Chapter 10
Ego Networks and Firm Innovativeness

Innovation is all about people. Innovation thrives when the population is diverse, accepting and willing to cooperate.
(Vivek Wadhwa)

Abstract In this chapter we seek to analyze how firm innovativeness is related to individual cooperation events and the structure and dynamics of firms' ego networks. On the one hand, we analyze to what extent individual cooperation events have a direct effect on firm innovativeness. On the other hand, each cooperation event changes the structural configuration of a firm's portfolio of cooperative relationships. Evolutionary network change processes at the micro-level – i.e. tie-formation as well as tie-termination – shape the structural configuration of firm-specific ego networks which are assumed to have an indirect effect on innovation output. Consequently, the aim of this second empirical section is to disentangle these two cooperation-related innovation effects. To shed some light on the questions raised, we apply the longitudinal panel dataset described above (cf. Sect. 6.1.2). Network measures are calculated on the basis of 570 knowledge-related publicly funded R&D cooperation projects. Firm innovativeness is measured by patent grants with a 1 and 2 year time lag. Several robustness checks are performed on the basis of patent application counts. The following empirical analysis is organized as follows. We start in Sect. 10.1 with a short introduction. In Sect. 10.2 we provide a theoretical foundation, present our conceptual framework and derive a set of testable hypotheses. A description of the data sources together with a brief presentation of the variables used follow in Sect. 10.3. In Sect. 10.4 we discuss some methodological issues, specify the econometric estimation approach and present our empirical results. Finally the paper closes with a brief discussion of our main findings.

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10.1 Motivation and Research Questions

The very aim of this analysis is to investigate how firm innovativeness is related to individual cooperation events and the structure and dynamics of firms' ego networks.[1]

New knowledge in innovation processes is mainly generated through the exchange and recombination of existing knowledge content. From a firm's perspective, this recombination may be achieved either through internal learning processes within the boundaries of the firm or by interacting with other economic actors (Graf and Krueger 2011, p. 69). Long-term cooperation projects provide a particularly important way for firms to reach beyond their own corporate boundaries (Alic 1990). These projects often take the form of strategic alliances (Grunwald and Kieser 2007, p. 369) which can be defined as "[. . .] voluntary arrangements between firms involving exchange, sharing, or co-development of products, technologies, or services" (Gulati 1998, p. 293). Strategic alliances can be categorized based on the underlying motivation, goals or organizational forms (Osborn and Hagedoorn 1997; Mowery et al. 1996).[2] The number of R&D partnerships has increased considerably since the 1980s, especially in high-tech industries (Hagedoorn 2002). Thus, firms increasingly face the challenge of managing and controlling a portfolio of national and international alliances simultaneously.

In this analysis we apply an ego network perspective in order to capture the firm-specific cooperation patterns and subsequent innovation outcomes over time.[3] Ego networks are constructed on the basis of a specific type of cooperative relationship: knowledge-related publicly funded R&D alliances that aim to increase the innovativeness of the organizations involved. The subject of our analysis includes various types of individual cooperation events as well as firm-specific R&D cooperation project portfolios which are defined from the focal actor's perspective and consist of a set of direct, dyadic ties between the focal actor and its alters as well as indirect ties between the alters (Ahuja 2000). They do not include second-tier ties or second-step ties to which the focal actor is not directly connected (Hite and Hesterly 2001).

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[1] This chapter draws upon a joint research project conducted together with Guido Buