little doubt that as scale becomes larger, this results in potentially more complementary resources and a more diverse set of skills and experiences for project implementation. Similarly, as the scale of the project becomes larger, particularly in terms of the number of participants, the greater the likelihood of problems among partners. For example, it is more difficult for a large number of project participants to coordinate activities among themselves. Similarly, it is more difficult, ceteris paribus, to align motives and objectives driving their participation in the project. Even though this is not necessarily so, greater numbers bring – all else being equal – the likelihood of widely differing agendas that may make such an alignment a difficult task.

In contrast, point (b) deserves more attention. The finding that scale increases learning follows from the assumption that, as scale becomes larger, it is more likely that the partners will have more resources to share, combine, and synthesise in order to produce new knowledge. The counter-argument is, of course, that as scale increases so does the likelihood of friction and higher transaction costs among the partners, and consequently it will be less (not more) learning taking place. But these arguments bring us back to the point noted just above: learning is positively affected by complementarity and diversity of resources, and negatively affected by transaction costs, and it is through them that scale affects learning. Hence, we admit that the hypothesis of a direct positive influence of scale on learning is a simplification of an otherwise more complex relation; it would be more defensible to hypothesise that the effect of scale on learning is mediated: positively by the pool of resources and negatively by transaction costs. But this, as already noted, would make our conceptual framework too complex to test empirically. Hence, in what follows, we will present the effects of scale on learning as if they were direct, even though we acknowledge this to be a simplification of an otherwise much more complex relation.

Returning to our key question, the discussion thus far implies that we expect a mixture of positive and negative indirect effects of scale on performance – effects that are assumed to be mediated by the complementarity and diversity of the pool of resources, learning, and transaction costs. Specifically, we expect two positive indirect effects in the following causal chains: (a) scale → complementarity and diversity → performance, (b) scale → learning → performance, and (c) a negative indirect effect in the chain: scale → transaction costs → performance.

Finally, as shown in the Figure above, we also expect that these mediated effects may be based conditionally on some moderator variables. Put differently, we hypothesise that the effects of scale on the mediating variables may be moderated by such factors as the 'quantity' of resources devoted by each partner, the characteristics of the project per se, and the 'quality' of project management.

With regards to the 'quantity' of resources, we argue that if partners devote more resources to the project, the positive effect of scale on the collective pool of resources will be (quite obviously) higher. Within the same line of reasoning, this will also increase the positive effect of scale on collective learning. In connection to transaction costs, we expect that a high quantity of resources devoted by each partner will decrease the positive (in the statistical sense) effect of scale, because in such circumstances the partners will have more stakes invested in project success and hence more to lose if things go wrong because of transaction costs.

Similar arguments can be put forward as to the moderating effects of project management 'quality'. We expect that the effects of scale on the collective pool of resources and on learning will be higher in a well managed project. Conversely, the positive (in a statistical sense) effects of scale on transaction costs will be reduced by effective project management.

With regards to the moderating effects of project characteristics, we expect that the character of the project, such as its degree of scientific and commercial risk, whether it is an entirely 'new area' project, and so forth, will naturally have bearing on how scale affects the mediator variables. Because this is 'uncharted ground', we do not posit specific hypotheses as to the direction of the moderating effects.

In our discussion above, we have referred to scale in an abstract manner. In our empirical analyses, scale is operationalised by the number of partners in the consortium and budget. (We also use the average budget per participant as an alternative operationalisation). Admittedly, the arguments presented above make more sense when we conceptualise scale through the number of partners, than when we use budget. As an example, it is less clear whether a high budget leads to increased transaction costs; it may well be the opposite. As before, we prefer to leave the matter open for empirical verification, and return to this issue in the discussion of results. In addition, we have presented our arguments mainly in terms of scale, not project scope. Implicitly, we assume that the same arguments apply with regards to scope.

Based on these arguments, and to summarise the discussion thus far, we put forward the following (tentative) hypotheses to be tested empirically:

- Hypothesis 1: The effects of scale on project performance are mediated by (a) complementarity and diversity in the collective pool of resources, (b) absorptive capacity, and (c) transaction costs.
- Hypothesis 2a: Scale affects positively all three mediator variables.
- Hypothesis 2b: The positive effects of scale on all three mediator variables will be moderated by: (a) the 'quantity' of resources by each partner, (b) the 'quality' of project management, and (c) by the characteristics of the project per se.
- Hypothesis 3a: Complementarity and diversity of resources affect positively project performance.
- Hypothesis 3b: Absorptive capacity affects positively project performance.
- Hypothesis 3c: Transaction costs affect negatively project performance.

CHAPTER 3 DATA USED IN THE STUDY

3.1 Introduction

The study team aimed to leverage existing datasets to the extent possible as well as to collect new data to allow analysis of all the variables of the conceptual model presented in Chapter 2. After the construction of the analytical framework, an assessment was made of sources to establish a basis of existing data. Three sources in particular were considered to be of relevance:

- Innovation Impact data (gained from the previous project 'The evaluation of the impact on innovation of projects of Community Fifth and Sixth RTD Framework Programmes'[7]) looking at the questions that corresponded to variables of the Erascope study,
- CORDIS for overall project and participant data such as type of instrument, thematic area, project acronym and title, project budget, number of partners in the project,
- EPO PATSTAT data to add to the measures of output.

Data for the remainder of the variables were to be sought through the survey.

The following sections briefly outline the different data sources and how they were used.

3.2 CORDIS data

CORDIS data were used in several steps of the process and to collect several sets of data for the analytical work in the study. CORDIS data were initially used to identify respondents for the survey. As explained below the initial sample was drawn from Innovation Impact data, and CORDIS data were used to identify additional partners and the coordinators of the sampled projects.

Several variables from CORDIS were pre-entered into the survey (i.e. previously known data did not have to be re entered) to facilitate survey response.

7 http://www.innovationimpact.org/joomla/result/innoimpact%20final%20report%20OPOCE%20NBNA23100ENC.pdf online.

For analytical purposes, CORDIS data were used to calculate (average) consortium sizes in terms of partners and budgets for the different instruments/thematic areas. Finally, CORDIS data were used to analyse potential bias and the representativeness of the data sample.

3.3 Data from the Innovation Impact Study

The Innovation Impact study designed an extensive questionnaire (40 questions with 240 sub-questions) aimed at identifying factors that had an impact on the results of projects, especially their innovation output. The questionnaire included a large number of questions on organisational and project characteristics.

CORDIS yielded the relevant project information (including type of instrument, thematic area, project acronym and title, etc.) on all FP5 and FP6 projects (both for the current study as for InnoImpact). In addition, the project data were related to the relevant participating organisation data (organisation name, type, size, address, contact details, etc.).

On the basis of the CORDIS data, we subsequently made a sample selection of the organisations to be invited to participate in the survey. Including activities to filter the CORDIS data and enhance the quality, the Innovation Impact study collected over 8,200 responses from FP5 and FP6 projects, gathering a wide variety of data which served as a major basis for the Erascope study.

Several questions in the Erascope survey were available from the Innovation Impact study. Some additional questions relevant to the hypothesis under investigation could be derived from the literature review and finally some questions were completely new. Extensive mapping between extant data sources and the current survey was undertaken during the set up of the questionnaires. Furthermore, responses from more partners per project were sought as well as information from project coordinators while additional questions were added to be answered only by the project coordinator.

3.4 Survey construction and implementation

The Erascope survey was developed and tested on the basis of the Conceptual Framework presented earlier in Chapter 2. Based on the framework, the ERASCOPE survey developed two questionnaires, for enterprises and research institutions respectively.

The Erascope questionnaire had nine sections. Each section was built through subjective and/or objective measures. Some of them stemmed from the Innovation Impact study while others represented scales from the literature or completely new scales developed for the purposes of this study (such as learning processes). The following table illustrates in greater detail the way we built the final questionnaire for the current study.

This approach allowed us to fully leverage the existing data and knowledge and perform consistent statistical and econometric analyses.

Table 1: Sections of the questionnaire

	Scales from Innovation impact study	New scales for Erascope study
Section 1: Partner's Characteristics		
1.1 Partner's Demographics	✓	
1.2 Innovation History	✓	
1.3 Cooperation History	✓	✓
1.4 Objectives/Motives	✓	
1.5 Innovation and Technology-related Capabilities		✓
1.6 Complementary Assets	✓	
Section 2: Pool of Resources		
2.1 Human Capital		✓
Section 3: Project Management Mechanisms		
3. Project Management Mechanisms		✓
Section 4: Characteristics of the Project		
4.1 Direct Assessment of Scale and Scope		✓
4.2 Assessment of project Characteristics		✓
4.3 Past Research	✓	
4.4 Project Ambitions	✓	
Section 5: Objectives and Relations		
5.1 Partners as Competitors		✓
5.2 Project Objectives	✓	
5.3 Communication	✓	
5.4 Coordination	✓	
5.5 Trust	✓	
Section 6: Effectiveness of learning within the consortium		
6.1 Learning Processes		✓
Section 7: Industry and Market Environment		
7.1 Environmental Uncertainty	✓	
7.2 Demand Conditions	✓	
Section 8: Project Results		
8.1 Technical Goals		✓
8.2 Knowledge-oriented, Technological and Network-oriented Outputs	✓	
8.3 Knowledge-oriented, Technological and Network-oriented Impacts	✓	
8.4 Commercial Exploitation Outputs	✓	
8.5 Commercial Exploitation Impacts	✓	
Section 9: Coordinators' Section		
9.1 SMEs in the Consortium		✓
9.2 Patents and/or publications		✓

The survey was implemented online and is accessible on the project website (http://www.erascope.eu).

Much attention was paid to user friendliness, such as pre-loading known data (organisation and project information as well as questions that had been answered in Innovation Impact), extensive online guidance, and an email based helpdesk that was set up to answer all issues raised by the participants.

3.5 Sampling

To allow the full leverage of previously collected data and to enhance the return rate and efficiency of the survey, the starting point of our sample was the set of organisations that had answered the Innovation Impact questionnaire.

It was established in the Innovation Impact study that the data coverage was very good and the surveyed sample of organisations representative of the whole population of FP participants. In this regard our data collection strategy for Erascope was to re-contact those organisations that had responded to the Innovation Impact study. The new survey was compiled from the Innovation Impact questionnaire and additional questions relevant for the current study. The responses from the Innovation Impact study were loaded into the online Erascope questionnaire where the respondents were able to reconfirm or alter their earlier responses to Innovation Impact questions as well as answer the new questions for the current study.

From the 8,200 questionnaires received under Innovation Impact, we selected 2,921 respondents that represented projects for which more than 1 completed questionnaire was received. The 2,921 participants represented 1,005 projects.

The second step was to identify the coordinators of the projects who were not already present in the sample. Finally the remaining participants in these 1,005 projects were identified, making up a total of 8,000 identified organisations to be contacted.

All these participants were first contacted by mail, including a letter from our team and a recommendation letter from the Commission. Each prospective respondent organisation was assigned a unique User ID and login to the survey.

The mailing was done in three batches in order to manage the response and the helpdesk. The mailings went out between the beginning of October and mid November 2009. The order began with the previous respondents, followed by the coordinators and finally the other participants.

3.6 Response and data quality

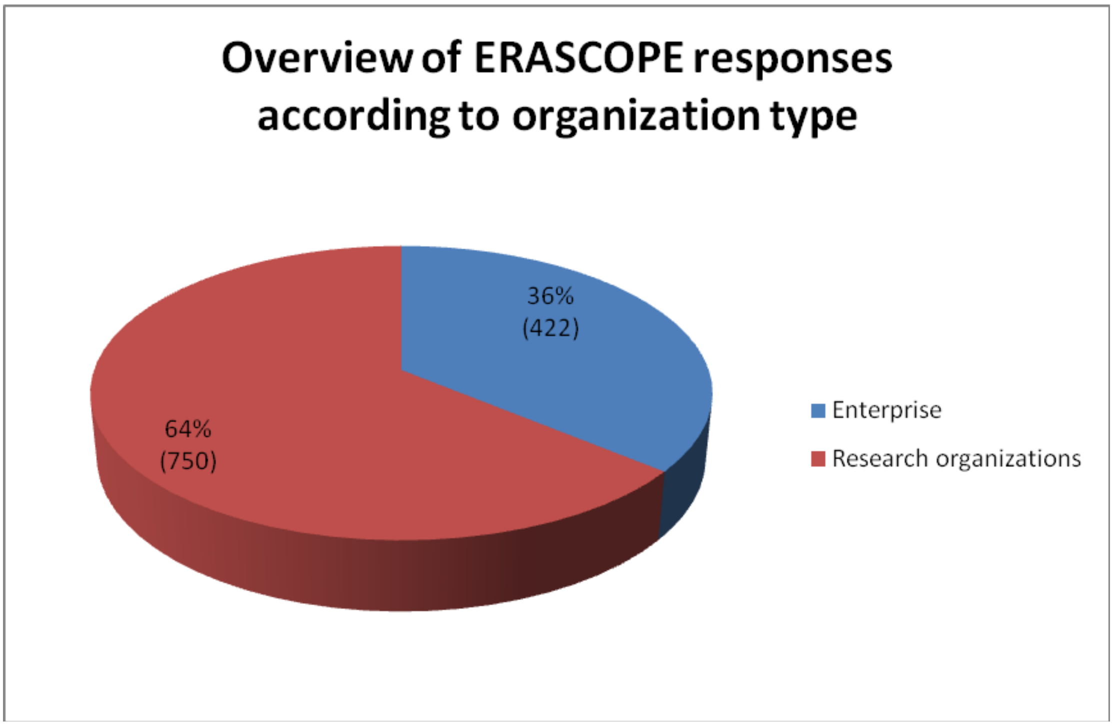
The data collection period ran for 3.5 months. Of the 8,000 letters mailed out, around 15% were returned as undeliverable.

The dedicated helpdesk answered around 250 queries, most queries related to access and to the User ID and password provided.

The next chapter provides more detail of the coverage. Here we limit ourselves to a brief characterisation of the responses received for the Erascope survey, which amounted to a grand total of 1,172 responses, of which 422 were classified as enterprises and 750 as research organisations.

The overall response rate to the survey was 14.7%. The response rate of the coordinators was 16% and for the contractors 14.5%.

Figure 3: Overview of Erascope responses per organisation type



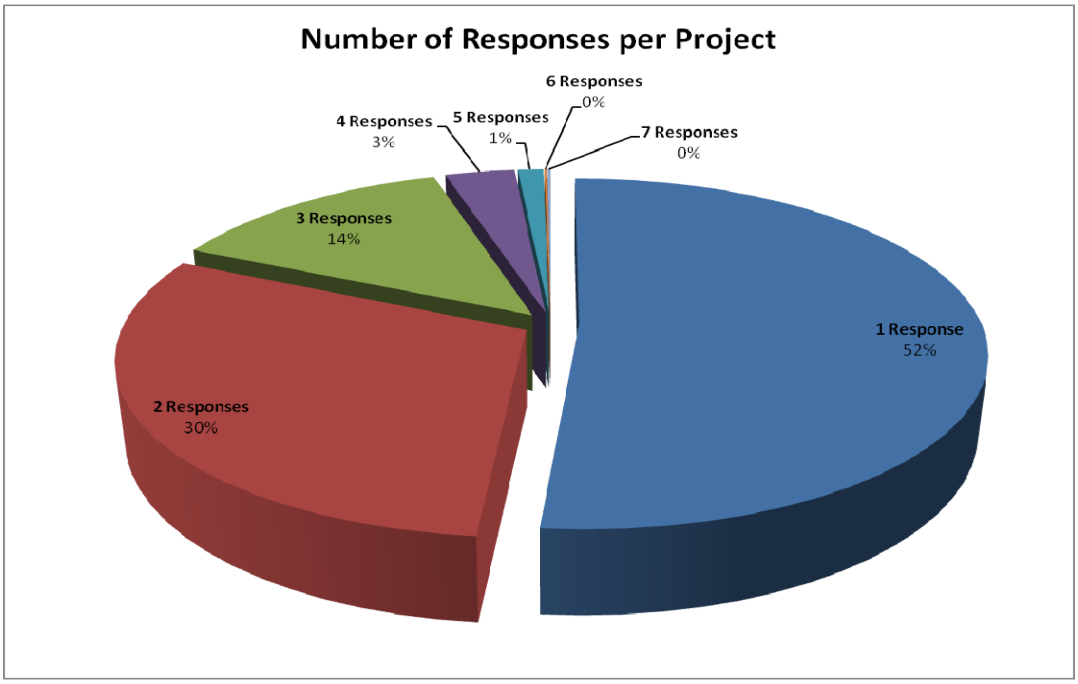
The following table provides a summary of the number of unique projects which responded to the Erascope survey along with the number of responses received per project.

Table 2: Response survey

# Responses	Projects	Total Responses
1 Response	348	348
2 Responses	205	410
3 Responses	91	273
4 Responses	22	88
5 Responses	8	40
6 Responses	1	6
7 Responses	1	7
TOTAL	676	1,172

The table above shows that 676 unique projects responded to the Erascope survey. The number of responses per project varied from 1-7. Single-response projects were the most frequent. The following pie chart presents a graphical representation of the breakdown of projects on the basis of responses per project shown in the table above.

Figure 4: Number of responses per project



Concerning the data quality of the survey, the ratio of valid responses for both questionnaires indicates good quality, (Appendix 1) as all variables had a valid result above 80%. This confirmed the quality of the data collection process.

Questions with a low valid percent were those that required a positive answer in the first question in order to continue to the next one, otherwise they were skipped.

These questions were:

- 'Did the specific project represent an entirely new area for your organisation?'
- If the specific project does represent an area where your organisation had prior experience, did it build on past R&D activities conducted in previous collaborative projects? If yes,
- Did it build on past R&D conducted in:
    - another Framework project?
    - a national program?
    - a cooperative project?
- In a project exclusively funded from own resources of the (or some of the) partners in the specific project?

3.7 Representativeness of our sample

In this section of the report we analyse the representativeness of our sample. As mentioned above, of the 8,000 organisations that received the invitation to participate in the survey, 1,172 responses were returned. The participation in the survey was voluntary and the respondents received guarantees that their individual replies would be treated confidentially, for research purposes only.

With 49% of responses from FP5 participants and 51% from FP6 participants, the sample shows an almost equal distribution among FP5 and FP6 projects. Additionally, the overall representativeness per Thematic Area and per theme is high across the board.

Table 3: FP5 total population

Participants	EESD	GROWTH	HUMAN POTENTIAL	IST	LIFE QUALITY	Grand Total
CRS	1.26%	5.59%	0.00%	0.37%	2.05%	9.28%
CSC	15.89%	17.29%	2.52%	21.56%	17.35%	74.61%
THN	2.28%	5.96%	1.95%	4.42%	1.50%	16.11%
Grand Total	19.43%	28.85%	4.47%	26.35%	20.90%	100.00%

Table 4: FP5 Erascope actual response sample

Participants	EESD	GROWTH	HUMAN POTENTIAL	IST	LIFE QUALITY	Grand Total
CRS	0.21%	8.77%	0.00%	0.00%	2.71%	11.69%
CSC	18.37%	24.84%	2.71%	18.58%	12.94%	77.45%
THN	2.71%	4.18%	0.21%	3.55%	0.21%	10.86%
Grand Total	21.29%	37.79%	2.92%	22.13%	15.87%	100.00%

A summary of the difference between the FP5 total population and the FP5 actual response sample is presented in the table below.

Table 5: Difference between FP5 total population and the Erascope actual response sample

Participants	EESD	GROWTH	HUMAN POTENTIAL	IST	LIFE QUALITY	Grand Total
CRS	-1.05%	3.17%	0.00%	-0.37%	0.66%	2.41%
CSC	2.48%	7.56%	0.19%	-2.98%	-4.40%	2.84%
THN	0.43%	-1.79%	-1.74%	-0.87%	-1.29%	-5.25%
Grand Total	1.86%	8.94%	-1.55%	-4.22%	-5.03%	0.00%

As the tables above illustrate the representativeness of the response to the total population is high and within a margin on 10% and thus underpins the importance of our sample selection. Representativeness tables for FP6 projects are presented below.

Table 6: FP6 total population

Participants	FP6-AEROSPACE	FP6-CITIZENS	FP6-FOOD	FP6-IST	FP6-LIFESCIHEALTH	FP6-NMP	FP6-SUSTDEV	Grand Total
IP	3.89%	0.84%	3.82%	12.56%	5.96%	6.83%	11.65%	45.56%
NoE	0.19%	1.51%	0.77%	5.55%	3.17%	1.36%	1.99%	14.54%
STREP	4.61%	2.41%	2.19%	13.17%	4.38%	5.82%	7.32%	39.90%
Grand Total	8.69%	4.77%	6.77%	31.27%	13.52%	14.01%	20.96%	100.00%

Table 7: FP6 Erascope actual response sample

Participants	FP6-AEROSPACE	FP6-CITIZENS	FP6-FOOD	FP6-IST	FP6-LIFESCIHEALTH	FP6-NMP	FP6-SUSTDEV	Grand Total
IP	5.38%	0.00%	7.09%	8.80%	3.67%	15.65%	15.65%	56.23%
NoE	0.00%	1.47%	2.44%	3.42%	2.93%	3.18%	1.96%	15.40%
STREP	4.16%	2.93%	3.91%	3.91%	0.98%	5.38%	7.09%	28.36%
Grand Total	9.54%	4.40%	13.45%	16.14%	7.58%	24.21%	24.69%	100.00%

Table 8: Difference FP6 total population and the Erascope actual response sample

Participants	FP6-AEROSPACE	FP6-CITIZENS	FP6-FOOD	FP6-IST	FP6-LIFESCIHEALTH	FP6-NMP	FP6-SUSTDEV	Grand Total
IP	1.49%	-0.84%	3.27%	-3.76%	-2.30%	8.81%	4.00%	10.68%
NoE	-0.19%	-0.05%	1.68%	-2.12%	-0.24%	1.82%	-0.04%	0.86%
STREP	-0.45%	0.52%	1.72%	-9.26%	-3.41%	-0.44%	-0.23%	-11.54%
Grand Total	0.85%	-0.36%	6.67%	-15.14%	-5.94%	10.20%	3.73%	0.00%

Generally speaking, the straightforward way to correct oversampling is through weighting. Nevertheless, weighting changes the point estimates and the confidence intervals, rendering the latter wider. This means that weighting tends to reduce the number of statistically significant relations.

Again, however, it is worth noting that we need to do that only if we suspect that partners participating in certain types of projects (e.g. FP5 – Growth) are over-represented relative to the true proportion of such partners in the population. Yet, in this case and based on the tables above it can be concluded that the participants in our sample reasonably (with a margin of ±10%) represent the population proportions.

Here it must be stated that the total population comprises partners from small and large consortia, but that the sample is more likely to randomly pick up partners from larger ones, since the number of such partners is (necessarily) larger than the number of partners from smaller ones.

3.8 EPO data

The conceptual model of the current study is largely operationalised through subjective measures like Likert scale items that were extracted or developed after extensive literature review. In addition to subjective measures of project success, we aimed to capture project outputs also through objective measures such as patents and publications. As these can only be collected at project level (and not at respondents level for individual organisations), we asked project coordinators for the number of patents and a count of publications of the projects.

The level of response received was insufficient however, as many coordinators did not provide the information and the answers could not be considered as completely covering the project output.

The study team decided to try to remedy the lack of output data by extracting relevant data from the European Patent Office (EPO) PATSTAT database.

The approach we followed involved three major steps. The first was to process each organisation's name and to identify the participants in the survey in the Patstat database. For this purpose we used the standard name attributed to applicant and inventor names for inclusion in the DOCDB (EPO master documentation database) and performed a manual check of the organisation names of survey respondents against the database.

The second step was to relate the projects in our survey to the International Patent Classification (IPC). We used an online tool of the World Intellectual Property Organisation (WIPO), designed to help classify patents at IPC subclass level. For the categorisation we used the project title as a quote and formulated a list of IPC subclass levels used in our queries in order to identify patents in the same field by the project participants.

We are aware of the attribution problem here: a patent obtained by an organisation in the same field in the same period is not necessarily the outcome of an FP project this organisation participated in. However, we considered patents in the same field by research project participants for the respective time period to be a reasonable approximation for technological outputs associated with a specific strand of research activities.

The third step was to actually run the queries individually for each organisation and for the technologies we had identified for the project the organisation participated in. For each query run, we implemented a time filter so as to search for any potential patents in the five years before the project, for the duration of the project and in the five years after the end of the project. The number of patents identified for each period was used for further analysis.

Although the results of the method proved accurate, the use of the results was very limited, as only a very small and insignificant number of attributable patents came out of the analysis and they had no impact on the results of the study.

CHAPTER 4 -ECONOMIES OF SCALE AND SCOPE IN R&D PROJECTS

4.1 Descriptive analysis

4.1.1 Introduction

This chapter provides an explorative analysis of the dataset on collaborative FP5 and FP6 projects.

In a first step we describe distinct patterns of the dataset obtained by the survey. These allow us to portray the coverage of thematic areas, the funding provided by the different thematic areas, the coverage of different funding instruments and its funding.

In a second step we provide a first insight into the core research question of this study, i.e. to assess to which extent the size of publicly funded collaborative R&D projects affects its outcome. Based upon the survey results the descriptive statistics illustrate in particular whether there are differences regarding:

- scientific, technological and economic performance patterns,
- mediating variables which facilitate project success (i.e. the learning capacity/ absorptive capacity, transaction costs and complementarity of resources),
- characteristics of the project partners,
- project profiles vis á vis typical internal projects.

In pursuing the analysis we consider that project size may be measured by different variables such as:

- number of project participants respectively organisations,
- total budget of the collaborative research endeavour
- funding per participant.

While the number of project participants and the total budget reflect the absolute size of the research project, the funding per participant reflects the hypothesis that the success of a research project may not only depend on the absolute size of a research project but also on the individual funding each partner receives. Hence, the descriptive analysis differentiates between the absolute and the relative project size:

- The absolute project size in the following analysis is mostly measured by the total number of project participants. The total budget of the collaborative research project is portrayed only in a few parts of the descriptive analysis as we did not observe considerable differences regarding project performance measured by the number of project participants versus the total funding.
- The relative project size is measured via the average funding per project participant. As the project database did not provide information on the individual funding per participant, the average funding per participant (total funding divided by the number of partners) is the only available measure to estimate the project size at the participant level.

4.1.2 Overview of the sample data

The sample retrieved through the online survey contained a total of 1172 observations. 750 observations (64%) stemmed from Research Organisations and 422 (36%) from private enterprises. These corresponded to 676 collaborative R&D projects of which 328 projects had more than two responses. With 49% of responses from FP5 participants and 51% from FP6 participants, the sample showed an almost equal distribution among FP5 and FP6 projects.

4.1.2.1 Coverage of different thematic areas

Both FP5 and FP6 contained programmes which covered different thematic areas. The thematic programmes of FP5 as outlined in CORDIS[8] were:

- Quality of life and management of living resources: Key objectives of this thematic area are to link the ability to discover with the ability to produce, in order to address the needs of society and to meet consumer requirements. This will lead to future wealth and job creation and improvements in the state of the environment. Activities under the programme focus on specific areas where growing knowledge potentially contains technical answers to some of the pressing questions posed by European citizens, whilst respecting fundamental ethical values.
- User-friendly information society: Key objectives of this thematic area are to realise the benefits of the information society for Europe both by accelerating its emergence and by ensuring that the needs of individuals and enterprises are met. The programme's interrelated research objectives focus on the technology developments of the information society and enable the close articulation between research and policy needed for a coherent and inclusive information society.

[8] Source: http://cordis.europa.eu/fp5/src/struct.htm online.

- Competitive and sustainable growth: Key objectives are to support research activities contributing to competitiveness and sustainability, particularly where these two objectives interact. Industry's role will not only be to identify areas for collaboration but also to bring together and integrate projects, especially cross-sectoral projects along the value chain, so that technology uptake and innovation are more effectively ensured across Europe.
- Energy, environment and sustainable development: Key objectives are to contribute to sustainable development by focusing on key activities crucial for social well-being and economic competitiveness in Europe.

The thematic areas in FP6 as described in CORDIS[9] are:

- Life sciences, genomics and biotechnology for health: Key objectives are to integrate post-genomic research into the more established biomedical and biotechnological approaches. Involvement of key stakeholders e.g. industry, healthcare providers and physicians, policymakers, regulatory authorities, patient associations and experts on ethical matters.
- Information society technologies: Key objectives are to contribute to European policies for the knowledge society and the e-Europe Action Plan, medium and long term RTD on the future generation of technologies integrating computers and networks into everyday environment, placing the individual at the centre.
- Nanotechnologies and nanosciences, knowledge-based multifunctional materials and new production processes and devices: Key objectives are to contribute to the creation of the scientific base for the transition of European production industry from resource-based towards knowledge-based, more environment-friendly approaches.
- Aeronautics and space: Key objectives are to strive towards higher levels of technological excellence by consolidating and concentrating RTD efforts in the context of the Advisory Council for Aeronautics Research in Europe and the European Strategy for Space.
- Food quality and safety: Key objectives are to assure health and wellbeing of European citizens through a better understanding of the influence of food intake and environmental factors on human health, providing safer, high-quality and health-promoting food.
- Sustainable development, global change and ecosystems: Key objectives are to strengthen the S&T capacities needed for Europe to be able to implement a sustainable development model in the short and in the long term, integrating its social, economic and environmental dimensions, and contributing to international efforts mitigating adverse trends in global change.

[9] Source: http://cordis.europa.eu/fp6/activities.htm online.

- Citizens and governance in a knowledge-based society: Key objectives are to provide a sound scientific base for the management of the transition towards a European knowledge based society, conditioned by national, regional and local policies and by decision making by individual citizens, families and other societal units.

For the sake of our analysis we have grouped thematic areas of FP5 and FP6 as follows:

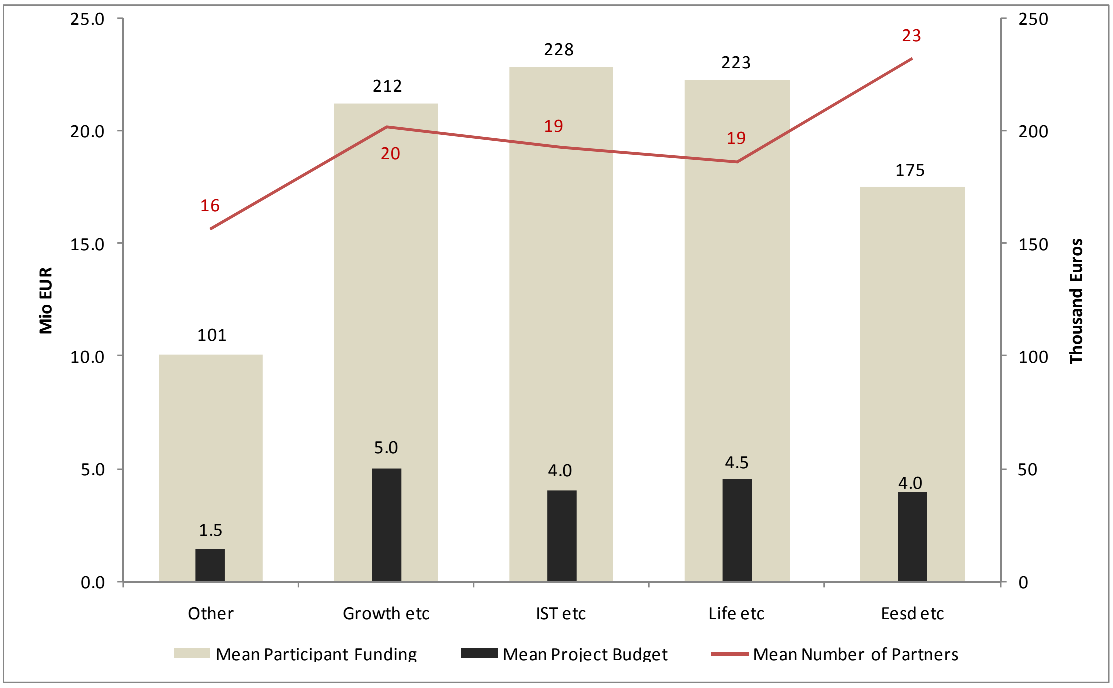
Table 9: Mapping thematic areas

Thematic Area Growth	FP5 Competitive and Sustainable Growth FP6 Aeronautics and Space FP6 Nanotechnologies and Nanosciences
Thematic Area Information Society	FP5 User friendly information Society FP6 Information society technologies
Thematic Area Life	FP5 Quality of life and management of living resources FP6 Life sciences, genomics and biotechnology for health FP6 – Food quality and safety
Thematic Area Energy, Environment and Sustainable Development (EESD)	FP5 Energy, environment and sustainable development FP 6 Sustainable development global change and ecosystems FP6 Citizens and governance in a knowledge-based society[10]

The coverage of the different thematic areas of the joint sample of FP5 and FP6 projects shows that all thematic areas were represented fairly well in the sample: 29% of responses stemmed from the thematic area 'Growth', 21% stemmed from the thematic area 'Information Society' and another 21% from the thematic Area 'Sustainable Development'. The thematic area 'Life' accounted for 15% of responses, while 14% of the responses stemmed from projects which could not be attributed to the thematic areas outlined above.

[10] Although technically not part of the IST programme, the (very small part of the) sample of this programme was classified here. The sample of too small top significantly influence the results of the analyses.

Figure 5: Project size and project funding by thematic area*



* Calculations of project size and project funding are based upon the 676 individual projects.

The graph above portrays the Mean Project Funding, the Mean Participant Funding, and the Mean Number of Partners.

The thematic area Growth had the highest Mean Project Budget. The Mean of Average Participant Funding was almost equal for the thematic areas Growth, IST and Life. Due to the higher number of project partners, the Mean of Average Participant Funding was considerable lower in the thematic area Eesd.

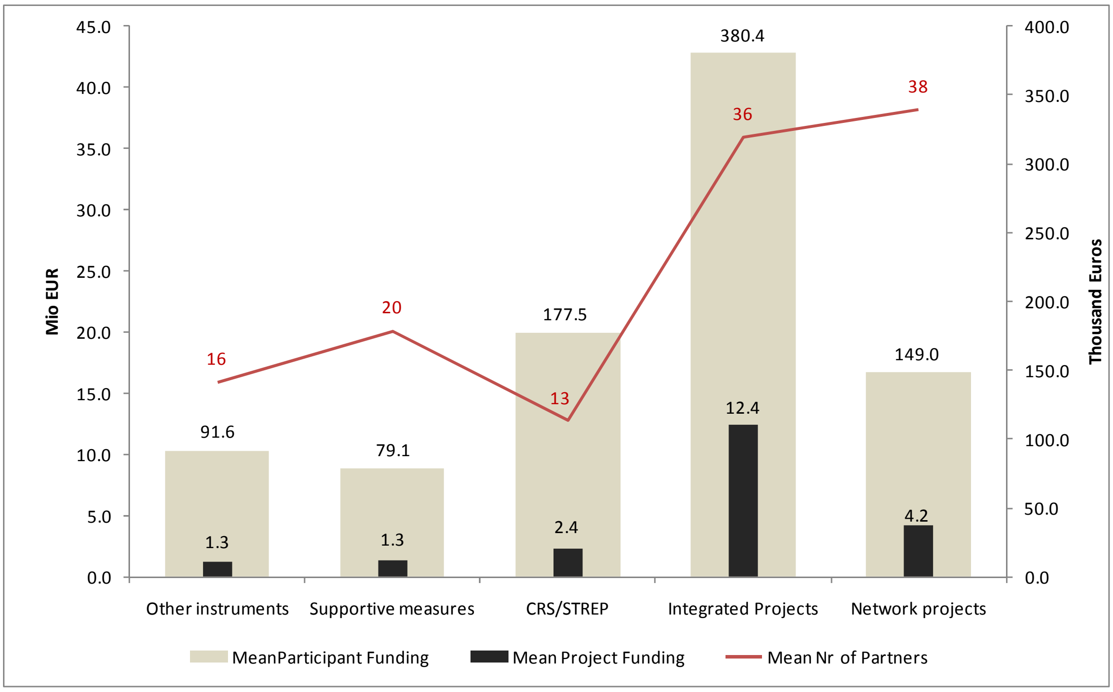
4.1.2.2 Funding instruments

The sample also contained a large variety of different funding instruments of FP5 and FP6. There were 20% of the respondents who participated in Integrated Projects, 11% in Network Projects (Networks of Excellence and Thematic Networks), and 10% of respondents in Coordination Actions and Accompanying measures. The largest share of projects consisted of Specific Targeted Research Projects (STREPS), Cooperative research contracts (CRS) and Cost-sharing contracts (CSC) at 54%. Lastly, 5% of the measures were funded via other funding instruments.

The graph below portrays the mean number of project partners, the mean project funding and the mean average funding per participant for the different funding instruments. In terms of number of partners, unsurprisingly, Integrated Projects and Network Projects have the largest number of project participants. Integrated Projects furthermore strike out in terms of total project funding and average funding per participant: Total project funding is about five times higher than for CRS/STREPS and average participant funding is more than twice the number of CRS/STREPS. This means that Integrated Projects account for the majority of large scale projects in terms of absolute project size and relative project size.

In terms of funding per participant STREPS and CRS in the range of network projects, the total project budget of these projects is about 55% of the network projects. Supportive measures and other instruments have on average more partners than CRS and STREPS, but the data show that their funding is quite limited with respect to total funding and funding per participant.

Figure 6: Project size and project funding by instrument



* Calculations of project size and project funding are based upon the 676 individual projects.

4.1.2.3 Project scale

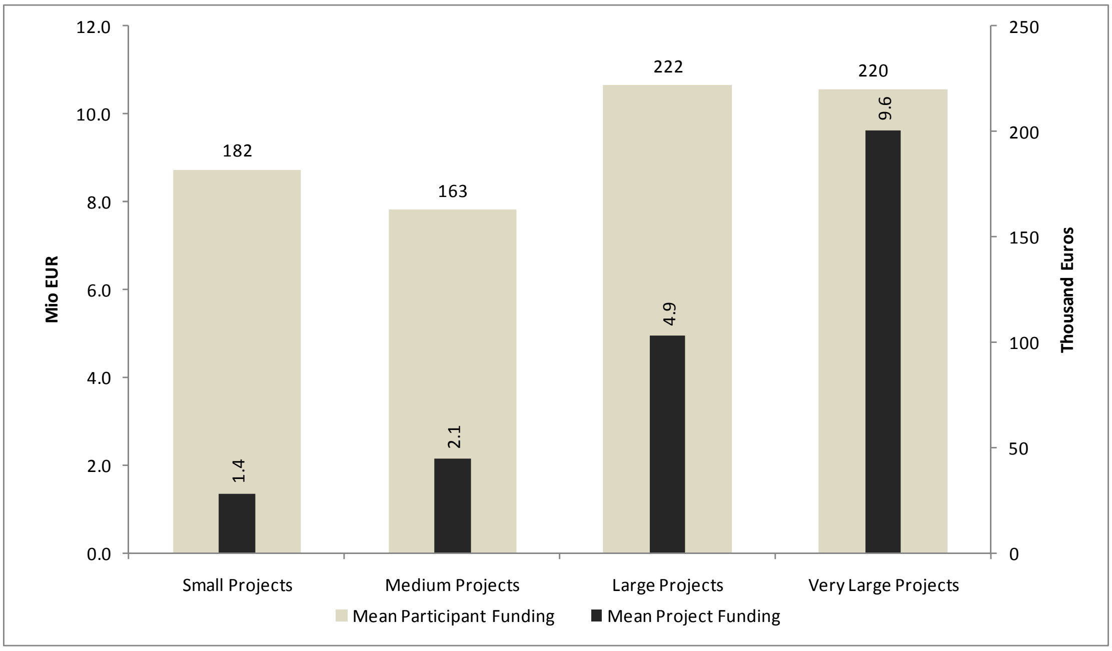
As indicated above, we measure project scale by the number of project participants, project funding and the average funding per participant. In order to differentiate between small, medium, large and very large projects we use the quartiles of the variables Project participants, Project funding, and Average project funding (see table below). The quartiles have been calculated by using the full dataset of 1,172 observations.

Table 10: Quartiles partners, project funding, and participant funding

Number of Partners	Average Funding per Participant
Small Projects: <= 10	Low Funding: 0-88,276.52
Medium Projects: 11 – 16	Medium Funding: 88,276.53 – 156,250.00
Large Projects: 17 – 28	High Funding: 156,250.01 – 253,998.31
Very Large Projects: 29+	Very High Funding: 253,998.32 +
	Total Project Funding
	Low Total Funding: <= 1,102,230
	Medium Total Funding: 1,102,231 – 2,036,195
	High Total Funding: 2,035,196 – 5,056,304
	Very High Total Funding: 5,056,305 +

Figure 7 seeks to portray the relation between project size (measured by the number of participants) and project funding. We witness that large projects in the range of 17-28 participants receive about the same average funding per participant as the very large projects with 29 and more project participants. Hence, a larger number of partners does not necessarily mean higher average funding per partner.

Figure 7: Funding by project size (number of partners)



* Calculations of project volume and participant funding are based upon the 676 individual projects.

Figure 8 shows the relation of average participant funding and the different funding instruments. Integrated Projects account for 58% of the Very High Funding projects and

18% of the High Funding projects. STREPS/CRS projects account for 76% of the High Funding projects and 29% of the Very High Funding projects. In addition, STREPS/CRS projects also account for large shares of the Medium and Low funding categories.

Figure 8: Average participant funding by instrument

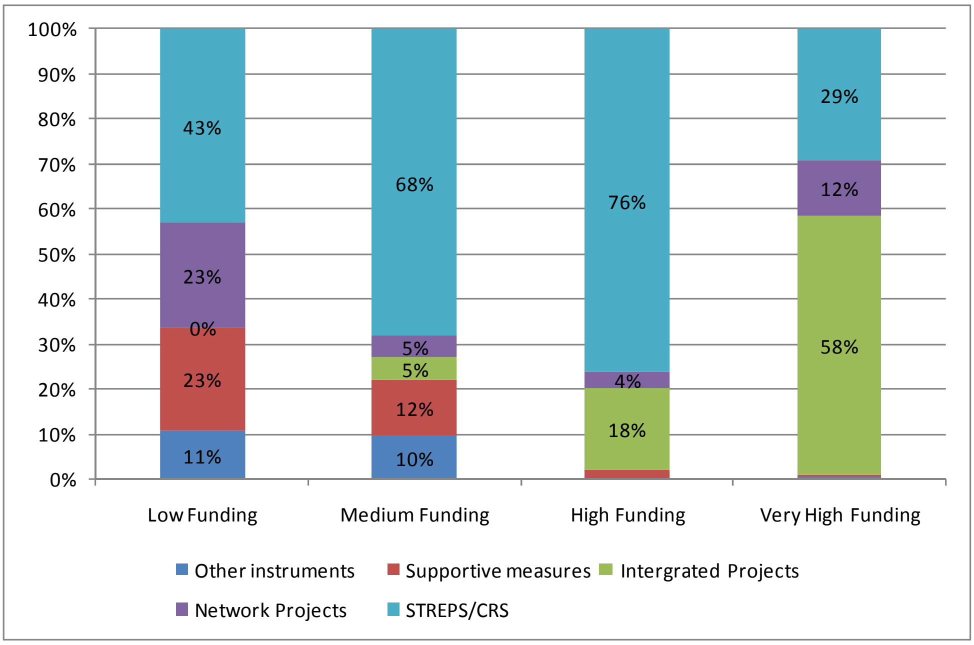


Figure 9: Project funding by Instrument

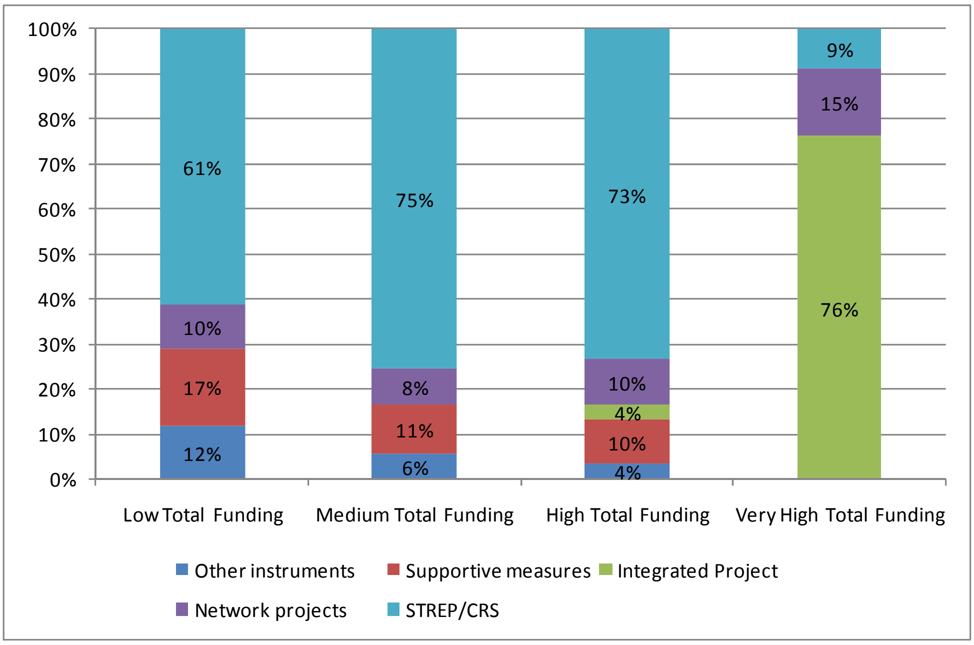
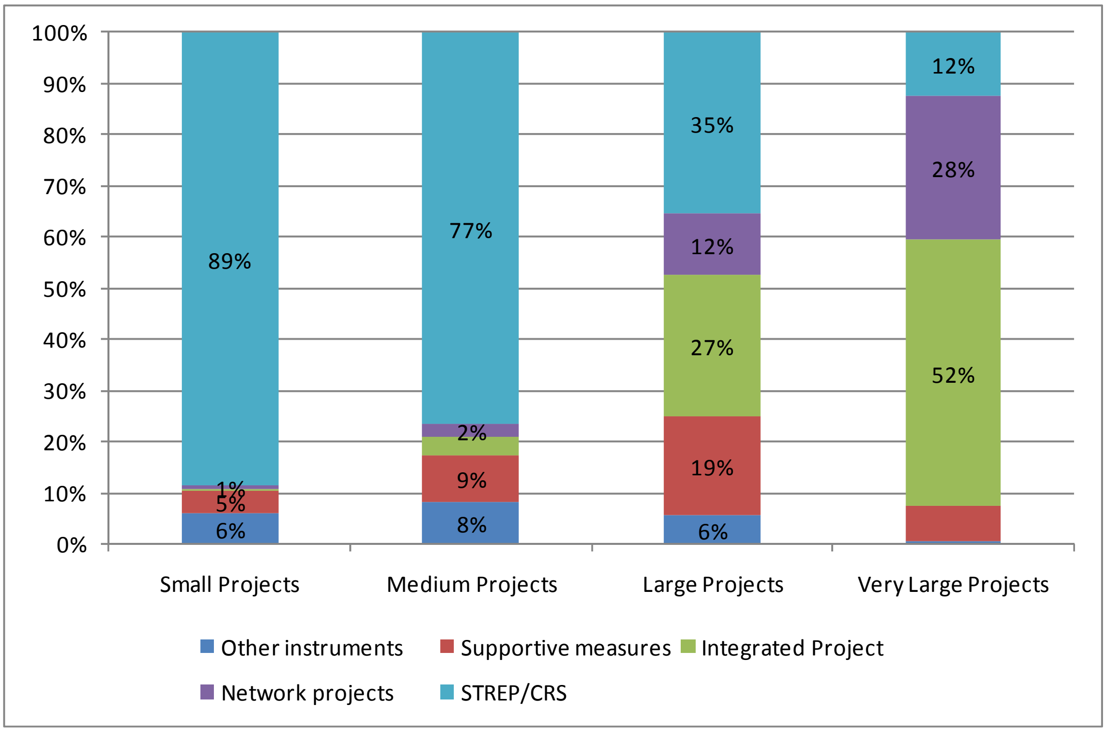


Figure 9 above shows the relation of the total project volume and the different funding instruments. Unsurprisingly, Integrated Projects account for more than three quarters of the Very High Total Funding projects. Again, STREPS/CRS projects are distributed over all other funding categories. They account for the largest shares of High, Medium and Low –Total Funding projects.

Whereas there is a very distinct distribution of funding instruments by project volume and participant funding, the distribution of the different funding instruments by the number of project partners is much more scattered. The figure below shows that STREPS/CRS account for the majority of Small and Medium Projects. Very Large Projects are dominated by Integrated Projects and Network Projects. In this category, the share of STREPS/CRS is only 12%. Most interesting is the fact that Large Projects, in the range of 17-28 partners, show a balanced mix of all different funding instruments in the sample.

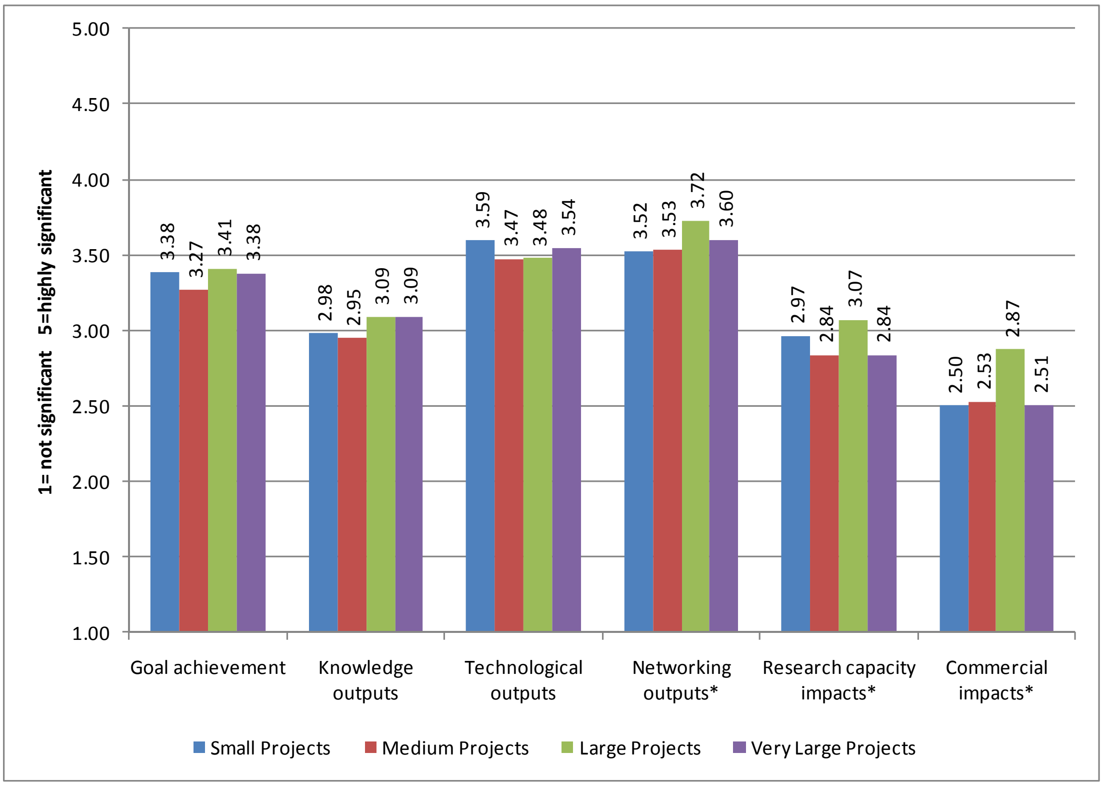
Figure 10: Number of project partners by instrument



4.1.3 Performance dimensions

As the main research question is to identify whether project scale has an impact on project performance this section provides cross-tabulations of the subjective performance dimensions of the project and our measures for project scale. The subjective performance dimensions of the sample include: (a) project goal achievement, (b) knowledge outputs, (c) technological outputs, (d) network outputs, (e) research capacity impacts, (f) commercial impacts, (g) goods/services innovation and (h) process innovation (as a result of the project). The last three of these measures (i.e. commercial, goods/services and process innovation) concern enterprises only.

Figure 11: Performance dimensions by project size (by number of partners)

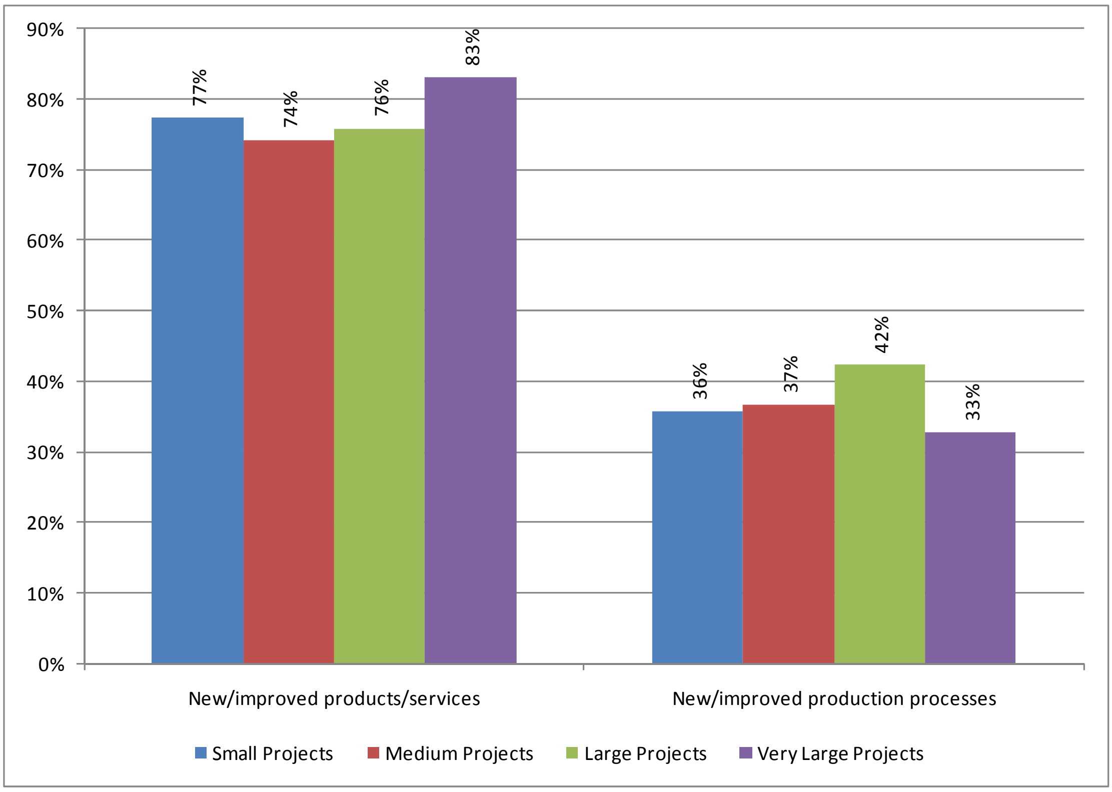


*indicating statistical significant differences of 10% level.

Figure 11 plots the results for the first six performance dimensions against the number of project partners. As an overall observation we witness that Technological Outputs and Networking Outputs are ranked higher than Knowledge Outputs, Research Capacity Impacts and Commercial Outputs.

Taking into account project scale measured by the number of partners, we witness that the number of project partners has no significant effects on Goal achievement, Knowledge outputs and Technological outputs. For Networking outputs, Research capacity impacts and Commercial impacts significant differences in project performance exist. This is because Large Projects with 17-28 partners have significantly higher Networking outputs than Small and Medium Projects, significantly higher Research Capacity impacts than Medium and Very Large Projects, and significantly higher Commercial impacts than Small Projects.

Figure 12: Percentage of projects that realised product and process innovations (by number of partners)

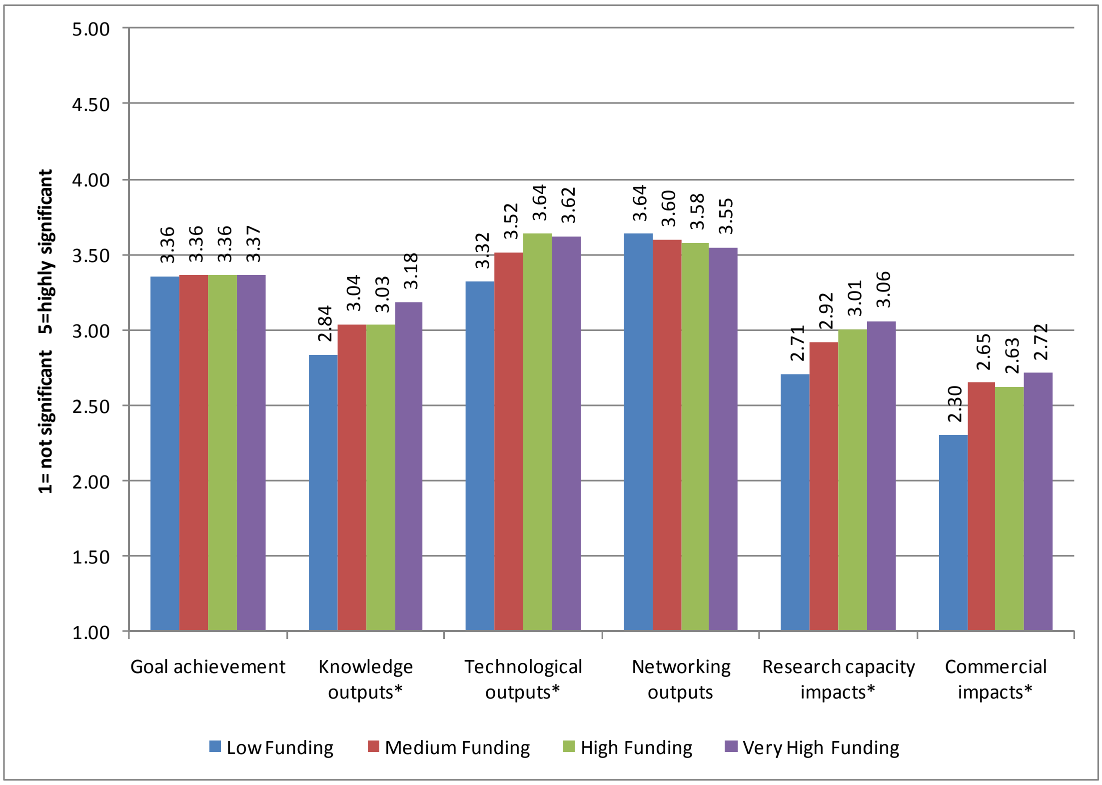


Regarding the introduction of new and/or improved products and services and new and/or improved production processes however, the consortium size does not seem to be a decisive factor: Very Large Projects seem to have slightly higher chances for introducing new products and services but differences are not statistically significant. As regards the introduction of new or improved production processes, Large Projects seem to have a higher probability for introducing these types of innovations, but also here differences are not statistically significant.

We may conclude that the absolute size of research projects has some effects on project performance. The relation does not seem to be linear as Large Projects also show higher performance levels than Very Large Projects, although differences are only significant for the Performance Category Research Capacity Impacts.

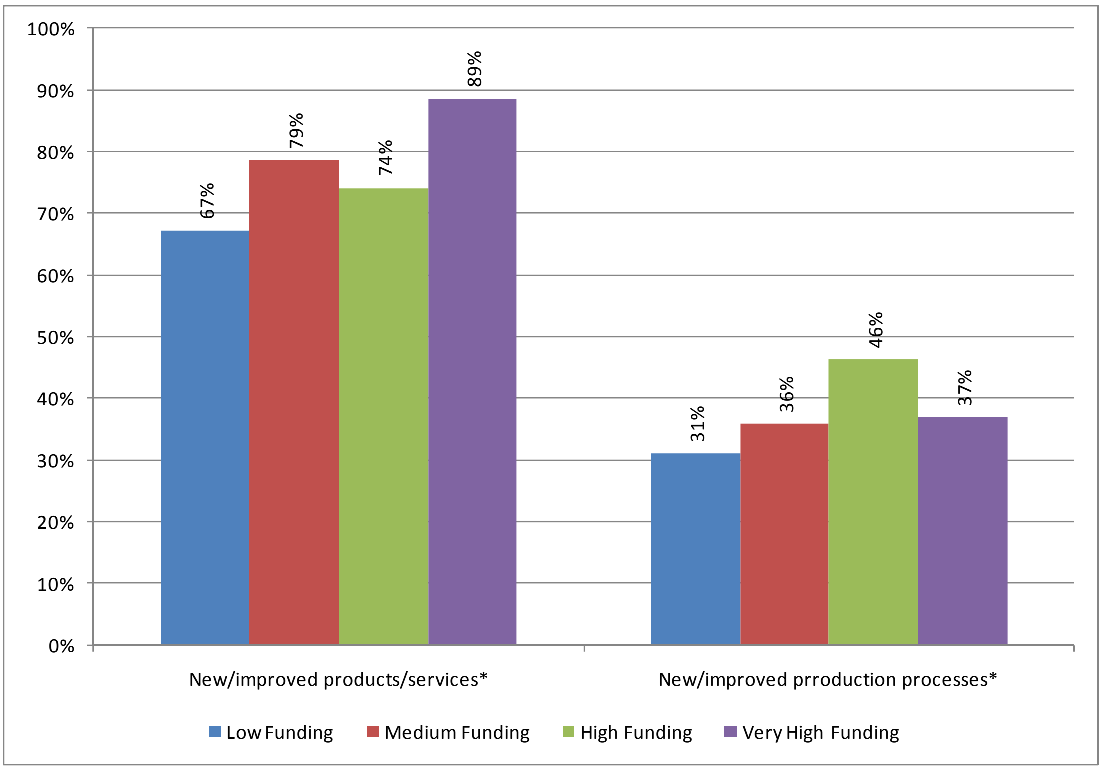
When turning our attention to the relation between project performance and participant funding (Figure 13), we witness an even stronger and most presumably linear relation between project size and project performance. In particular, there seems to be a positive correlation between individual level of funding on the one hand and knowledge output, with technological output and research capacity impact on the other. Projects with low levels of average funding per participant exhibit significantly lower performance in these indicators than projects in the categories High Funding and Very High Funding. Furthermore, there is also a positive correlation between individual funding and the introduction of new or improved services and new or improved production processes (Figure 14).

Figure 13: Performance dimensions by project size (by average partner funding)



*Indicating statistical significant differences of 10% level.

Figure 14: Percentage of projects that realised product and process innovations (by partner funding)



4.1.4 Mediator Variables

In the conceptual framework we assumed that a large(r) consortium or a large(r) budget should, in principle, significantly affect the project's internal (team) dynamics and be strongly associated with performance. In terms of both scientific and technological outputs, the efforts and skills of multiple (as opposed to just a few) partners in an R&D project would lead to a larger pool of resources and expertise, and hence would, ceteris paribus, increase the likelihood for success. At least equally (if not more) important, a large consortium, composed of carefully chosen participants, would increase the heterogeneity of resources pooled together for project use. Increased heterogeneity in skills and experiences could foster creative problem solving, be a source of learning and new knowledge creation, and thus could, ceteris paribus, increase the likelihood of project success. Taken together, these effects should have direct bearing on the consortium's absorptive capacity, and particularly on the effectiveness of learning. Apart from these positive effects, a larger and more heterogeneous pool of resources associated with large consortia size also increases the transaction/coordination and administrative costs of running the project.

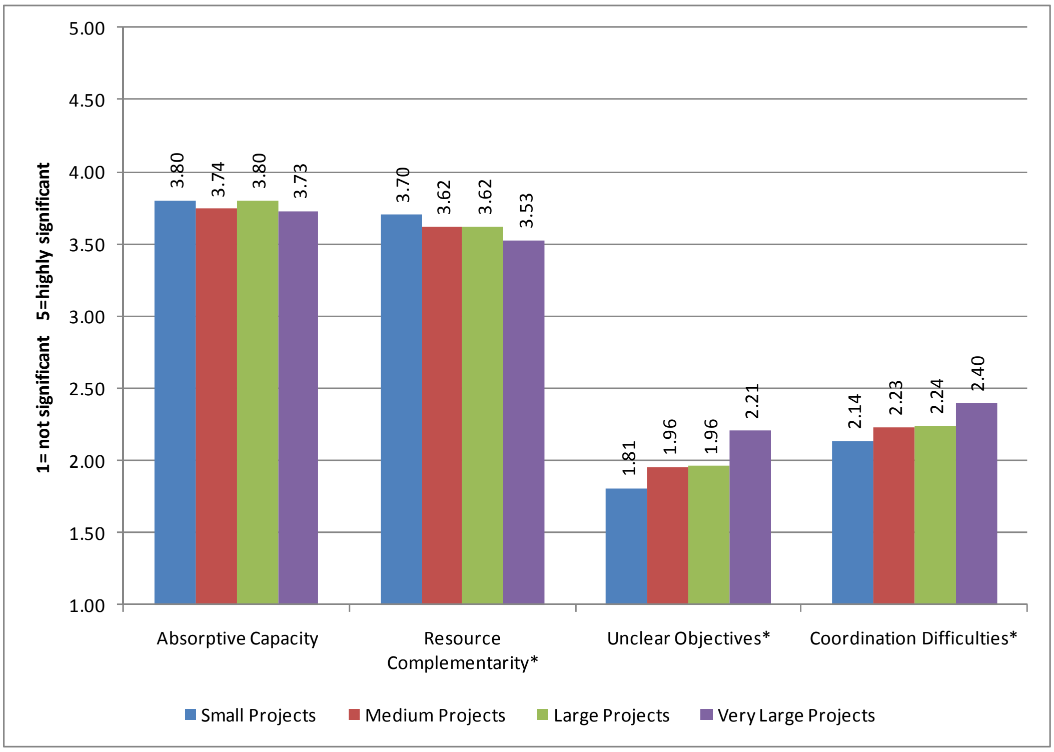
Based upon this, the following four mediator variables, which may be dependent on project size and thus might indirectly translate size into effects on performance, have been operationalised and used in the survey:

- Complementarity of resources: The collective pool of resources made available to the project by the partners (not the responding organisation – see below) was measured in terms of the complementarities achieved among partners. This variable is a Likert-type scale reflecting the extent of synergies with respect to scientific, technical/engineering, and managerial skills and assets.
- Absorptive Capacity (AC): This is a construct assessing degree of knowledge acquisition, assimilation, and integration resulting from the learning-related activities among partners in the project.
- Clarity of Objectives: This variable and Difficulties in Coordination (see below), represent two dimensions of transaction costs incurred among partners in the course of project implementation, as derived by the confirmatory factor analysis of the original scale. This reflects the degree to which partners agree that the project is characterised by clear and accepted objectives as well as by a clear allocation of tasks. The scale was reverse-coded for the analysis to depict the influence of Unclear Objectives.
- Difficulties in Coordination: As above, this is a reverse-coded scale that reflects the extent of difficulties in coordination among partners in terms of information sharing, smooth planning of activities, efficiency of working together, etc.

As the mediator variables relate to the absolute project size only, the variables are plotted against the absolute project size in terms of number of partners and project funding.

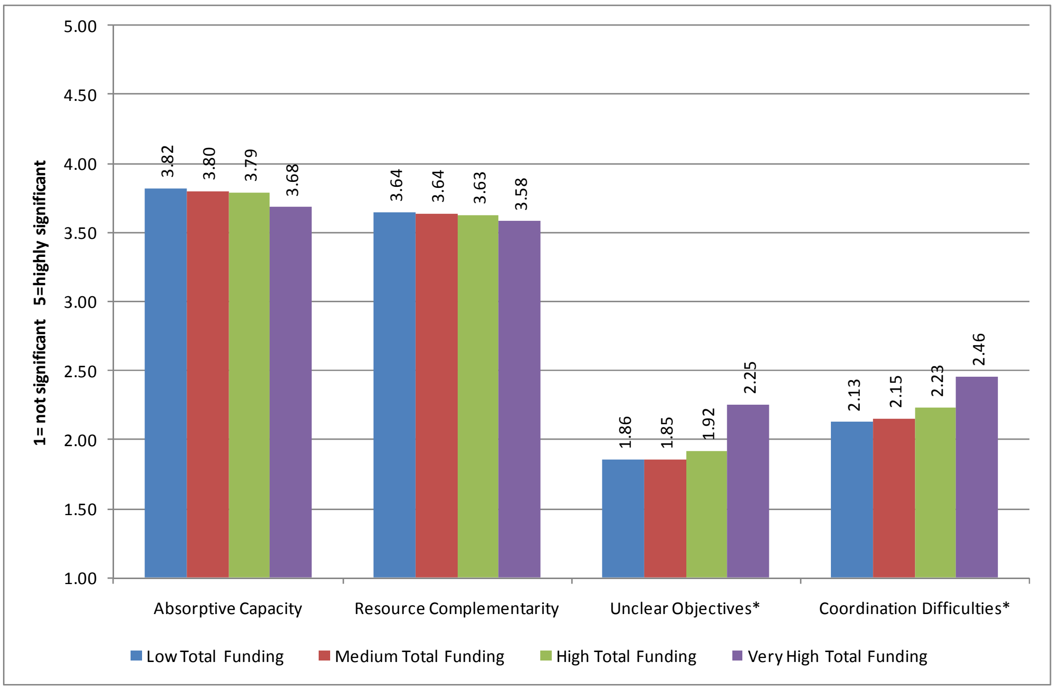
The descriptive statistics in Figure 15 show that no positive correlation between the size of a research project and the variables absorptive capacity and resource complementarity can be observed. However, as the theoretical framework suggests, the project size seems to be negatively related with transaction costs: Small and Medium sized projects have clearer objectives and less coordination difficulties than very large projects.

Figure 15: Mediator variables by project size (number of partners)



*Indicating statistical significant differences of 10% level.

Figure 16 Mediator variables by project size (total funding)



*Indicating statistical significant differences of 10% level.

4.1.5 Partner Characteristics and Project Profile

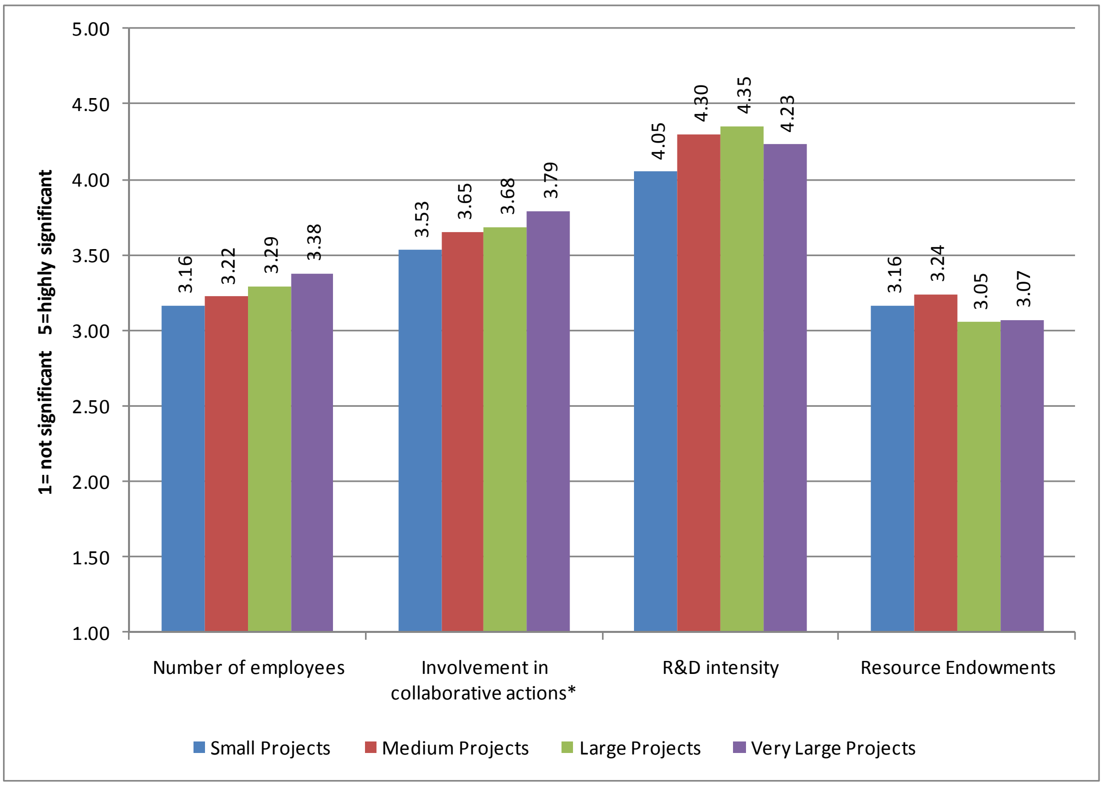
The performance of collaborative R&D projects may also be influenced by certain characteristics of the partners involved in the project. It is, for instance, widely acknowledged that R&D project performance (in terms of innovative output), as well as partnership formation depend on distinct firm characteristics such as the size of the firm and the sector affiliation. Partner characteristics considered in the literature further include factors relating to the innovation and cooperation history and capabilities, and factors relating to the motivation and objectives to participate in a project. Project performance also needs to be controlled for certain characteristics of the project, which may have an impact on types of output expected, and hence also project performance. Possibilities to distinguish between different types of projects are by type of R&D conducted, the level of risk associated with the project, and the embeddedness of the project within the R&D strategies/activities of the consortium.

The following results of the survey present a selection of variables which reflect basic characteristics of the responding organisation and qualitative characteristics of the projects vis-à-vis a typical internal project. Variables which cover firm characteristics are:

- Size: This variable represents the size of the participant/project partner, as reflected in the number of its employees. It is an ordinal measure, ranging from 1-5, with higher values indicating larger size (e.g. 5 = 501+ employees).
- Involvement in collaborative R&D: This variable measures the frequency of participation in prior collaborative R&D projects. It reflects experience with such projects. It is a Likert-type item, ranging from 1 (= never involved) to 5 (= involved in many projects).
- R&D expenditures: An ordinal variable indicating the percentage of R&D expenditure of total budget/revenue for the period just prior to the project. It ranges from 1 (='no R&D) to 6 (= >10%).
- Resource endowments: A Likert-type scale reflecting the firm's ability to commercially exploit research results (i.e. ability to speedily introduce new products, marketing skills in launching new products, etc.).

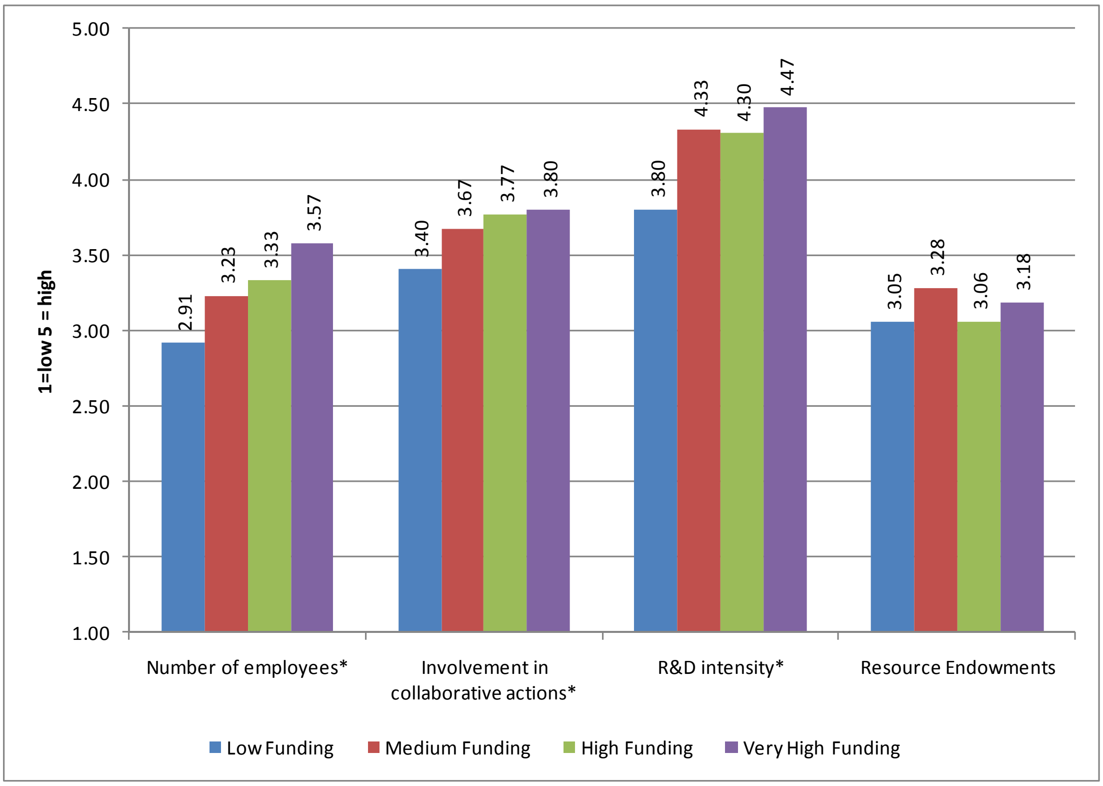
Figure 17 shows that there are only some links between distinct firm characteristics and the probability to participate in larger or smaller projects. First, although not statistically significant, there seems to be a relation between firm size and participation in Very Large Projects. Second, firms that have been involved in collaborative actions in the past have a higher tendency to be involved in very large projects than small projects. Differences are, however, not statistically significant.

Figure 17: Firm characteristics by project size (number of partners)



When average participant funding is taken into account firm patterns are more distinct. Project partners that participate in projects with very high and high average participant funding have a significantly higher number of employees, and are more often involved in collaborative actions. Furthermore their R&D intensity is considerably higher. The commercial exploitation capacity does not vary with average participant funding.

Figure 18: Firm characteristics by project size (participant funding)

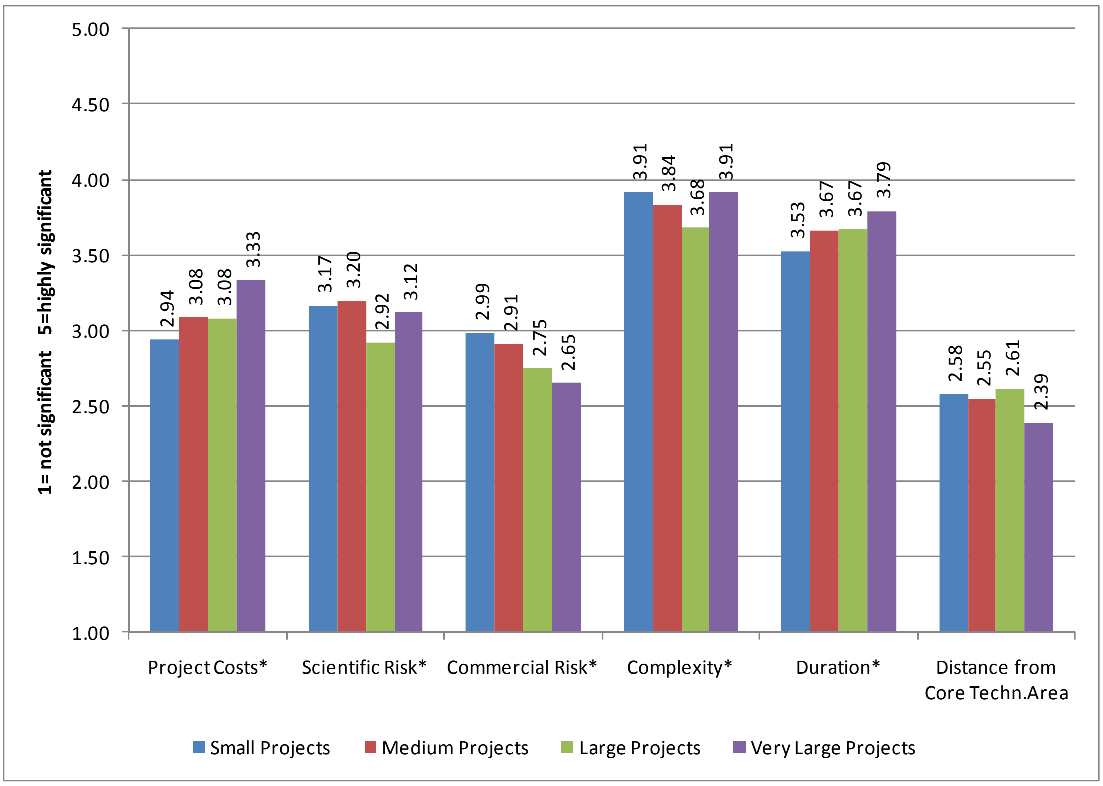


As regards qualitative characteristics of the project the following variables have been considered for the descriptive analysis:

- Cost vis-à-vis an average project: A five-point Likert-type item, with high values indicating high project costs in comparison to the responding organisation's 'average' R&D project.
- Scientific risk: As above, reflecting scientific risk in comparison to an 'average' project.
- Commercial risk: As above, reflecting commercial risk.
- Complexity: As above, reflecting the project's complexity.
- Long term: As above, higher values point to a longer time horizon vis-à-vis an 'average R&D project'
- Distance from core: As above, higher values point to a greater distance from the partner's technological core area.

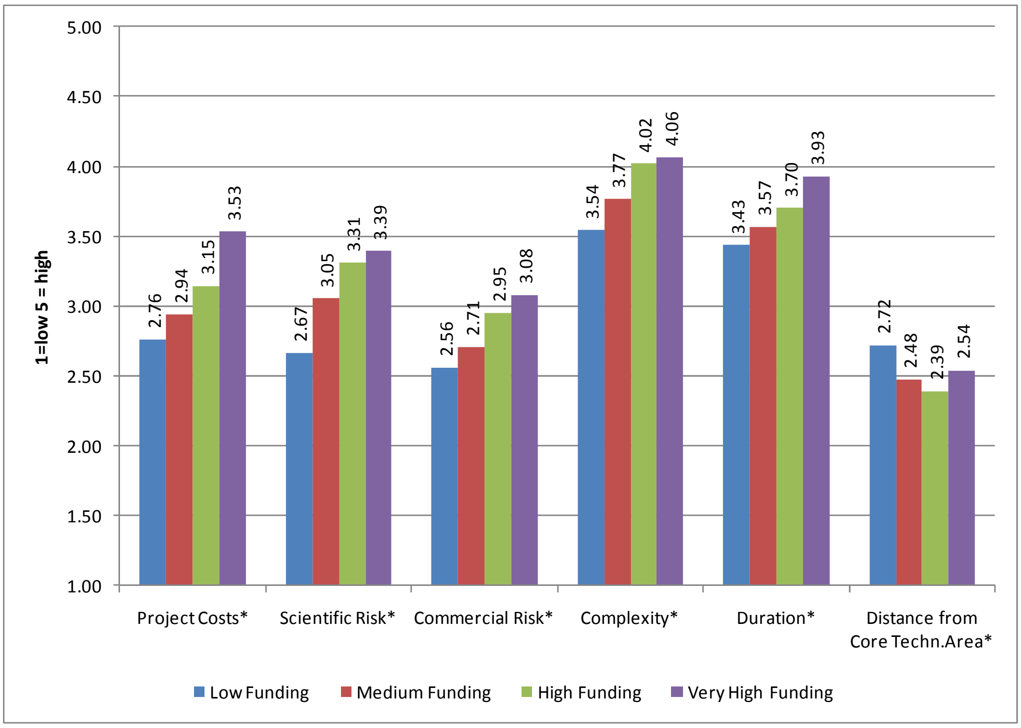
When project size is measured by the number of partners participating in a project, we observe (compared with an internal project) that Very Large projects have significantly higher project costs than Small- and Medium-sized projects. We furthermore observe that projects with a large number of participants are significantly less complex than Small, Medium and Very Large projects. Another interesting observation is that there is a negative correlation between project size and commercial risk.

Figure 19: Project profile vis-à-vis typical internal project (by number of partners)



When average participant funding is taken into account, we witness an even clearer relation between the size of a research project and the project profile compared to an internal project. The figure below shows that average funding per partner is positively correlated with project costs, scientific risk, commercial risk, complexity, and project duration.

Figure 20: Project profile vis-à-vis typical internal project (by partner funding)



4.1.6 Conclusions

The descriptive analysis shows that some evidence of direct scale effects can be observed:

- When considering the number of partners as a measure for project scale, we observed statistically significant differences regarding the following three out of eight performance dimensions: Networking Outputs, Research Capacity Impacts and Commercial Impacts. Interestingly, the relation between project size and project performance was not linear in these respects. Large projects with 17-28 participants performed considerably better than Small, Medium and Very Large Projects, although for Very Large Projects only differences regarding Research Capacity Impacts were statistically significant. The underlying structure of projects shows that Large Projects cannot be attributed to a single funding instrument: 35% of these projects are STREPS/CRS, 27% are Integrated Projects, 19% are Supportive Measures and 12% are Network Projects.
- When average funding per partner is taken as a measure of project scale we observe a linear relation between project size and some impact dimensions, as we witnessed that there is a positive correlation between individual funding and the performance dimensions of knowledge output, technological knowledge output, research capacity impacts, and commercial impacts. Regarding the underlying structure of projects, we observed that projects within the best performing categories High Funding and Very High Funding are predominantly Integrated Projects and STREPS/CRS projects.

- As regards the mediating variables in the dataset we observed that large projects are at first sight no better than smaller ones in terms of learning capabilities (absorptive capacity) and complementarity of resources. While the expected positive effects of these mediating performance dimensions did not occur, the hypothesised negative impacts of an increased project scale in terms of transaction costs could be observed. In particular, very large projects in terms of number of partners and total funding, which are by and large Integrated Projects, have considerably more unclear objectives and higher coordination difficulties.
- Also regarding firm characteristics and project characteristics some significant differences between small and large projects can be observed. Projects with higher average funding per partner and with a higher number of project partners have higher numbers of employees, are more often involved in collaborative actions, and have a higher R&D intensity (the latter is only true for average participant funding).
- The results of the descriptive analysis further point out that the project profiles compared with internal projects vary by project size. While there is a positive correlation between average participant funding and Scientific Risk, Commercial Risk, and Complexity, we witness a negative relation between the absolute project size and the Commercial risk: the higher the number of partners, the lower the Commercial Risk associated with the projects. Regarding the Scientific Risk and Complexity, Large Projects are outstanding. They are less complex and exhibit lower scientific risks. In addition, both Project Cost and Duration are positively correlated with the number of partners and average funding per partner.

4.2 Econometric Analyses

4.2.1 Introduction and Overview

The basic question we are dealing with in this project is whether economies of scale in R&D projects exist, and if so, to examine the causal mechanisms through which these economies materialise. As explained above, the basic rationale underlying these questions is that R&D projects may experience increasing returns to scale because of specialisation, complementarities of resources and skills, and more efficient utilisation of resources. However, there are also limits to the (presumed) scale effects: collaborative R&D projects may experience decreasing returns to scale as size becomes larger (that is, beyond a certain point) because of higher transaction and administrative costs associated with the implementation of a large project.

Using the conceptual framework described above as our starting point, we test whether scale, as reflected in consortium size and in project budget, exhibits an inverted-U shaped effect on project performance via its effect on a set of 'mediator' or intervening variables that underpin both positive and negative effects of performance. More specifically, we hypothesise that scale would have a positive influence on performance through positive effects on the pool of resources and on absorptive capacity (i.e. learning), and a negative effect by increasing the transaction costs, i.e. the administrative and coordination costs of running a (large) project. It is precisely because of this mix of positive and negative (indirect) effects that we expect an inverted-U shaped direct effect of scale on performance.

Our conceptual framework also posits that the mediated effects of scale on performance will depend on (i.e. moderated by) a set of other factors hypothesised to 'moderate' the relation between scale and the mediator variables. For example, we have hypothesised that project characteristics (such as the degree of its scientific and technical complexity) may condition the effect of scale on the 'pool of resources' (i.e. one of the mediating variables). Specifically, it may be argued that the greater the complexity of the project, the more increasing scale will have a positive effect on the pool of resources. This is because more complex projects may require a diverse array of skills and competencies that a large consortium can, ceteris paribus, provide.

Taken overall, our hypotheses develop as a series of basic questions regarding the role of scale in collaborative R&D projects' performance. To begin with, we ask 'Does scale affect performance?' As noted, we would expect a positive answer here, specifically that scale has an inverted-U shape direct effect.

Assuming that scale affects performance, we next ask 'What are the causal mechanisms explaining this effect?' Here we first put forward the hypothesis of 'unconditional' (simple) mediational effects. We posit that scale has a mixture of positive and negative effects on performance through a set of key intervening variables (i.e. pool of resources, absorptive capacity, and transaction costs).

Finally, we ask whether these mediating effects are not 'simple', that is, whether they depend on other variables such as project and partner characteristics or variables related to project management.

Our analyses below follow the same scheme: first we test for the direct effects of scale on performance (Step 1), then we test unconditional mediation (Step 2), and finally conditional mediation effects (Step 3) of scale on performance.

4.2.2 Methodology

4.2.2.1 Data and Measures

As noted earlier in this report, our sample contains a total of 1,172 observations (750 from ROs and 422 from private enterprises). These correspond to 676 collaborative R&D projects (328 projects with >= 2 responses). It is important to note, however, that our sample contains a large number of missing variables (i.e. item non-response). This means that we had to be selective with regard to the variables used to represent the key constructs of interest in our analyses, with a view to obtaining the largest possible number of usable observations for our models. Being selective means that from any given class of variables contained in our questionnaire (e.g. variables measuring various facets of partners' innovation 'history'), we chose the variable for which we had the largest number of observations and which was also more strongly associated with our dependent variables (i.e. project performance dimensions). Put differently, given the pattern of missing values, we sought to build parsimonious models in the sense that we looked for maximum statistical validity with the minimum number of independent variables.

Except for single item measures, all 'composite' variables used in the analyses (see below) were constructed following Confirmatory Factors Analysis. All of these composite variables were constructed as averages of multi-item Likert-type scales, where higher numbers pointed to a 'higher quantity' of what was measured. Annex 4-1 presents all relevant details. As shown there, all measures were reasonably valid and reliable, as judged by their respective psychometric properties.

Dependent Variables

We obtained data for eight dimensions of performance at the level of the individual participant. In other words, our dependent variables reflect outputs and/or impacts obtained by individual participants as a result of their participation in a given project. Moreover, these eight performance dimensions represent 'subjective' evaluations on the part of the respondent regarding these outputs; they are not 'objective' indicators of what has been actually achieved. We would have certainly preferred to complement these variables with outputs measured at the project level. As was explained above, however, this did not prove feasible (see also Chapter 3 on data).

These subjective performance dimensions include: (a) project goal achievement, (b) knowledge outputs, (c) technological outputs, (d) network outputs, (e) research capacity impacts, (f) commercial impacts, (g) goods/services innovation and (h) process innovation (as a result of the project). The last three of these measures (i.e. commercial, goods/services and process innovation) concern enterprises only.

- Goal Achievement: reflects the degree to which the project achieved its scientific, technical and commercial objectives. As such, it represents an overall (subjective) evaluation of project success.
- Knowledge outputs: reflects significance of outputs such as publications, PhDs, etc.
- Technological outputs: reflects significance of technical outputs, such as tools and techniques, models and simulations, and prototypes.
- Network outputs: reflects the significance of networking results, such as links with ROs and other businesses.
- Research capacity impacts: measures the significance of impacts that concern the ability of the partner to carry on research activities (i.e. increased number of research staff, enhanced technological skills, critical mass of research).
- Commercial impacts: measures the impact of possible exploitation outputs resulting from the project in question. These outputs concern, for example, increased turnover, profitability, enhanced competitiveness, etc. As noted above, this variable – as the next two – are obtained only from private enterprises in our sample.
- Goods/services innovation: an indicator variable (yes/no) showing whether the enterprise has produced new or improved goods/services as a result of the project. It is a 'subjective' variable in the sense that the respondent 'attributes' specific goods/services innovations that have to a lesser or greater extent resulted from project implementation.
- Process innovation: as above, but reflecting innovations in production processes.

We utilised one more dependent variable in our analyses, which unlike the previous ones, was an objective (rather than subjective) indicator of performance, again measured at the level of the individual participant. It concerned the number of patents granted to the responding organisation in a five-year, post-project window. We have limited our search of patents granted to a responding organisation only to those 'technology class(es)' that were the same as those in which the project in question fell. In this way, it was (at least theoretically) possible to make a connection between participation in a given project and the patenting activity of the responding enterprise. The details of constructing this measure, as well as of relevant controls (i.e. number of patents in the same technology classes granted up to a five years period prior to project start date, and number of patents granted during project implementation), have been detailed above and will not be repeated here. It suffices to stress that we acknowledge the limitations inherent in the construction of such measures. As will be shown below, the value of the 'number of patents' as a dependent variable in our analyses was minimal because of the extremely small number of observations with one or more patents (relative to the number of observations with zero patents).

Independent Variables

Scale: This is the key variable of interest to this study, and it is operationalised using two indicators: (a) number of partners, and (b) project budget (measured in euros). Because both variables are heavily skewed, as is common in the literature, we measure scale (and scale squared) using the number of partners and project budget in a log scale to compensate for skewing. Using the logarithm of scale allows the effect on performance of increased scale to be greater when moving from small-sized to medium-sized projects than when moving from large to very large projects. We have also constructed an alternative measure of scale, which combines those just mentioned, i.e. average funding per participant (in the log scale), and which was also used in the econometric analyses.

Scope: The questionnaire contained two questions intended to provide measures of project scope, both solicited from project coordinators (as opposed to project participants): the first asked coordinators to indicate whether the project in question involved 'sub-projects' (a yes/no question), and (b) if yes, the exact number of such sub-projects. It was felt that only coordinators, by having an overall picture of the project, would be in the position to provide a reliable answer to these questions. Unfortunately, only a relatively small number of coordinators participated in the survey and hence we have a large number of missing values on these variables. Because of that, in our analyses we use a proxy measure that basically reflects the vertical scope of the project. More specifically, this variable asks respondents to indicate whether the project involved 'R&D activities only', 'R&D plus developing a prototype', 'R&D plus prototype plus pilot activities', or finally, 'R&D plus prototype plus pilot plus market-oriented activities'. This is treated as an ordinal variable ranging from 1-4, with higher values denoting higher vertical scope of project activities.

The following four variables represent the mediator constructs in our framework; they reflect subjective assessment (on the part of the responding organisation) of project phenomena. More specifically:

- Complementarity of resources: The collective pool of resources made available to the project by the partners (not the responding organisation) was measured in terms of the complementarities achieved among partners. This variable is a Likert-type scale reflecting the extent of synergies with respect to scientific, technical/engineering, and managerial skills and assets. It is important to stress that we have not been able to collect a sufficient quantity of data on the diversity (heterogeneity) of the pool of resources. We solicited such data from project coordinators, for the same reason noted above. In the absence of such data, we attempted to construct a proxy based on the heterogeneity of participants in terms of their reported R&D expenditures and resource endowments (see below for a description of these variables). Unfortunately these measures are only relevant for the firm sub-sample. However, again the number of missing values was too high to permit meaningful and trustworthy results. (For more details, see below, the section on Additional analyses).

- Absorptive Capacity (AC): This is a construct assessing the degree of knowledge acquisition, assimilation, and integration resulting from the learning-related activities among partners in the project. This measure is a new one, specifically developed for the present study. It attempts to operationalise as faithfully as possible the theoretical conceptualisation of absorptive capacity as the ability of partners to acquire, assimilate and integrate knowledge. As such it refers to the cognitive processes that make learning possible within an R&D consortium. By construction, it is conceptually distinct from complementarity of resources or diversity, which should be seen as 'antecedents' to absorptive capacity.
- Unclear objectives: This variable, together with 'difficulties in coordination' (see below), represents two dimensions of transaction costs incurred among partners in the course of project implementation, as derived by the confirmatory factor analysis of the original scale. It reflects the degree to which partners agree that the project is characterised by clear and accepted objectives as well as by a clear allocation of tasks. The scale was reverse coded for the analysis to reflect 'unclear objectives'.
- Difficulties in coordination: As above, this is a reverse-coded scale that reflects the extent of difficulties in coordination among partners in terms of information sharing, smooth planning of activities, efficiency of working together, etc.

The following variables reflect some basic characteristics of the responding organisation as well as the 'quantity' of the resources it (the particular partner) has committed to the project. Here we also include a measure of the market environment in which it operates.

- Size: This is a variable representing the size of the partner, as reflected in the number of its employees. It is an ordinal measure, ranging from 1 to 5, with higher values indicating larger size (e.g. 5 = 501+ employees).
- Frequency of participation: This variable measures the frequency of participation in prior collaborative R&D projects. It reflects experience with such projects. It is a Likert-type item, ranging from 1 (= never involved) to 5 (= involved in many projects).
- Acquaintance with partners in the project: This is an indicator (dummy) variable that references whether the partner has collaborated before with one or more partners in the consortium.
- Organisation type: Dummy variable, referencing a RO (vs. a private firm).
- Resources committed to the project: An ordinal variable measuring the number of senior staff devoted to project implementation. It ranges from 1 (= 1 to 3 persons) to 4 (= 10+ persons).
- Market & Technological dynamism: This Likert scale reflects the degree of turbulence and uncertainty in the firm's market and technological environment.

The next two variables are also referring to the responding organisation, but this time they refer to its 'general' innovation-related resources and skills.

- R&D expenditures: An ordinal variable indicating the percentage of R&D expenditure of total budget/revenue for the period just prior to the project. It ranges from 1 (='no R&D) to 6 (= >10%).
- Resource endowments: A Likert-type scale reflecting the firm's ability to commercially exploit research results (i.e. ability to speedily introduce new products, marketing skills in launching new products, etc.).

The following set of variables characterises the 'type' of the project.

- Framework Programme: A dummy variable representing a project under FP6 (vs. FP5).
- Thematic Category: An indicator variable with four categories (i.e. Growth, IST, Life, and Eesd). The reference category is 'Other'. (We have chosen 'Other' as the reference category because it collects all remaining thematic categories and as such it presents itself as a 'natural' category against which to compare the others. The same applies to the variable just below.)
- Instrument: Another indicator variable with four levels: 'Supportive measures, Large projects, Network projects, and Small and medium projects. The reference category is Other.
- Project duration: It is measured in months. As with scale, we log transformed this variable to compensate for extreme skewing.

The following set of variables measures some 'qualitative' characteristics of the project.

- 'New area' project: A binary variable indicating whether the project is assessed to represent an 'entirely new scientific' area for the partner.
- Cost vis-à-vis an average project: A five-point Likert-type item, with high values indicating a high cost project in comparison to the responding organisation's 'average' R&D project.
- Scientific risk: As above, reflecting scientific risk in comparison to an 'average' project.
- Commercial risk: As above, reflecting commercial risk.
- Complexity: As above, reflecting the project's complexity.
- Long term: As above; higher values indicate longer horizon vis-à-vis an 'average R&D project.
- Distance from core: As above, higher values indicate higher distance from the partner's technological core area.

Finally, the following two variables refer to issues of project management. More specifically:

- Communication: A Likert-type scale reflecting perceptions regarding the efficiency of communication among partners in the consortium.
- Coordination: As above, but referring to the efficiency of mechanisms and tools used by the consortium to coordinate activities among partners.

4.2.2.2 Analytical Strategy and Methods

As noted above, we consider three basic questions of successively increasing complexity. In the first we address the question whether scale affects project performance. In what we shall henceforth refer to as Step 1 in our analyses, we specifically examine whether these effects take the form of an inverse-U shaped relation with performance, controlling for all the variables identified above. In Step 1, therefore, we assess the direct effects of scale on performance by including in our models both scale and scale squared to accommodate the possibility of a non-linear relation (i.e. inverse-U). Our hypothesis will be supported whenever we find a significant positive effect of scale and a significant negative effect of scale squared.

To test this hypothesis, we fit regression models separately on the different performance dimensions identified above. Specifically, for the dependent variables whose original questionnaire items are measured with Likert-type scales (i.e. goal achievement, knowledge outputs, technological outputs, network outputs, research capacity impacts, and commercialisation-related impacts) we fit OLS regressions.[11] With regards to the two binary dependent variables (i.e. goods/services innovation and process innovation) we fit logistic regression models. Finally, we employ Poisson regression to examine the effects of scale on counts of patenting activity (i.e. number of patents). For all models in Step 1 we request robust standard errors to correct for non-independence among observations pertaining to the same project (recall that in the original sample of 1,172 observations, we have 824 responses coming from 328 projects).

In Step 2 we examine the hypothesis of 'simple' mediational effects. Recall that we hypothesise that scale affects performance through a set of intervening variables (i.e. Complementarity of Resources, AC, Unclear Objectives, and Difficulties in Coordination). Essentially, we posit that whatever influence scale exerts on performance is basically transmitted through its effects on the mediator variables.

Mediation indicates that the effect of an independent variable on a dependent variable is transmitted through a third variable, called a mediator variable. To test the mediation hypotheses, we draw on the seminal contribution of Baron and Kenny (1986) as well as more recent related work (see for example, Kenny, Kashy, and Bolger, 1998, and Shrout and Bolger, 2002). Assuming for a while a single mediator model (i.e. there is only one hypothesised mediator variable), the original key idea, as articulated by Barron and Kenny, is that four conditions have to be met in order to establish the role of a mediator (say, AC) in the scale-performance relation:

[11] This is consistent with the commonly held assumption that a dependent variable constructed as the average of a multi-item scale is distributed as a quasi-normal variate.

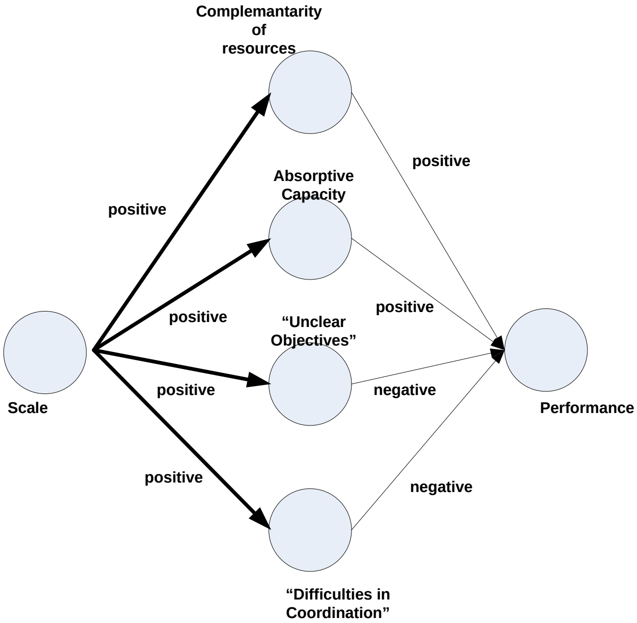
1) scale is related to AC (denote this as the 'a' parameter),
2) AC is related to performance ('b' parameter),
3) scale is related to performance ('c_0' parameter),
4) strength of the relation between scale and performance (c_1) when AC is added to the model as a mediator is lower than the effect (c_0) when AC is not controlled for.

However, as Kenny et al. (1988) and Shrout and Bolger (2002) note still one more possibility: If conditions (1) and (2) hold, but scale does not relate to performance, when in other words scale and performance are not directly related, thus invalidating condition (3) and consequently condition (4), then scale is said to have an indirect effect on performance through AC (Kenny et al., 1998:260).

In the technical literature's parlance, c_1 is the direct effect, a*b is the mediated or indirect effect, and c_0 is the total effect (MacKinnon, 2008; Shrout and Bolger, 2002). The key quantity of interest here, a*b, reflects how much a unit change in (the logarithm of) scale affects performance indirectly through AC. The estimate of the mediated effect, a*b, and its standard error are used to construct confidence intervals for testing mediation. Standard error is usually estimated using Sobel's (1986) approximate formula, which assumes, however, that the product a*b will be asymptotically normally distributed. There exists evidence, however, that the product a*b is not normally distributed (see for example, Shrout and Bolger, 2002); instead it is found to be positively skewed if a and b are of the same sign, and negatively skewed if of opposite signs. It follows that ignoring this problem can reduce the power to detect mediation when in fact it exists in the population. Bollen and Stine (1990) and, more recently, Shrout and Bolger (2002) proposed using bootstrap methods for computing non-symmetric confidence bounds for the product a*b.

In our particular case, the model we propose involves simultaneous mediation by multiple (i.e. four) variables; this is the case of multiple mediation. As shown in the figure below, we hypothesise that scale may affect performance through some mediating variables, (i.e. complementarity of resources, AC, and two facets of transaction costs: 'unclear objectives' and 'difficulties in coordination'). Essentially, our model postulates that there exists a mix of positive and negative indirect effects of scale on performance through the mediating variables. Specifically, we expect that scale affects positively all mediators. In essence, we hypothesise that scale increases complementarity and learning, and also that it makes transaction costs higher. In turn, complementarity and AC positively affect performance, whereas the two dimensions of transaction costs affect performance negatively. Consequently, the product 'a*b' will be positive for the following causal chains: (a) scale → complementarity → performance, and (b) scale → AC → performance. It will be negative for: (c) scale → 'unclear objectives' → performance, and (d) scale → 'difficulties in coordination' → performance.

Figure 21: 'Simple' multiple mediation model



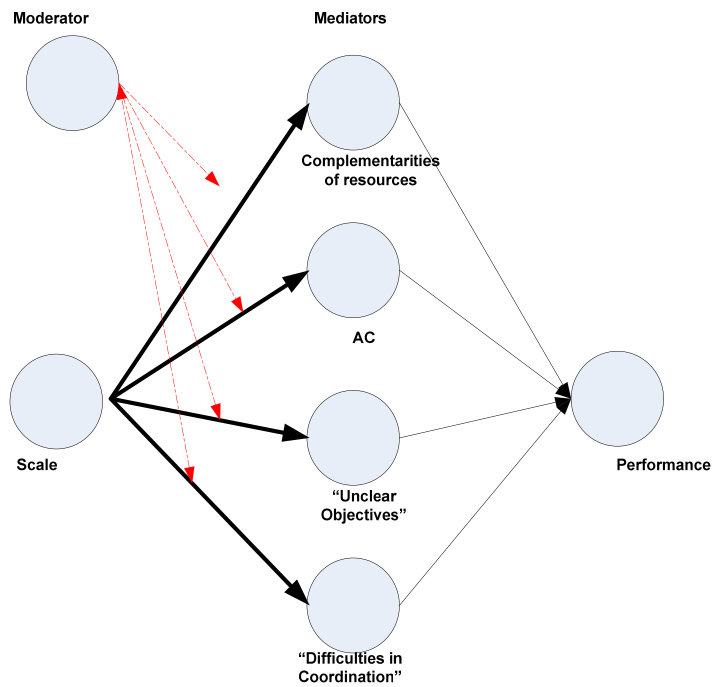
The total indirect effect of scale on performance is the sum of the specific indirect effects: $\sum a_i b_i, i=1$ to j=4 (four mediator variables).

As noted above, because the product a*b (both for total and specific indirect effects) is not normally distributed, we test its significance via bootstrapping (see for example, Preacher and Hayes, 2008). In simple terms, bootstrapping the sampling distribution of the specific and total indirect effects involves taking a sample of size n cases with replacement from the original sample. In other words, a given case can be selected as part of a bootstrap sample either not at all, once, twice or multiple times. Using this new resample of size n, the procedure re-estimates all j values of a_i and b_i and then calculates ai*bi and $\sum a_i b_i$ for each resampled data set. The process is repeated k times, usually 1,000, thus yielding k estimates of the specific and total indirect effects of scale on performance. Now, the important point is that the distribution of these k estimates represents empirical, nonparametric approximations of the sampling distributions of the indirect effects of interest. Based on these, the bootstrap confidence interval (CI) is derived by sorting the k values of the specific and total indirect effects from low to high. Values defining the lower and upper 100(a/2)% are taken as the bounds of the CI, where a is the desired nominal Type I error rate. When the CI thus constructed does not contain zero, the product a*b (either for a specific or the total indirect effect) is considered significant.

To perform these analyses, we employ the 'indirect' macro in SPSS (Preacher and Hayes, 2004). It is important to note that in our analyses we take into account as controls all the variables identified above. Furthermore, we consider an indirect effect as significant at (the rather 'liberal') a=10%.

Step 3 goes a step further, in that we test whether these indirect effects are not 'simple', that is, whether they are conditionally based on upon certain variables that moderate (i.e. interact with) scale to influence the mediators (and through them, performance). This is what the technical literature refers to as a moderated mediation (see for example, Preacher, Rucker and Hayes, 2007). As shown in the following Figure, we hypothesise that some moderator variable(s) (e.g. the partner's innovation skills) affects the 'a' paths (i.e. recall that the 'a' paths represent the influence of scale on each of the four mediator variables). For example, we hypothesise that the positive effect of scale on the complementarity of resources will be higher for partners with innovation-related skills and experiences. Similarly, the effect of scale on AC will be higher for partners experienced in innovation. Conversely, we expect that the positive effect of scale on transaction costs (i.e. Unclear Objectives and Difficulties in Coordination) will be decreased when a partner has extensive innovation skills.

Figure 22: Moderated Mediation



In a series of models, we examine the interaction effects of scale – i.e. log (number of partners) and log (project budget) – separately with a number of moderating factors (see 4.2.3.4 for details).

As before, we employ the 'indirect' macro in SPSS, using the same specifications (we use all the remaining variables as controls, we use a=10% as the nominal Type I error, and we perform 1000 bootstrap replications to construct the CI for each conditional indirect effect).[12]

4.2.3 Results and Discussion

4.2.3.1 Step 1 – Direct effects of Scale on Project Performance

To examine the hypothesised curvilinear (inverse-U shaped) effects of scale on performance, we run a series of regression models, one for each performance dimension. In all these models we test for both linear and quadratic terms of log (# of partners) and log (budget) to capture (possible) non-linearity in the effects of scale on performance. We include all remaining variables as controls, to remove whatever effects these other variables may have on performance. We begin our exposition with the results obtained in the 'full sample', i.e. the sample containing data collected from both private enterprises and ROs; this is our primary sample. In a section below, we present results using an alternative measure of scale, i.e. average funding per project, and also results from fitting the same and similar models in different sub-samples (e.g. the firm sub-sample) of theoretical and/or substantive interest.

Table 11 presents the findings. Because commercial impacts, goods/services innovation, and process innovation are relevant only for the firm sub-sample, these dependent variables do not appear in Table 11 (they will be discussed below, the same for the findings from fitting the negative binomial regression models on the number of patents). Hence, the results in Table 11 pertain to following performance dimensions: (1) goal achievement, (2) knowledge outputs, (3) technological outputs, (4) network outputs, and (5) research capacity impacts. As noted above, we employ simple linear regression for these variables.

We specify linear and quadratic terms for both variables representing scale simultaneously. Admittedly this creates problems of co-linearity. Indeed, the variance inflation factors (VIF) for these variables is, as would be expected, very high. Nevertheless, we obtain significant results of scale on two of the five dependent variables in Table 11. To check the robustness of these results, we run a series of checks that will be detailed in a subsequent section.

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12 A different approach to test for the moderated mediation effects would be the following: Denote the effect of scale on a mediator as 'a', the interaction of scale with a moderator variable, W, as 'z', and the effect of the mediator on performance as 'b'. Then, the conditional indirect effect of scale on performance can be expressed (following some simple algebra, see Preacher et al., 2007) as $b*(a + zW)$. In this formulation, the conditional indirect effect depends on W, the moderator variable, to the extent that the interaction coefficient, z is significantly different from zero. The significance of the quantity $b*(a + zW)$ would be again assessed using the bootstrap procedure. A macro in SPSS, 'modmed' (Preacher et al., 2007), could be used for the purpose. Unlike the 'indirect' macro, however, 'modmed' does not allow for the simultaneous estimation of the multiple conditional indirect effects hypothesised in our model. Recall that our model specifies four mediator variables. Hence, we would like to estimate simultaneously (and we actually do by using the 'indirect' macro) four conditional indirect effects of scale on performance for each potential moderator variable W. It is also worth noting that we cannot examine simultaneously all possible conditional indirect effects; both the 'indirect' and the 'modmed' macro do not allow for such a specification. But even if we could, the number of parameters to be estimated would make our models extremely complex and unwieldy.

Table 11: Direct effects of scale on project performance (full sample)

	(1) Goal achievement	(2) Knowledge outputs	(3) Technological outputs	(4) Network outputs	(5) Research capacity impacts
lg_nrpar	0.38	0.23	0.24	**1.00****	0.54
lg_nrpar_sq	-0.08	-0.08	-0.07	**-0.15***	-0.12
log budget	**-1.08***	0.88	0.39	0.72	0.27
log budget squared	**0.04***	-0.03	-0.01	-0.02	-0.01
resource complementarity	0.06	0.15+	0.03	0.19***	0.19**
absorptive capacity	0.27***	0.15	0.12+	0.16*	0.20*
unclear objectives	-0.04	-0.11	-0.07	-0.05	-0.01
coordination difficulties	-0.17**	0.01	0.01	-0.03	-0.05
# of employees	-0.03	0.06	-0.02	-0.03	-0.05
frequency of prior collaborative R&D	0.02	-0.00	0.02	0.02	0.02
knows one or more of the partners	0.02	0.29+	0.20+	-0.01	0.24*
# of senior staff to project	0.03	0.18**	0.04	0.07	0.07
FP6 vs. FP5	0.02	-0.08	0.10	0.07	-0.10
thematic: Growth	-0.22*	-0.49*	-0.01	-0.06	-0.36*
thematic: IST	-0.06	-0.09	0.21	0.02	-0.08
thematic: Life	-0.19	-0.25	0.03	0.02	-0.27
thematic: Eesd	-0.23*	-0.28	0.09	-0.05	-0.25
Instrument: Supportive measures	0.34*	-0.03	0.18	0.30	0.07
Instrument: Large projects	0.06	0.48	0.05	0.03	0.25
Instrument: Network projects	0.40*	0.79*	0.22	0.34+	0.43+
Instrument: Small/medium projects	0.14	0.22	0.10	0.11	0.07
log project duration	0.09	0.41	-0.02	0.03	0.24
vertical scope of the project	0.01	-0.05	0.13***	0.06*	0.03
entirely 'new area' project	0.03	-0.23+	0.01	-0.03	0.05

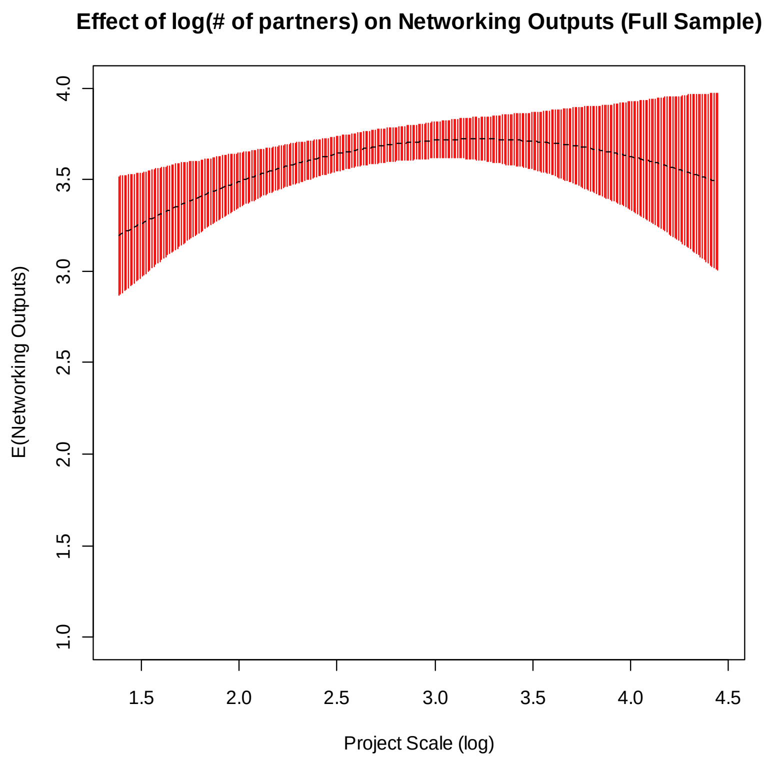
cost vis-à-vis average project	0.04	0.01	-0.00	0.04	-0.02
scientific risk vis-à-vis average project	-0.02	-0.03	0.01	-0.05	0.04
commercial risk vis-à-vis average project	0.00	-0.05	0.03	0.02	0.06
complexity vis-à-vis average project	0.07+	0.07	0.13**	0.04	0.15*
long term vis-à-vis average project	-0.05	0.03	0.02	0.09*	-0.00
distance from core area vis-à-vis average project	-0.01	-0.02	-0.02	0.03	0.01
efficiency of communication	0.07	0.23*	0.16**	0.10	0.12
efficiency of coordination	0.04	-0.02	0.07+	0.10*	-0.01
RO vs. enterprise	0.09	0.38***	0.10	0.11	0.22*
constant	8.92**	-7.87	-2.86	-6.09	-3.99
observations	570	586	583	593	588
adjusted R^2	0.303	0.217	0.210	0.227	0.179

+ p<0.10, * p<0.05, ** p<0.01, *** p<0.001

The predictive validity of the models in Table 11 is reasonable. The adjusted R^2 for the different models ranges from 0.18 to 0.30, which is normal for dependent variables measured with subjective (perceptual) measures. The sample size varies between models because of differences in the number of missing values for the dependent variables, and ranges between 570 and 593 observations.

Turning to our key question, when scale is operationalised as log(# of partners) and log(# of partners) squared, the results in Table 11 suggest increasing up to a point and then decreasing returns to scale for one performance dimension, i.e. network outputs. Notice that consistent with the inverse U-shaped hypothesis we also obtain a positive linear and negative quadratic term for the remaining dependent variables, but these coefficients are not statistically significant. Hence, with respect to network outputs, up to a certain threshold, higher scale (i.e. higher number of partners – in the log scale) is associated with increased performance. However, beyond that threshold, the returns are diminishing (see next Figure)[13].

Figure 23: Effect on network outputs



What is the size of the estimated threshold? Setting the first derivative with respect to scale (# of partners) equal to zero and then taking the antilog yields 28 partners (with respect to network outputs). For illustrative purposes, we repeat the same computations

[13] This Figure, as well as the following, is constructed based on 1,000 simulations using the Zelig package in R. The vertical (red) lines represent the 95% CI of the estimated value of y for each value of x (i.e. project scale), holding all remaining variables at their sample means. Because they are derived from simulating the estimated coefficients, the graphical location of the maximum (minimum for Figure 24) of the function does not coincide with the point estimates. The figures are used for illustrative purposes.

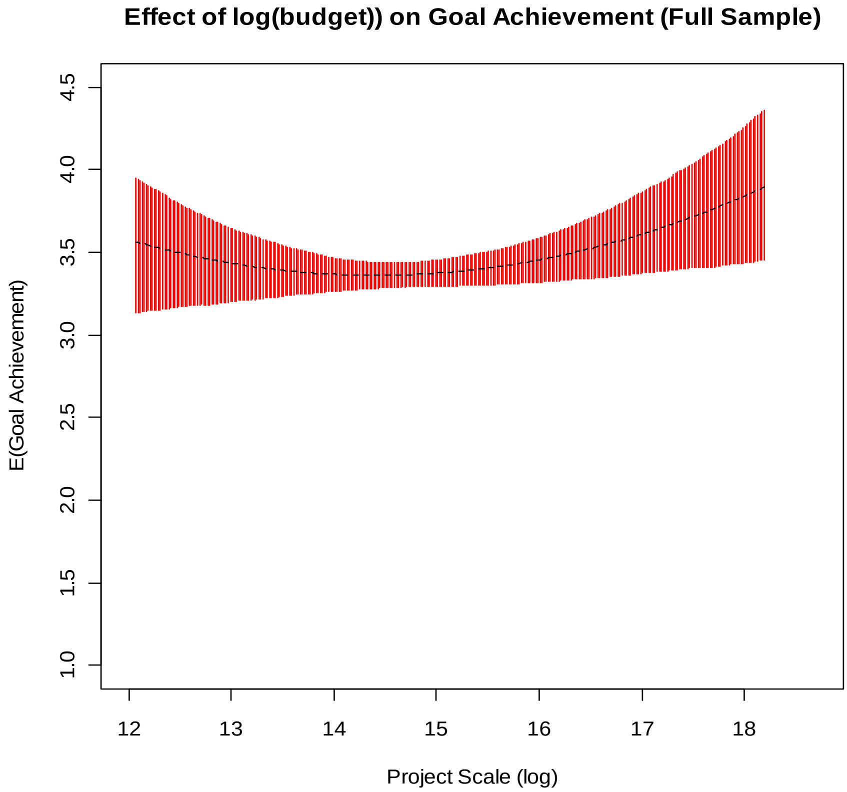
for the remaining performance variables – even though the coefficients of scale for these are not significant – and obtain the following figures: 10.7 (for goal achievement), 4.21 (for knowledge outputs), 5.5 (for technological outputs), and 9.5 (for research capacity impacts). These figures represent the 'optimal' size of the consortium for each of these dependent variables, respectively. Do these values make sense? One way of answering this question is to look at the empirical distribution of the number of partners observed in our estimation sample.

When looking at the 593 observations used to fit the regression model for network outputs, we find that the average size is 19.6 (standard deviation = 14.4), while the 25% and 75% percentile values are 9 and 25 partners, respectively. It follows therefore that the estimated optimal size of the consortium is well within the empirical distribution of the number of partners; in fact it is just slightly above the size of the higher 75% (and well below the higher 90%) of the projects in the sample. This result is reasonable, in the sense that possibilities for networking increase when the consortium is large, not small. Still, however, as the results indicate, when the consortium becomes too large, these effects begin to diminish.

In contrast, the optimal size with regard to the remaining performance dimensions is well below the respective average size. Even though these coefficients are not statistically significant (and, therefore, strictly speaking, not trustworthy), it is perhaps worth noting how the optimal size differs among performance dimensions. It is quite small for knowledge and technology related outputs, i.e. 4.2 and 5.5, respectively, and moderately higher (but still considerably lower with respect to networking) for goal achievement (10.7) and research impacts (9.5).

With respect to budget (log budget and log budget squared), the results are somewhat surprising, in that we find a significant curvilinear effect on goal achievement, but contrary to our hypothesis the effect is found to be U-shaped (instead of inverse-U shaped – see next Figure), since the linear term is negative and the quadratic is positive (see Table 11). (As will be shown later, our robustness checks reveal that this effect generally holds for various different specifications of the functional form of scale, as well as for one of the different sub-samples in which we run the same basic model).

Figure 24: Effect on goal achievement



Following the same procedure as above, we approximate the point at which the estimated function attains its minimum with respect to budget. We find that the expected value of goal achievement is at its minimum when the budget is 729,416 EUR. The empirical distribution of the size of project budgets in the sample of 570 observations used to fit this model is as follows: mean = 4,649,512 (standard deviation = 7,695,584), 25% percentile = 1,189,822, 75% percentile = 4,860,001. Clearly, the minimum scale in terms of budget with respect to goal achievement is at the lower end of the empirical distribution (i.e. just below the lower 10% of the distribution). What does this finding tells us? Simply put, goal achievement begins to increase when the project budget is higher than approximately 700,000 EUR.

As already noted, our finding of a significant U-shaped relation between budget and goal achievement is contrary to our hypothesis. Instead of initially positive effects that begin to diminish after a certain threshold, we observe the exact opposite pattern. According to our estimations, the project budget has to be higher than the minimum threshold of 700,000 EUR for goal achievement to start increasing. This is, of course, a reasonable result. At low levels of budget, respondents feel that little can be achieved because of limited resources. It is only when the budget becomes sizeable (i.e. higher than the threshold of 700,000 EUR) that respondents feel there is a match between goal expectations and the resources available to meet these goals. In this light, it is interesting to note that the estimated minimum budget is relatively low when compared to the empirical distribution of budget across projects in our sample. In other words, it appears that budget does not have to be too high for participants to indicate positive goal achievement.

At a more theoretical level, however, it is worth noting that, compared to the interpretation of the effects of log number of partners (as an indicator of scale) on performance, the situation with log budget is perhaps less clear. In the former case, it can be argued that the number of partners exerts both positive and negative influences on performance through its effects on the mediating variables. As noted above, a large number of partners may influence positively the complementarity of resources and learning[14], but also the transaction costs among project participants (i.e. intuitively, the higher the number of partners the more difficult it would be to manage the project effectively). But do these (or similar) arguments hold with respect to budget? Clearly, it may be argued that the higher the budget, the higher the likelihood for a larger pool of resources available for project implementation. This may be the most straightforward explanation for our finding. But what is the theoretical rational connecting budget with learning? The direction of the relation between the two is arguably more ambiguous. Moreover, on what grounds can one posit a positive effect of budget on transaction costs? In contrast to scale measured by the number of partners, it may be more prudent to argue that a high budget will, ceteris paribus, improve (rather than the opposite) the management of the project (hence, a negative effect on e.g. difficulties in coordination). We will return to these issues when examining the causal mechanisms that carry the influence of scale on performance in the mediational analyses in Steps 2 and 3.

The results with respect to the other variables are generally in the expected direction. For example, the four mediating variables, whenever found to be significant, have the correct sign. More specifically, complementarity of resources is found to be positive and significant for knowledge outputs (.15, $p<.10$), network outputs (.19, $p<0.001$) and research capacity impacts (.19, $p<0.001$). AC is also found to positively influence goal achievement (.27, $p<0.001$), technological outputs (.12, $p<0.10$), network outputs (.16, $p<0.05$) and research impacts (.20, $p<0.01$). Also note that difficulties in coordination affect goal achievement negatively (-.17, $p<0.01$).

Somewhat surprisingly, experience with collaborative R&D projects (frequency of participation) does not seem to exert any influence on performance. The same holds for the size of the partner. In contrast, having established prior collaborative relations with some of the partners yields positive effects on knowledge outputs (.29, $p<0.10$), on technological outputs (.20, $p<0.10$), and on research capacity impacts (.24, $p<0.05$). As would be expected, the more resources committed to the project, the higher the score for knowledge outputs (.18, $p<0.01$). We find no difference in any of the five performance dimensions between FP5 and FP6 projects. Similarly, we find no effect of project duration. In contrast, we find that ROs (vs. enterprises) obtain significantly more positive results in terms of knowledge outputs (.38, $p<0.001$) and research capacity impacts (.22, $p<0.05$).

[14]Recall, however, that as noted in the description of the conceptual framework, the effect of scale on learning is really a simplification of a more complex relationship.

Vertical scope, a variable of special interest to this study, is found to positively influence technological outputs and network outputs (.13, $p<0.001$ and .06, $p<0.05$, respectively). With respect to the 'qualitative' characteristics of the project, we find that new-area projects are less successful with respect to knowledge outputs (-.23, $p<.10$). Complexity influences positively goal achievement (.07, $p<0.10$), technological outputs (.13, $p<0.01$) and research capacity impacts (.15, $p<0.05$), while long term projects appear to produce more network outputs (.09, $p<0.05$).

We also find that efficient project management plays a positive role in performance. Specifically, communication is positively related to knowledge and technological outputs (.23, $p<0.05$; and .16, $p<0.01$, respectively), whereas coordination affects positively and significantly technology outputs (.07, $p<0.10$) and networking (.10, $p<0.05$). Finally, we obtain some significant results with regards to the controls representing different thematic categories and instruments. More specifically, 'Growth' projects appear to be significantly less successful (in terms of goal achievement, knowledge outputs, and research impacts) relative to the 'Other' reference thematic category. Similarly, projects in the 'Eesd' thematic category are less successful with respect to goal achievement. With regards to instruments, projects under 'supportive measures' are more successful with respect to goal achievement than the reference ('other instruments') category. While 'Large projects' and 'small/medium projects' are no different than the reference, 'network' projects are more likely to produce results in terms of goal achievement, knowledge outputs, research impacts, and (obviously) network outputs.

4.2.3.2 Additional Analyses and Robustness Checks

The results presented above pertain to what we shall call the 'basic specification' of our models in step 1, that is, they are the findings obtained from fitting simple OLS models in the full sample, where we specify both linear and quadratic effects for both number of partners and budget (in the log scale). In this section, we explore various possible extensions of the basic specification in order to verify the robustness of our results.

The first set of additional analyses involves fitting our models in different sub-samples, which are derived as a 'natural' breakdown of the original full sample. There exist four sub-samples that can be used for our purposes:

1. The 'collaborative research projects' sub-sample, which contains data on projects that belong to the following instrument categories: IP, CSC, CRS, STIP and STREP. Put differently, the 'collaborative research projects' sub-sample excludes projects that fall within the Supportive measures, Network projects, as well as Other instruments, which are arguably not clean-cut examples of collaborative R&D activities. Hence, this sub-sample contains observations of what may be viewed as 'pure' R&D projects.
2. The 'firm' sub-sample, which contains data obtained exclusively from private enterprises. The rationale here is that in this sub-sample we can more closely examine the behaviour of, and performance impacts for, firms in collaborative R&D.

3. The 'FP5' sub-sample, which – as the name implies, contains only FP5 projects.
4. The 'FP6' sub-sample, containing only FP6 projects. The Fifth and Sixth Framework Programmes have qualitatively different characteristics in terms of overall design and aims and as such it would be interesting to examine more closely our questions separately in these sub-samples.[15]

Fitting the same OLS models with the exact same specification of variables as in Table 11 yields results that are summarised in the following Table (also including results from Table 11 for comparative purposes). Detailed results are shown in the Annexes.

Before discussing the findings, a few remarks are in order. Sub-sample sizes (used for estimation) are lower than those of the Full sample (see Table 11); for the 'collaborative research projects' sub-sample the number of usable observations ranges from 449 to 463 (conditional on the different dependent variables). For the firm sub-sample, the numbers are much lower, ranging from 167 to 182 observations. Finally, in the FP5 sub-sample, the usable observations ranged from 277 to 288, whereas the respective figures for the FP6 sub-sample ranged from 293 to 305.

Analyses in the firm sub-sample include three additional dependent variables (i.e. commercial impacts, goods/services innovation, and process innovation) and three more independent variables (relative to those used in Table 11). These include: R&D expenditures, resource endowments, and market/technological dynamism. These additional independent variables are only measured for firms, not ROs. The two models for product and process innovation are fit using logistic regression, as these two variables are binary. For these two models, including the quadratic terms of number of partners and budget led to severe misspecification. Hence, in these models we only test for linear effects of scale. Given the relatively small size of usable observations in the firm sub-sample, particularly when compared with the number of independent variables in the equations (i.e. 35 independent variables), the respective results should be considered with caution.

The results in Table 12 show a rather mixed picture, but looking at the table vertically, and with respect to the number of partners, we see that scale has:

1. an inverse U-shaped effect on goal achievement, but only in the collaborative research sub-sample,
2. no effect on knowledge outputs,
3. an inverse U-shaped effect on technology but only in the FP5 sub-sample, with surprisingly a U-effect in the FP6 sub-sample,
4. the inverse U-shaped effect on network outputs in the full sample, as well as in the 'collaborative research' and FP5 sub-samples,

[15] Recall that in our basic specification we have included two dummies (i.e. organisation type and framework programme) that are meant to capture performance differences between ROs and private firms, and between FP6 vs. FP5 projects, respectively. By performing separate analyses on these sub-samples, we are interested to see whether these differences extend to the estimated effects of all other variables, notably the effects of scale.

5. almost no significant results for performance dimensions specific to private enterprises (i.e. commercial impacts, and product and process innovation).

Again looking vertically, but this time with respect to log budget:

1. the U-shaped effect on goal achievement in the collaborative research sub-sample,
2. an inverse-U effect on knowledge and technology outputs also in the collaborative research sub-sample, also found in the FP6 sub-sample.

Looking at the Table horizontally, it is clear that the firm sub-sample provides the least evidence of scale effects on performance. This lack of strong results may be a statistical artefact, because of the small number of observations.

Admittedly the results reported in Table 12 are mixed, making it difficult to paint a broad and consistent picture. Nonetheless, it would be possible to argue that, at the broadest level, we do find support for the hypothesis that scale affects performance in a curvilinear manner. Even though the evidence is not overwhelming, at least some dimensions of performance, most notably network outputs, goal achievement and technology outputs, are affected by the scale of the project. It is also true, however, that contrary to our hypothesis, in addition to inverse U-shaped effects we also find U-shaped relations to performance. In the latter case, this has to do with goal achievement and technology outputs. Also in the latter case, it is quite surprising that we find the exact opposite relation between log partners and technology outputs in the FP5 and FP6 sub-samples. In FP5 projects the relation is, as expected, inverse-U, whereas in FP6 it is U-shaped. Moreover, again in the FP6 sub-sample, log budget has the opposite effect on technology outputs (i.e. inverse U).

Another general finding is that both measures of scale seem to affect performance. Interestingly, even though there seems to be no pattern with regard to the performance dimensions they influence (i.e. as would be the case if, for example, budget affected only goal achievement and consortium size affected network outputs), in those cases in which they both influence significantly the same performance dimension, they do so in opposite ways. Specifically, consider the case of goal achievement in the collaborative-research sub-sample. Whereas number of partners exerts an inverse U-shaped effect, budget also affects achievement but in the opposite way (U-shaped)! Hence, it would appear that the two scale 'dimensions' operate in opposing ways when affecting the same performance dimension. (As noted above, the same pattern is found in the FP6 sub-sample with respect to technology outputs).

Table 12: Summary of results in the different sub-samples

	Goal achievement	Knowledge outputs	Technology outputs	Network outputs	Research Impacts	Commercial impacts	Product innovation	Process innovation
	Full sample (for comparison)							
Partners[1]	ns[3]	ns	ns	Inv U[4]	Ns	n/a[6]	n/a	n/a
Budget[2]	U[5]	ns	ns	ns	Ns	n/a	n/a	n/a
	Collaborative research projects sub-sample							
partners	Inv U	ns	ns	Inv U	Ns	n/a	n/a	n/a
budget	U	Inv U	Inv U	ns	Ns	n/a	n/a	n/a
	Firm sub-sample							
partners	ns	ns	ns	ns	Ns	Linear -[7]	ns	ns
budget	ns	ns	ns	ns	Ns	ns	ns	Linear -[8]
	FP5 sub-sample							
partners	ns	ns	Inv U	Inv U	Ns	n/a	n/a	n/a
budget	ns	ns	ns	ns	Ns	n/a	n/a	n/a
	FP6 sub-sample							
partners	ns	ns	U	ns	Ns	n/a	n/a	n/a
budget	ns	ns	Inv U	ns	Linear +[9]	n/a	n/a	n/a

Notes:

1. partners – both linear and quadratic effects of log (# of partners) except for the logistic regressions in the firm sub-sample
2. budget - both linear and quadratic effects of log (budget) except for the logistic regressions in the firm sub-sample
3. ns = not significant
4. Inv U = significant inverse U-shaped effect
5. U = significant U-shaped effect
6. n/a = not applicable (only estimated in the firm sub-sample)
7. Linear - = the linear term was found negative and significant (but not the quadratic)
8. Linear - = the linear term was found negative and significant (the quadratic was not tested in the logistic regressions)
9. Linear + = the linear term was found positive and significant (but not the quadratic)

Another set of additional analyses involves experimenting with different ways of including the linear and quadratic terms of the two variables representing scale. As noted earlier, the inclusion of both terms –for both number of partners and budget; in total four terms- inevitably creates problems of collinearity. It follows that if we do not find significant effects of scale (represented by e.g. the number of partners) on, say, knowledge outputs (see Tables Table 11 and Table 12), this may result from severe collinearity between log (# of partners) and log (# of partners) squared. We experiment with the following alternative specifications of the linear and quadratic terms in the equations:

- log (# of partners) + log (# of partners) squared + log (budget) (i.e. 'budget linear')
- log (# of partners) + log (budget) + log (budget) squared (i.e. 'partners linear')
- log (# of partners) + log (# of partners) squared (i.e. 'partners only')
- log (budget) + log (budget) squared (i.e. 'budget only')

We wish to see whether these different, alternative specifications yield different results in comparison to our 'basic specification' – i.e. log (# of partners) + log (# of partners) squared + log (budget) + log (budget) squared. The results of these analyses in the full sample are detailed in Annex 4-2 and are summarised below.

Table 13 shows clearly that whatever specification of the functional form of scale we use, yields the same results regarding the significance or not of the curvilinear effect. Hence, we can be confident that, in this respect, the findings presented in Table 11 are robust.

Table 13: Summary of results with different specifications of linear and quadratic terms for scale (full sample)

		Goal Achievement	Knowledge Outputs	Technology outputs	Network outputs	Research impacts
Basic specification	Partners (linear + quadratic)	Ns	ns	ns	Inv U	ns
	Budget (linear + quadratic)	U	ns	ns	ns	ns
'Budget linear'	Partners (linear + quadratic)	Ns	ns	ns	Inv U	ns
	Budget (linear)	Ns	ns	+	ns	ns
'Partners linear'	Partners (linear)	Ns	+	ns	+	ns
	Budget (linear + quadratic)	U	ns	ns	ns	ns

'Partners only'	Partners (linear + quadratic)	Ns	ns	ns	Inv U	ns
	---	n/a	n/a	n/a	n/a	n/a
'Budget only'	Budget (linear + quadratic)	U	ns	ns	ns	ns
	---	n/a	n/a	n/a	n/a	n/a

Next we examine whether our treatment of the dependent variables in the full sample (i.e. goal achievement, knowledge outputs, technological outputs, network outputs, and research capacity impacts) as quasi-linear affects in any way the results obtained. An obvious alternative is to transform them into ordinal variables, since the original items from which they have been constructed are also measured with ordinal (Likert-type) scales. We have therefore fitted in the full sample the models in Table 11, but this time employing ordinal regression. The results (see Annex 4-3 for details) show a qualitatively similar picture. More specifically, as in Table 11, we find significant inverse U-shaped effects of the number of partners on network outputs. In contrast, we find no significant effect of budget on any of the five dependent variables (in Table 11 we found a significant U-shaped effect of budget on goal achievement). Taken overall, the results from ordinal and simple regression in the full sample seem to converge towards a basic conclusion: scale, as reflected in the number of partners in the consortium, has an inverse U-shaped effect on at least one of the performance dimensions examined (i.e. networking).

As an additional robustness check, we performed a seemingly unrelated regression (SURE) on all five dependent variables simultaneously. Recall that the results reported in Table 11 refer to each of the dependent variables separately. However, these performance dimensions are not independent of one another; they are just different facets of the same underlying variable (i.e. project performance). The results, which are detailed in Annex 4-4, clearly confirm the findings in our basic specification. As in Table 11, we find significant inverse U-shaped effects on networking outputs from log partners, and a significant U-shaped relation of log budget to goal achievement.

One obvious limitation in the specification of models reported thus far is the absence of any variable representing the composition (or heterogeneity) of the consortium. As noted earlier, this is basically due to the very large number of missing values on relevant variables, which were solicited from project coordinators. One possible proxy is the diversity among partners in the consortium in terms of R&D expenditures (or in terms of resource endowments). We explored whether the inclusion of, say, diversity in R&D expenditures, would change the results obtained. Note that R&D expenditures is measured only for firms, so we fitted the same models as before in the firm sub-sample, but this time with the addition of diversity in R&D expenditures. Unfortunately, however, the number of usable observations, after the inclusion of diversity, was even lower than the comparable numbers before the inclusion (i.e. the numbers ranged between 63 and 75). We found no significant effects of diversity of the consortium on any performance dimension, but even if we had found any, the results obtained could not be trusted. (Particularly with respect to the logistic regression on goods/services innovation, the model did not even converge).

Another issue examined during these additional analyses was whether an alternative operationalisation of scale would provide useful results. More specifically, we constructed an alternative measure of scale, defined as the average budget per partner. It is worth noting that even though this measure looks appealing at first sight, it rests on the (rather strong) assumption that the distribution of budget among partners is homogenous (at least in broad terms). However, conventional wisdom suggests the opposite. Moreover, as noted earlier, we have found evidence that scale as consortium size and scale as budget often work on opposing directions when influencing the same performance dimension. At any rate, we substituted the linear and quadratic terms of number of partners and budget with log (budget per partner) and log (budget per partner) squared, and fitted the same models as in Table 11. We found a significant U-shaped effect to goal achievement, echoing the effect of log budget on achievement (see Annex 4-5).

A final extension that seems appropriate in our context is to examine the effects of scale on the number of patents granted to project participants within a five-year time window after the completion of the project. A special consideration here is to address the problem of attribution. Put simply, this means that we need to be able to distinguish between those patents that can be attributed (even indirectly) to participating in the particular project and those patents that have nothing to do with the project. The details of retrieving information on patents granted to project participants (see Section 3.6 above) should make it clear that the only way we could approach the problem of attribution when constructing the variable was to search for patents in the same technology class as that of the project. But this is clearly an imperfect solution to the problem. The only available alternative is to statistically control for patents that have been granted before (and during) project implementation. In this way, any effect of scale we might observe on the number of patents can be viewed as the net effect over and above of that which can be attributed to the firm's prior patenting activity. We have therefore included one additional independent variable (i.e. total prior) that captures the total number of patents granted to the partner in a five-year window prior to the project's stating date plus the patents granted during the period of project implementation.

It should be stressed from the outset that the empirical distribution of number of patents is highly problematic. More than 95% of the available observations is 0 counts (mean = 3.63; standard deviation = 97.10). There are also 12 cases with very high counts of patents, which we eliminated from analyses as outliers. (The models would not converge in the firm sub-sample, presumably because of the small sample size and the ill-conditioned distribution of the dependent variable).

We have fitted Poisson and negative binomial regression models[16] on the full sample and the 'collaborative research' sub-sample. Notice that because the variance of number of patents overwhelmingly exceeds its mean, the 'correct' model for these data is the negative binomial. Because number of patents was collected for the same length of time window for all ROs and firms in the sample, we did not specify an offset. Including the quadratic terms of number of partners and budget resulted in model misspecification; hence we specified only the linear terms. Finally, as with all analyses thus far, we requested Huber/White sandwich estimators of standard errors to control for non-independence of multiple observations per project. Annex 4-6 details the results obtained with the negative binomial models in the full sample and 'collaborative research' sub-sample.

Apart from an obvious strong positive effect of prior patents, we also find that number of partners has a positive (linear) effect on the number of patents granted after project completion in the full sample. Budget has negative but insignificant effects in both samples. We would not consider these results conclusive, however. As already noted, the data available on the number of patents are ill conditioned (too many zeros), which may have an adverse effect on the predictive validity of the estimated models.

Taken overall, our additional analyses provide reasonable confidence that the results obtained in the full sample are quite robust. The results are less clear when we calibrate the models in different sub-samples, but they generally provide (partial) support to the hypothesis that scale affects (at least some dimensions of) performance in a curvilinear manner.

The following table summarises the results obtained from Step 1 in terms of the optimal project scale, which can be a maximum size – if the relation is inverse U-shaped, or can be the minimum size – if the relation is found to be U-shaped. The table organises the results according to (from left to right): (a) scale variable (i.e. number of partners or budget), (b) the estimated optimal size, (c) whether it is maximum or minimum size, (d) the type of the significant relation found (i.e. inverse U-shaped or U-shaped), (e) the performance dimension for which the scale effect was found to be significant, and finally (f) the (sub)sample in which the result was obtained.

[16] We have also tried the zero-inflated and 'hurdle' models on our data, but they would not converge.

Table 14: Summary of Step 1 results with regards to optimal scale

Scale Variable	Optimal Scale	Max/Min	Type of Relation	Performance Dimension	(sub)Sample
partner	15	Max	inv U	Goal achievement	Collaborative
budget	729,416	Min	U	Goal achievement	Full
budget	568,070	Min	U	Goal achievement	Collaborative
budget	34,523,225	Max	inv U	Knowledge outputs	Collaborative
partner	28	Max	inv U	Network outputs	Full
partner	40	Max	inv U	Network outputs	Collaborative
partner	22	Max	inv U	Network outputs	FP 5
partner	9	Max	inv U	Technology outputs	FP 5
partner	26	Min	U	Technology outputs	FP 6
budget	6,582,993	Max	inv U	Technology outputs	Collaborative
budget	3,704,282	Max	inv U	Technology outputs	FP 6

As noted earlier, success as measured by goal achievement requires a budget above the minimum size indicated in the table above. At the same time, however, the consortium size should not exceed 15 partners (at least for projects falling in the 'collaborative research' sub-sample). Knowledge outputs, in contrast, require projects with a high budget. Beyond the estimated budget 'threshold', however, knowledge outputs begin to diminish. Similarly, network outputs require projects with a large number of partners (which varies according to the sample). With regard to technology outputs, the table above shows a striking difference between FP5 and FP6 projects: whereas in the former case the optimal maximum number of partners is nine, in the latter case (i.e. FP6) the minimum number of partners should be 26. In contrast, there is no such inconsistency with respect to budget: the last two rows in the table show that there is an optimal maximum for project success in terms of technological outputs.

4.2.3.3 Step 2: Unconditional mediational effects

We now turn our attention to examining the causal mechanisms that underpin the effects of scale on performance. Whereas in Step 1 we sought to establish that scale does in fact affect performance, we are now interested in investigating more deeply how these effects materialise. As noted earlier, the key argument to be tested here is that the effects of scale are 'transmitted' through a set of intervening variables (i.e. complementarity of resources, AC, 'unclear objectives', and 'difficulties in coordination').

Methodologically, this means that we test whether the total indirect effects of scale on performance through the above mentioned mediators (Σaj*bj) and/or specific indirect effects (i.e. through one of the mediators) are statistically significant, controlling for all independent variables. As already described above, we employ the 'indirect' macro in SPSS, with 1,000 bootstrap replications, specifying a rather liberal confidence interval (CI) of 90%. As with Step 1, we run the analyses separately for each performance dimension. The results obtained for the full sample are presented in Table 15 (we only present the results that are significant at a=10% or lower).

Table 15 shows that we obtain significant unconditional ('simple') indirect effects for only a few performance dimensions (i.e. goal achievement, knowledge, technology, network outputs for number of partners, and goal achievement for budget). Specifically, for log (number of partners), we find that scale exerts a significant 'specific'[17] indirect effect on goal achievement by influencing positively 'unclear objectives' (i.e. 'a' path), which in turn affects negatively goal achievement (i.e. 'b' path). The product of the two (a*b) is negative, is estimated as -0.0522 and is significant at a=10% since the 90% CI does not include 0 (CI: -0.1104…-0.0181).

Perhaps more important, we find that log (number of partners) has significant negative total indirect effects, that is, effects through all four of the mediators, on goal achievement, knowledge, technology, and network outputs. This represents Σaj*bj, the sum of all indirect effects of scale transmitted through all mediators to affect each of the above performance dimensions.

What do these findings tells us? With respect to goal achievement, the results indicate that as number of partners becomes larger this intensifies ambiguities in objectives among partners in the consortium, and because the latter (obviously) has a negative effect on goal achievement, the indirect effect is (again obviously) negative. In connection to knowledge, technology, and networking outputs, we find that as the number of partners becomes larger this affects all mediator variables and the resulting total indirect effect is significant and negative! In other words, the combined indirect effects through all mediators affect negatively knowledge, technology, and network outputs. This finding of significant total indirect effects, even though it holds for only three of the performance dimensions, provides some support to the hypothesis that scale (in this case, consortium size) influences performance indirectly through intervening variables.

Turning to budget as measure of scale, the results show only one significant effect: as log (budget) gets larger, learning among partners (i.e. AC) becomes more effective (the 'a' path is positive albeit marginally significant: p=0.0833), and since learning has a strong

[17] The term 'specific' is used to denote an indirect effect involving scale and a certain mediator variable – in this case, 'unclear objectives'. It is to be distinguished from 'total indirect effects', which denote the overall effect of scale on performance through all the mediators; it is the quantity Σai*bi.

positive effect on goal achievement ($p<0.001$), the indirect effect is positive and significant. Hence the unconditional indirect effect of budget on achievement is positive, and involves learning as the mediator.

We fitted the same models in the 'collaborative research' sub-sample to see whether we obtain similar results. As shown in

Table 16, we find significant indirect effects only for number of partners. More specifically, the table shows significant and negative total indirect effects of number of partners on goal achievement, network outputs, and research impacts. Hence, we have evidence that as consortium size increases this has an overall negative indirect effect on several performance dimensions.

We also find some of the 'specific' indirect effects to be negative and significant. Specifically, scale affects positively (i.e. intensifies) difficulties in coordination, and this has a negative indirect effect on goal achievement and on network outputs. A striking result obtained in this sub-sample, is that as scale (number of partners) increases, this has a negative effect on the complementarity of resources, and hence a negative indirect effect on network outputs and research impacts. This finding is contrary to our hypothesis that as scale increases this will have positive effects on the complementarity of resources devoted to the project. In addition, even though complementarity has positive effects on network outputs and research impacts (i.e. the 'b' paths are positive, as expected), the 'a' paths are negative and hence the significant negative indirect effects.

We have also run the same analyses in the firm sub-sample, and the only significant finding involves the positive effect of number of partners on research impacts through unclear objectives. Specifically, we find that increasing consortium size increases ambiguity in objectives, and (surprisingly) that these ambiguities have a positive influence on research impacts. This may mean that larger consortia permit partners to pursue own (and not necessarily common) objectives, which has a positive effect on their ability to derive (own) research benefits out of the project.

Taken overall, the results obtained in Step 2 provide some support to the hypothesis of unconditional indirect effects of scale through the mediators on project performance. Even though the results in the three samples are not identical, they nevertheless provide the impression of basically negative indirect effects of scale (mainly in terms of consortium size) on at least some dimensions of project performance. The exception here is the positive indirect effect in the firm sub-sample. Overall the evidence is not overwhelming, however, and this raises the question whether scale affects the mediators (and through them, performance) conditionally based on some third variable; this leads us to Step 3.

Table 15: Unconditional mediational effects of scale on project performance (full sample)

Through Mediator…	Dependent	Indirect Effect (90% CI)	Total Indirect Effect (through all mediators) (90% CI)	A path (p-value)	B path (p-value)
		Scale as: log (number of partners)			
Unclear Objectives	Goal Achievement	-0.0522 (-0.1104…-0.0181)	**-0.0857** (-0.1424…-0.0223)	+ 0.0008	- 0.0067
	Knowledge Outputs[a]		**-0.0481** (-0.1079…-0.0004)		
	Technology Outputs[a]		**-0.0325** (-0.0726…-0.0008)		
	Network Outputs[a]		**-0.0516** (-0.1066…-0.0084)		
		Scale as: log (budget)			
AC	Goal Achievement	0.0089 (0.0009…0.0199)	0.0124 (-0.0036…0.0286)	+ 0.0864	+ 0.0004

[a] Only total indirect effects are significant.

Table 16: Unconditional mediational effects of scale on project performance (Collaborative research sub-sample)

Through Mediator …	Dependent	Indirect Effect (90% CI)	Total Indirect Effect (through all mediators) (90% CI)	A path (p-value)	B path (p-value)
		Scale as: log (number of partners)			
Difficulties in Coordination	Goal Achievement	-0.0531 (-0.1038...-0.0176)	**-0.0828** (-0.1429...-0.0225)	+ 0.0011	- 0.0037
Complementarity	Network Outputs	-0.0168 (-0.0476…-0.0004)	**-0.0573** (-0.1151…-0.0121)	- 0.1368	+ 0.0128
Difficulties in Coordination	Network Outputs	-0.0333 (-0.0857...-0.0017)	**-0.0573** (-0.1151...-0.0121)	+ 0.0038	- 0.0715
Complementarity	Research Impacts	-0.0240 (-0.0654…-0.0020)	**-0.0478** (-0.1151…-0.0016)	- 0.0691	+ 0.0129

4.2.3.4 Step 3: Moderated mediation analyses

Recall that in our conceptual framework we hypothesise that certain factors may condition the effect of scale on the mediator variables. For example, we hypothesise that as the size of the consortium increases, the positive effect on the complementarity of resources will be higher (i.e. more positive) when the consortium is composed of partners willing to commit significant resources to the project. In contrast to Step 2, here we conceptualise the 'a' paths from scale to the mediators to be 'conditional', that is, to interact with some third variable. Following this line of reasoning, in Step 3 we examine whether the total conditional (interactive) indirect effects from scale to performance through the mediators are significant. Put differently, we examine whether the interaction between scale and some other variable, by being mediated through an 'intervening' variable, has a significant effect on performance (see

Figure 22: Moderated Mediation).

As in Step 2 we employ the same macro, using the same specifications. We run a separate analysis for each performance dimension, and each time the 'a' path is the interaction of scale with one of the following moderating factors:

- resources committed to the project (i.e. senior staff),
- project management (i.e. communication and coordination),
- characteristics of the project (i.e. vertical scope, 'new area' project, cost, scientific risk, commercial risk, complexity, duration and distance from core vis-à-vis an 'average' project),
- innovation-related resources (i.e. R&D expenditures and resource endowments). Note that these variables are measured only in the firms sub-sample.

The results for the full sample are presented in Table 17, for log (number of partners), and in Table 18 for log (budget). Both tables show a number of significant conditional indirect effects. Generally, we find that a much larger number of performance dimensions are influenced by the interaction of scale with a moderating variable, an effect transmitted indirectly through one (or more) of the hypothesised mediators.

A significant conditional indirect effect can, in general, be interpreted as follows: for each additional unit increase in the scale of a project, in high levels of the moderator variable, there is a significant positive (negative) effect on performance, transmitted though one or more mediator variables. It is important to note that we are testing a large number of potential effects, i.e. the interaction of scale (for number of partners and project budget) with many potential moderators, and we are testing each conditional effect separately (also separately for each performance dimension). Because of the large number of tests, our analysis is prone to obtain some significant effects purely by chance. Hence, the findings shown below should be considered with care.

Returning to the results, in Table 17 we find that with respect to goal achievement:

- Increasing scale (i.e. each additional partner) in projects with high vertical scope leads to more difficulties in coordination; the latter has a negative effect on goal achievement, and hence the conditional indirect effect is negative. Notice here that the 'a' path is not significant (p=0.17), but the product a*b is negative and significant (-.0097) because of the strongly negative 'b' path. The key finding, therefore, is that high vertical scope combined with a large number of partners contributes to difficulties in coordinating the project, and hence to lower goal achievement!
- Increasing scale in projects that are perceived as high cost relative to an 'average' project lowers the effectiveness of learning among partners, and increases difficulties in coordination, and thus lowers goal achievement.
- Similarly, increasing scale in projects that are perceived to be of high commercial risk increases difficulties in coordination and lowers the effectiveness of learning among partners, and thus decreases goal achievement.

With respect to knowledge outputs, we find that:

- Increasing scale (i.e. each additional partner) in projects that are perceived as high cost relative to an 'average' project, lowers the complementarity of resources among partners and lowers the effectiveness of learning among partners, and thus lowers the amount of knowledge outputs.
- Increasing scale in projects of high commercial risk lowers the degree of complementarity of resources and thus reduces knowledge outputs. The exact opposite effect materialises in project of high complexity: in those cases, increasing scale increases complementarity and thus increases knowledge outputs.

With respect to technological outputs, we find that:

- Each additional partner in projects that are perceived as high cost relative to an 'average' project lowers learning and increases 'unclear objectives' and thus lowers technology outputs.
- Similarly, increasing scale in projects perceived to be of high commercial risk has a negative effect on technology outputs (by lowering learning).

With respect to network outputs:

- Each additional partner in projects that are perceived to be distant relative to the partner's core technological area lowers complementarity and thus decreases network outputs.

With respect to research capacity impacts we find a large number of significant indirect effects, most of which turn out to be negative:

- Each additional partner in projects that are perceived as high cost relative to an 'average' project, lowers complementarity of resources and AC, and thus decreases research impacts.

- Similarly, each additional partner in projects that are perceived to be of high commercial risk lowers complementarity of resources and AC, and thus decreases research impacts.
- Increasing scale in projects that are distant from the 'core' again lowers complementarity of resources and AC, and thus decreases research impacts.
- In contrast, increasing scale in projects of high complexity increases complementarity and through that increases research impacts

Turning to Table 18 which presents significant findings with respect to scale as budget, we find that for goal achievement:

- Each additional euro budget in projects of high vertical scope lowers learning, and also increases difficulties in coordination, and thus has a negative effect on achievement.
- Each additional euro budget in projects that are perceived as of high commercial risk, or are considered to be distant relative to the partner's core technological area, lowers learning, and thus decreases goal achievement.
- Similarly, each additional euro budget in projects that are considered to be of high cost, increases difficulties in coordination, resulting in lower goal achievement.

With respect to knowledge outputs, we find that:

- Each additional euro budget in projects that are perceived as of high commercial risk, increases unclear objectives and hence lowers knowledge outputs.
- Similarly, increasing budget in projects distant to the core results in less (not more) learning and thus to lower knowledge outputs.

With respect to technological outputs, we find that:

- Each additional euro budget in projects that are perceived to be distant relative to the partner's core technological area lowers learning and thus lowers technology outputs.

With respect to network outputs, we find that:

- Each additional euro budget in projects of high commercial risk decreases learning and thus lowers network outputs.
- Each additional euro budget in projects distant relative to the partner's core technological area, decreases learning and thus decreases network outputs.

Finally, with respect to research capacity impacts:

- Increasing budget in projects that are considered to be 'high cost', or of high commercial risk projects, or in projects distant from the core, lowers learning and thus reduces research impacts.

Beyond these 'specific' conditional indirect effects, we also find significant total indirect effects, which as noted above, represent the combined impact (Σa_i*b_i) of scale (interacted with a moderator) on a performance dimension through all (not just one of) the intervening mediators. (These significant total effects are highlighted in bold font in Table 17 and Table 18).

As it turns out, it is possible, as shown in Table 17 and Table 18, that none of the 'specific' indirect effects are found to be significant, yet nevertheless the total combined indirect effect to be, in fact, significant. There are two instances where we find a significant total indirect effect without at the same time finding a significant 'specific' indirect effect. Both of these concern log budget. First, the interaction of log budget with high cost projects results in negative total indirect effects on knowledge outputs. Essentially this means that increasing budget in projects that are already considered to be of high cost relative to some 'average' projects has detrimental effects on knowledge, and these effects are brought about by all intervening variables. The second concerns the interaction of budget with commercial risk: increasing budget in such projects has again detrimental effects on technology outputs.

The vast majority of the total indirect effects reported in Table 17 and Table 18 are indeed significant. This provides further support to the moderated mediation hypothesis, i.e. that the conditional indirect effects of scale, transmitted through all of the mediators, on the performance dimensions are significant. In addition, and consistent with the 'specific' conditional indirect effects described above, almost all of these total indirect effects are negative, indicating that the (conditional) effect of scale on performance is negative. In other words, increasing scale, as it interacts with the hypothesised moderator variables, decreases project performance.

What is the general picture emerging out of this long list of results? One useful way to answer this question is by looking at the 'a' and 'b' paths in Table 17 and Table 18.

Beginning with the 'b' paths, we see that, without exception, the signs of the effects of the mediators on the performance dimensions are in the correct direction. That is, complementarity of resources and AC always affect performance positively, whereas 'unclear objectives' and 'difficulties in coordination' affect performance negatively. This result is important in that it provides support to one key argument in our conceptual framework, which states that the mediating variables affect differently project performance. Hence we could categorise the mediators as falling into the 'positive group', which comprises complementarity of resources and AC, and into the 'negative group' which comprises the two dimensions of transaction costs.

Another related finding is that the mediators do not appear equally important as 'members' of the 'b' paths that constitute the causal mechanisms by which scale affects performance. In Table 17 (log number of partners) complementarity appears eight times, AC seven times, 'unclear objectives' one time, and 'difficulties in coordination' three times. In Table 18 (log budget) the respective numbers are: 0, 10, 1 and 2. It appears, therefore, that the 'positive' group of mediators are affected by the conditional effect of scale much more than the 'negative' group. Put differently, complementarity of resources and learning are more critical as mechanisms transmitting the effects of scale on performance than transaction costs (i.e. 'unclear objectives' and 'difficulties in coordination').

What is striking is that the conditional effect of scale on the 'positive' group is most of the times negative. We see that by turning our attention to the 'a' paths. In Table 17, we find that the conditional effects of log (number of partners) on either complementarity or AC are at all times negative, with two exceptions, both involving complementarity of resources: the interaction of scale with project complexity has a positive effect on complementarity, that is, it makes the (perceived) complementarity among partners to be stronger, which in turn affects positively knowledge outputs and research impacts. In all other instances, the conditional effect of scale on complementarity or AC is negative, a result indicating that scale does not promote complementarity of resources or learning among partners; in contrast, according to our results, it makes complementarity and learning more difficult to achieve. To corroborate this negative (conditional) effect of scale, we also find that whenever it affects transaction costs, it does so as to make them higher!

The results in Table 18 tell a similar story: the conditional effect of log budget on AC is always negative! And at the same time, whenever increasing budget has an effect on transaction costs, these are positive, thus making transaction costs higher. In general, therefore, the conditional effects of scale on (a) the 'negative group' always operates in the direction of increasing (i.e. magnifying) their negative effects, whereas (b) on the 'positive group' almost always works in the direction of reducing its positive effects on performance.

Returning to the effects of consortium size, it is important to note that of the twenty significant conditional 'specific' indirect effects identified in Table 17, all but two are negative. It therefore appears that increasing the number of partners, conditional on some third moderator variable, turns out to be negative! The two exceptions, as described above, are when increasing scale 'combines' with complex projects, which result in better complementarity of resources, which in turn affects positively knowledge outputs and research impacts. We obtain the exact same picture in Table 18 when looking at the results concerning log budget. All thirteen significant 'specific' indirect effects of increasing budget, conditionally based on some third moderator variable, are (again) negative. Taken overall, increasing scale, in terms of both increasing the size of the consortium and budget, has a negative effect on performance.

In interpreting these findings, however, it is important to remember that increasing scale does not operate 'alone' in influencing performance negatively; it is the conditional effect of scale on performance that is negative. The results in Table 17 and Table 18 indicate that these conditional effects arise from the interaction of scale with the characteristics of the project itself. Project management does not appear to play any significant role, nor does the resources committed to the project.

Are these results robust when we fit the same models in the different sub-samples? Annexes 3.8 and 3.9 present the results for the 'collaborative research' and firm sub-samples, respectively. Beginning with the 'collaborative research' sub-sample, we obtain the same overall picture. The 'b' paths are consistently in the correct direction, the 'a' paths work in the direction of 'worsening' the negative effects of the 'negative group' of mediators, and 'decreasing' the positive effects of the 'positive group'. For both operationalisations of scale, all but three of the 'specific' indirect effects are negative. (The three exceptions, as in the full sample, involve the interaction of log (number of partners) with project complexity, which promotes the complementarity of resources among partners to produce more knowledge and network outputs and to increase research impacts. Another interesting result in this sub-sample is that increasing budget in project with large vertical scope reduces learning, and this has a negative effect on goal achievement. Furthermore, increasing budget in projects with high vertical scope, results into less effective learning and into more difficulties in coordination, which in turn affect negatively goal achievement.

Hence, consistent with our results in the full sample, the results here suggest that the conditional effects of scale on performance are (generally) negative.

The overall picture is different, however, when we look at the results obtained in the firm-sub-sample. The most notable difference here is that we find a relatively large number of significant positive 'specific' (and total) indirect effects. More specifically, we find that increasing the number of partners in projects distant to the core reduces unclear objectives and difficulties in coordination, thus producing more commercialisation impacts[18], more research impacts and higher goal achievement. In contrast, increasing the size of the consortium in projects where partners commit more senior staff in the project results into reduced learning, and hence lower goal achievement. Thus it appears that the higher the number of senior staff in a large consortium results into less (not more) learning! Apart from this rather surprising result, increasing budget in the firm sub-sample appears to produce even more positive results: in fact, all indirect effects found to be significant are positive. For example, increasing budget combined with effective communication and coordination results into reducing unclear objectives with a consequent positive effect on commercialisation impacts. More generally, the conditional effects of increasing budget in this sub-sample result in reducing the ambiguity of objectives with positive effects on commercial impacts. Moreover, increasing budget in projects where partners have a history of spending much on innovation is associated with lower difficulties in coordination and thus with higher goal achievement.

Taken overall, the results from all three steps of analyses indicate that increasing scale generally degrades project performance (with the notable exception of firms which seem to benefit from increasing scale, particularly in terms of budget, with a positive

[18] Except from commercialisation impacts, two more performance dimensions were tested in this sub-sample, namely goods/services innovation and process innovation. Presumably because these two performance dimensions were measured with binary variables, the mediational models on them as dependent variables did not converge.

effect mainly on commercial impacts). Step 1 showed a curvilinear effect on some performance dimensions. Recall, however, that in the firm sub-sample, analyses produced very little evidence of significant scale effects on performance. In addition, whereas Step 2 provided some indication of unconditional negative indirect effects of scale, Step 3 gave considerable evidence that, with the exception of the firm sub-sample, the conditional effects of scale are mostly negative.

It should be stressed however, that the 'exception' is important; private enterprises are key beneficiaries of the Framework Programmes, since they are expected to translate research results into concrete innovation outputs. It is perhaps not surprising that our results indicate firms in the sample obtain higher performance, mainly in terms of commercial impacts, in projects with large budget. While it is perhaps not too difficult to obtain 'intermediate' project results, such as network outputs or research impacts, ultimate results such as commercial impacts, may require large budgets.

Hence, even though our results from Steps 1, 2 and 3 do not provide a clear-cut, unequivocal picture as to the net effect of scale on collaborative R&D performance, it would seem reasonable to argue that, if anything, scale does affect performance in complex ways. Its effects are transmitted through critical intervening variables, such as the complementarity of resources, learning and transaction costs. When the net effect is negative (which is most of the time), it is because increasing scale lowers the positive effect of resources and learning, and magnifies the negative effect of transaction costs. Conversely, when it is positive, it is because it strengthens the positive effect of resources and learning, and diminishes the negative effect of transaction costs. Finally, we have also shown that these negative (or in certain cases positive) effects materialise conditionally based on other factors, which basically relate to the characteristics of the project itself.

Table 17: Conditional mediational effects of log (number of partners) on project performance (full sample)

Interaction Effect With…	Through Mediator…	Dependent	Indirect Effect (90% CI)	Total Indirect Effect (through all mediators) (90% CI)	A path (p-value)	B path (p-value)
Vertical Scope	Difficulties in Coordination	Goal Achievement	-0.0097 (-0.0290…-0.0003)	-0.0213 (-0.0548…0.0066)	+ 0.1679	- 0.0041
Cost vis-à-vis average	AC	Goal Achievement	-0.0221 (-0.0429…-0.0060)	**-0.0446** (-0.0765…-0.0174)	- 0.0211	+ 0.000
Cost vis-à-vis average	Difficulties in Coordination	Goal Achievement	-0.0141 (-0.0300…-0.0024)	**-0.0446** (-0.0765…-0.0174)	+ 0.0463	- 0.0043
Commercial Risk	AC	Goal Achievement	-0.0165 (-0.0421…-0.0063)	**-0.0348** (-0.0681…-0.0114)	- 0.0294	+ 0.000
Commercial Risk	Difficulties in Coordination	Goal Achievement	-0.0108 (-0.0284…-0.0013)	**-0.0348** (-0.0681…-0.0114)	+ 0.0692	- 0.0045
Cost vis-à-vis average	Complementarity	Knowledge Outputs	-0.0102 (-0.0359…-0.0007)	**-0.0376** (-0.0705…-0.0106)	- 0.0924	+ 0.0554
Cost vis-à-vis average	AC	Knowledge Outputs	-0.0131 (-0.0408…-0.0006)	**-0.0376** (-0.0705…-0.0106)	- 0.0113	+ 0.1680
Commercial Risk	Complementarity	Knowledge Outputs	-0.0090 (-0.0290…-0.0001)	**-0.0251** (-0.0585…-0.0057)	- 0.0816	+ 0.0537
Complexity	Complementarity	Knowledge Outputs	0.0112 (0.0005…0.0371)	0.0156 (-0.0140…0.0496)	+ 0.1034	+ 0.0531

Interaction Effect With…	Through Mediator…	Dependent	Indirect Effect (90% CI)	Total Indirect Effect (through all mediators) (90% CI)	A path (p-value)	B path (p-value)
Distance from Core	Complementarity	Network Outputs	-0.0120 (-0.0286…-0.0014)	-0.0173 (-0.0412…0.0057)	- 0.1180	+ 0.0001
Cost vis-à-vis average	Complementarity	Research Impacts	-0.0155 (-0.0392…-0.0020)	**-0.0376** (-0.0713…-0.0103)	- 0.0680	+ 0.0018
Cost vis-à-vis average	AC	Research Impacts	-0.0170 (-0.0419…-0.0023)	**-0.0376** (-0.0713…-0.0103)	- 0.0095	+ 0.0407
Commercial Risk	Complementarity	Research Impacts	-0.0129 (-0.0312…-0.0019)	**-0.0291** (-0.0590…-0.0072)	- 0.0774	+ 0.0013
Commercial Risk	Absorptive Capacity	Research Impacts	-0.0120 (-0.0383…-0.0028)	**-0.0291** (-0.0590…-0.0072)	- 0.0305	+ 0.0288
Complexity	Complementarity	Research Impacts	o.o166 (0.0017…0.0408)	0.0128 (-0.0195…0.0460)	+ 0.1074	+ 0.0008
Distance from Core	Complementarity	Research Impacts	-0.0125 (-0.0340…-0.0017)	**-0.0204** (-0.0484…-0.0003)	- 0.1010	+ 0.0015
Distance from Core	AC	Research Impacts	-0.0084 (-0.0297…-0.0003)	**-0.0204** (-0.0484…-0.0003)	- 0.1452	+ 0.0332
Cost vis-à-vis average	AC	Technology Outputs	-0.0103 (-0.0297…-0.0008)	**-0.0228** (-0.0430…-0.0050)	- 0.0129	+ 0.1016
Cost vis-à-vis average	Unclear Objectives	Technology Outputs	-0.0108 (-0.0273…-0.0003)	**-0.0228** (-0.0430…-0.0050)	+ 0.0064	- 0.1270

Interaction Effect With…	Through Mediator…	Dependent	Indirect Effect (90% CI)	Total Indirect Effect (through all mediators) (90% CI)	A path (p-value)	B path (p-value)
Commercial Risk	AC	Technology Outputs	-0.0075 (-0.0247…-0.0005)	**-0.0152** (-0.0329…-0.0032)	- 0.0261	+ 0.0947

Table 18: Conditional mediational effects of log (budget) on project performance (full sample) [a] Only total indirect effects are significant

Interaction Effect With…	Through Mediator…	Dependent	Indirect Effect (90% CI)	Total Indirect Effect (through all mediators) (90% CI)	A path (p-value)	B path (p-value)
Vertical Scope	AC	Goal Achievement	-0.0057 (-0.0136…-0.0002)	**-0.0143** (-0.0272…-0.0032)	- 0.1369	+ 0.0000
Vertical Scope	Difficulties in Coordination	Goal Achievement	-0.0063 (-0.0145…-0.0018)	**-0.0143** (-0.0272…-0.0032)	+ 0.0258	- 0.0043
Cost vis-à-vis average	Difficulties in Coordination	Goal Achievement	-0.0035 (-0.0096...-0.0005)	**-0.0092** (-0.0199…-0.0003)	+ 0.1157	- 0.0052
Commercial Risk	AC	Goal Achievement	-0.0054 (-0.0144…-0.0008)	**-0.0116** (-0.0263…-0.0014)	- 0.0950	+ 0.0000
Distance from Core	AC	Goal Achievement	-0.0065 (-0.0149…-0.0009)	**-0.0122** (-0.0242…-0.0010)	- 0.0901	+ 0.0000
Cost vis-à-vis average[a]		Knowledge Outputs		**-0.0074** (-0.0183...-0.0002)		
Commercial Risk	Unclear Objectives	Knowledge Outputs	-0.0045 (-0.0153...-0.0001)	-0.0085 (-0.0214...0.0002)	+ 0.0373	- 0.1282
Distance from Core	AC	Knowledge Outputs	-0.0046 (-0.0170...-0.0001)	**-0.0113** (-0.0276...-0.0031)	- 0.0134	+ 0.1713

Commercial Risk	AC	Network Outputs	-0.0030 (-0.0109...-0.0001)	-0.0077 (-0.0173...0.0009)	- 0.1245	+ 0.0229
Distance from Core	AC	Network Outputs	-0.0050 (-0.0135...0.0011)	**-0.0107** (-0.0221...-0.0028)	- 0.0229	+ 0.0211
Cost vis-à-vis average	AC	Research Impacts	-0.0032 (-0.0110...-0.0001)	-0.0061 (-0.0156...0.0019)	- 0.1453	+ 0.0260
Commercial Risk	AC	Research Impacts	-0.0044 (-0.0129...-0.0002)	-0.0077 (-0.0195...0.0022)	- 0.0867	+ 0.0222
Distance from Core	AC	Research Impacts	-0.0066 (-0.0170...-0.0014)	**-0.0124** (-0.0242...-0.0023)	- 0.0130	+ 0.0238
Commercial Risk[a]		Technology Outputs		**-0.0055** (-0.0130...-0.0003)		
Distance from Core	AC	Technology Outputs	-0.0037 (-0.0098…-0.0006)	**-0.0064** (-0.0142…-0.0013)	- 0.0259	+ 0.0809

CHAPTER 5 SUMMARY AND CONCLUSIONS

The objective of this study was to assess empirically whether economies of scale exist at the research project level. The assumption underlying European Union research policy is that such economies exist, hence the emphasis placed on the 'critical mass' of research and development (R&D) projects. More concretely, the research questions to be answered in the context of this project were:

- Are larger research projects more productive in scientific and technological terms than smaller research projects?
- Why is this or is this not the case? What can be explanatory factors? Under what conditions are larger research projects more/less productive than smaller research projects?

There are many factors that must be taken into account in determining the relation between scale and performance. An elaborate conceptual framework in this study, based on an extensive literature review, categorised them as follows:

- First, there are three sets of factors that mediate the relation between project scale and performance: (a) the pool of available resources, (b) the learning process (absorptive capacity), and (c) the transaction costs. That is to say, these factors 'sit between' scale and performance.
- The industry and market environment(s) in which the research project is positioned will affect performance as well. They do so because the industry and market environment(s) determine the technological opportunities, appropriability regimes, and market demand relevant to the respective project.
- Three additional sets of factors moderate the relation between project scale and the pool of resources, learning processes, and transaction costs, bearing additional indirect influence on the relation between scale and performance: (a) partner characteristics (mainly the resources committed to the project), (b) project characteristics (e.g. technical risk, commercial risk), and (c) project management (e.g. communication and coordination).

Of course, 'performance' can be measured in different ways: project performance is a broad and multidimensional concept which, for the purpose of this study, was comprised of eight dimensions:

- Goal achievement – the degree to which the project achieved its scientific, technical and commercial objectives
- Knowledge outputs – publications, doctoral dissertations and so forth
- Technological outputs – tools and techniques, models, simulations, prototypes, etc.
- Network outputs – building relationships with other organisations
- Research capacity impacts – effects on the capacity of the partner to undertake research such as research staff, technological skills, critical mass
- Commercial outputs – increased turnover, profitability, competitiveness
- Product innovation – new or improved products or services
- Process innovation – new or improved production processes

Our analysis sought to capture the effects of project scale on all eight dimensions of performance while controlling for the mediating and moderating sets of variables. It was thus a multi-layered analysis based on extensive statistical and econometric appraisals of a rich set of information covering all the thematic areas and research instruments of the Fifth and Sixth European Framework Programmes (FP5, FP6).

The study team aimed to leverage existing data sets to the extent possible as well as to collect new data as needed to enable the elaborate analysis required by the conceptual model. Ultimately, the utilised data were derived from three sources: (i) the 'InnoImpact' survey (a previous survey the team had carried out to identify the innovation performance of FP projects), (ii) a follow-up survey specifically devised and carried out for this project, and (iii) CORDIS data. The follow-up survey determined the final sample utilised in the study. This sample consisted of responses from 1,172 organisations participating in a total of 676 research projects funded by FP5 and FP6. We received one response per project for 348 projects, two responses for 205 projects, and three or more responses for the remaining 123 projects.

Summary Conclusion

Overall, our analysis cannot support a simple assumption that 'bigger is better' for the performance of collaborative R&D projects in the context of the European Framework Programmes. Some of the basic assumptions on increasing returns to scale to collaborative R&D underlying the change in the general orientation of the FPs towards larger projects are lacking strong empirical foundation and hence should be re-considered.

This aggregate conclusion is predicated on a set of results from the descriptive statistical analysis and the econometric analysis summarised in the remainder of this Section.

Main Results from the Descriptive Statistical Analysis

An extensive descriptive analysis provided the first visual summary of the obtained information and a first insight into the core research question of this study, which was to assess to which extent the size of Framework Programme collaborative R&D projects affect project outcome. Project size was approached on the basis of three measures:

- number of project participants (organisations)
- total budget of the collaborative research project
- average budget each project participant received

The first two measures reflect the absolute project size of a research project while the third measure reflects relative project size.

- The number of partners does not affect significantly three dimensions of project performance: overall goal achievement, knowledge outputs, and technological outputs. On the other hand, larger (but not the largest) projects seem to have significantly higher network output than small and medium size projects, significantly higher research capacity impacts than medium and very large projects, and significantly higher commercial impacts than small projects. No consortium size seems to stand out in terms of product and process innovations. Overall, while the absolute size of research projects in terms of numbers of partners has some effects on project performance, the relation is not linear. It rather varies across different performance dimensions, barring both product and process innovations where the project size makes no statistically important difference. It appears that 'more partners' is not tantamount to 'better performance'. The impression we get is rather that of an inverse U-shaped relation, implying that 'too small' projects as well as 'too large' projects perform less well. This is a confirmation of one of our main hypotheses and constitutes a mayor finding of our study. It reappears throughout the different sub-sequent levels of analysis.
- Turning to average participant funding as a (relative) measure of project size, we get a stronger relation between project size and project performance. In particular, there seems to be a positive correlation between average funding per partner and knowledge output, technological output, and research capacity impacts. Low funding projects with low levels of average funding per participant exhibit significantly lower performance in these indicators than projects in the categories 'high funding' and 'very high funding'. These positive relations predominantly surface in specific instruments, namely STREPS and IPs.
- Descriptive statistics generally do not support the hypothesised positive correlation between research project size (number of partners) and absorptive capacity and resource complementarities. Project size, however, seems to cause increased

transaction costs: small and medium sized projects have clearer objectives and less coordination difficulties than very large projects. An impression of negative mediation effects thus emerges.

All in all, the descriptive analysis points out that there is no absolute advantage of project size, when measured by the number of partners, on performance. When measured by the average funding per partner, (relative) project size is more strongly related to a number of performance dimensions, namely knowledge output, technological output, and research capacity impact. Commercial outputs, however, including product/service and process innovations are unaffected by project size irrespective of its measurement.

On the contrary, larger projects appear to add significantly to transaction costs. But larger collaborative projects in terms of average funding per participant also can attract larger and more sophisticated partners and allow them to undertake projects that are riskier, more complex, and of longer duration compared to what they do individually.

Comparison between the two measures of scale reveals that it is not necessarily the absolute size, but the relative project size which might be responsible for 'critical mass' effects. A possible conclusion for the FPs is to see to it that the number of partners does not dilute the potential scale effects of the amount of funding per partner.

Main Results from the Econometric Analysis

The econometric analysis was run both for the full sample – including all types of project participants – and various 'sub-samples' (including a firm sub-sample). The analysis of the full sample considered only five dimensions of performance, excluding commercial impacts and product/service and process innovations. The analysis of the firm sub-sample considered all eight dimensions of performance.

There were three analytical steps of progressively higher complexity. Step 1 asked directly whether scale affects project performance. Step 2 examined the hypothesis of simple mediational effects: simply put, that the effect of an independent variable (project scale) on the dependent variable (project performance) is transmitted through a third variable (mediator). The mediator variables included resource complementarity, absorptive capacity (learning process), clarity of objectives, and coordination difficulties. Step 3 went further to test whether these indirect effects are not 'simple', that is, whether they are conditionally based on certain variables that moderate (interact with) scale to influence the mediators and, through them, performance. Moderator variables included partner and project characteristics and project management.

Direct Effects

- Turning to the key question, results for the full sample suggest increasing and then decreasing returns to scale for one of the performance dimensions, network outputs. Hence, with respect to network outputs, up to a certain threshold, higher scale (higher number of partners) is associated with increased performance but, beyond that threshold, the returns to scale are diminishing. Consistent with the inverse U-shaped hypothesis, we also obtained similar results for the remaining performance dimensions, but these coefficients are not statistically significant.

The size of the estimated threshold varies considerably across project performance dimensions: just under 30 partners (network outputs), more than 10 (goal achievement), more than 4 (knowledge outputs), 5.5 (technological outputs), and 9.5 (research capacity impacts). These figures represent the 'optimal' size of the consortium for each of these dependent variables, respectively. The estimated optimal size of the consortium is well within the empirical distribution of the number of partners in the sample.

This result is reasonable, in the sense that possibilities for networking increase when the consortium is large, not small. Still, when the consortium becomes too large, these effects begin to diminish. In contrast, the optimal size with regard to the remaining performance dimensions is well below the respective average size that we observe. Even though these coefficients are not statistically significant (and therefore, strictly speaking, are not very trustworthy), it is perhaps worth noting how the optimal size differs among performance dimensions: it is quite small for knowledge and technological outputs and somewhat higher for goal achievement and research impacts – but still well below the average project sizes in our sample.

- When scale is defined in terms of total project budget, in contrast, we find a U-shaped effect with respect to goal achievement. The expected value of goal achievement is estimated at its minimum when the project budget is in the order of >700,000 EUR. Simply put, goal achievement begins to increase when the project budget is higher than this amount. It is interesting to note that the estimated minimum budget is relatively low when compared to the empirical distribution of budgets across projects in our sample. In other words, it appears that the budget does not have to be too high for participants to indicate positive goal achievement. Employing the scale measure of average budget per partner, we find confirmation of a U-shaped relation, which turns out to be significant for goal achievement[19].
- Quite remarkable in our view is also the finding that there is by and large no difference between FP5 and FP6 projects with respect to most of the performance indicators – which again runs counter to the assumption that the larger projects in FP6 would have a positive influence on performance. Among the different instruments of the FPs, it turned out that 'network' projects are more likely than

[19] Note though, that we did not employ this measure in the more elaborate steps of the econometric analysis. There, the assumption of equal distribution of funding among partners would have led to even greater doubts about the robustness of results.

other types of projects to claim results in terms of goal achievement, knowledge outputs, research capacity impacts and – not surprisingly - network outputs.

Indirect (Moderated and Mediated) Effects

- Turning to the causal mechanisms that underpin the effects of scale on performance (Step 2), we obtain the impression of basically negative indirect effects of scale on at least some dimensions of project performance (goal achievement, knowledge outputs, technology outputs, and networks outputs), though the overall evidence we gain from this step of the analysis is not overwhelming.

Hence, in a more elaborate analysis of the causal mechanisms between scale and performance (Step 3), we looked into the question whether scale affects the mediators and through them, performance, conditionally based on some third set of variables.

- In the part of the econometric analysis which looked into the potential channels by which scale might affect performance, we find a number of statistically significant relations, predominantly where scale (via some mediator variable) exercises a negative effect. This finding is very robust as it applies through all the mediator variables, and affects knowledge, technology, and network outputs. Thus we find that with increased size, the coordination costs become higher, the objectives of the project appear less clear to the partners, complementarities of resources and competences are diminished and absorptive capacity is reduced. All of this has a bearing on goal achievement, knowledge, technology and network outputs.

This finding of significant indirect effects, which holds for three of the performance dimensions, provides some support to the hypothesis that scale (in this case, consortium size) influences performance indirectly through intervening variables – and negatively in almost all cases.

- In the part of our econometric analysis which looked into the indirect effects of scale working through 'moderator variables', we found a large number of negative relations between different size and performance variables. Often, increasing the number of partners or the budget results either in increased difficulties in coordination and higher transaction costs. It also lowers the effectiveness of learning and the complementarity of resources or reduces clarity of objectives, which in turn negatively affects each single output category (goal achievement, knowledge output, technological output, network output, or research capacity impact) at least once.

  Again, we find hints that these negative effects are often due to the 'over-sizing' of projects, as negative relations are mostly to be found for projects which have already either high vertical scope and are perceived to be already 'higher-than-average' cost projects. Also, if projects have a higher commercial risk and lie in some distance to the core technological area of the partner, negative effects can be observed. Only when scale is increased in projects of high complexity, we find some positive effects with respect to knowledge and research outputs.

- The notable exception to this general assessment – and it is an important exception – are the results obtained from the firm sample. Here, we find a relatively large number of positive effects of size, both for the number of partners (which in some cases exercise positive influence on commercialisation impacts, research impacts and goal achievements) and for budget size (which influences all intermediary variables positively and hence has a positive mediated impact on performance). Recall, however, that in the analysis of the direct effects in the firm sub-sample, analyses produced very little evidence of significant scale effects on performance.

To sum up, the analytical results indicate that increasing scale can degrade project performance, and does so beyond certain reasonable levels (with the notable exception of firms, which seem to benefit from increasing scale, particularly in terms of budget, with a positive effect mainly on commercialisation impacts). We also found a curvilinear effect on some performance dimensions when we looked into the direct relations between scale and performance, including indirect effects, which provided some indication of unconditional negative effects of scale. The analysis of 'mediated' indirect effects, finally, gave considerable evidence that, with the exception of the firm sub-sample, the conditional effects of scale are mostly negative. Taken overall, the results from all three steps of the econometric analysis indicate that increasing scale generally degrades project performance (with the notable exception of firms, which seem to benefit from increasing scale, particularly in terms of budget, displaying a positive effect mainly on commercialisation impacts).

Step 1 showed a 'curvilinear' effect on at least some performance dimensions. Recall, however, that in the firm sub-sample, analyses produced very little evidence of significant scale effects on performance. In addition, whereas Step 2 provided some indication of unconditional negative indirect effects of scale, Step 3 gave considerable evidence that, with the exception of the firm sub-sample, the conditional effects of scale are mostly negative. It should be stressed however, that the 'exception' is important: private enterprises are key addressees of and actors in the Framework Programmes, since they are expected to translate research results into concrete innovation outputs. It is perhaps not surprising that our results indicate firms in the sample obtain higher performance, mainly in terms of commercialisation impacts, in projects with large budget.

Summing up the Main Findings

To sum up, the study indicates that increasing scale generally does not improve project performance unequivocally – with the notable exception of firms, which seem to benefit from increasing scale, particularly in terms of budget, displaying a positive effect mainly on commercial impacts.

- While the results from the various analytical steps do not always provide an unequivocal picture as to the net effect of scale on collaborative R&D performance, we have shown that scale does not seem to have a particularly strong effect on performance and that, if it does, it does so in complex ways: mostly, its effects are transmitted through critical intervening variables, such as the complementarity of resources, learning and transaction costs. When the net effect is negative (which is most of the time), it is because increasing scale lowers the positive effect of resources and learning, and magnifies the negative effect of transaction costs.
- Conversely, when it is found positive, it is because it strengthens the positive effect of resources and learning, and diminishes the negative effect of transaction costs. Finally, we have also shown that these negative (or in certain cases positive) effects materialise conditionally based on other factors, which basically relate to the characteristics of the project itself.

Overall, our results raise suspicion that the sizes of projects in the FPs are currently rather too large than too small. This is supported by comparisons of the respective hypothetical 'optimal sizes' (which are different for different performance indicators[20]) with actual project sizes. In quite a number of cases – for both number of partners and total budget – we find that optimal size with regard to performance is well below the respective average size, hinting to 'oversized-projects'.

In terms of lessons for policymakers and programme managers concerned with the FPs, a few quite clear messages emerge:

- The basic assumption of 'bigger is better' in collaborative R&D projects is not supported by our analysis. Hence, we believe that the rationale for increasing project sizes in the FPs should be carefully reconsidered.
- Especially, we would warn against increasing the scale of collaborative R&D projects in the FPs without very good knowledge about the 'optimal' or rather 'most appropriate' size. It remains doubtful, though, whether such knowledge can actually be obtained ex-ante.
- A case could be made for having a closer look at the distribution of funds among partners, and especially with an eye to the participants of the business sector, where size is indeed translated into positive effects on performance – at least in some instances.
- Given the importance of the issue for the European Research Area (ERA), monitoring the effects of R&D project scale and scope on performance for the

[20] Quite small for knowledge and technology related outputs (4-6 partners), somewhat larger for goal achievement and research impacts. Also it appears that budget does not have to be too high for participants to achieve project goals.

various broad technology areas and main funding instruments should become a regular part of the monitoring and evaluations of the Framework Programmes.

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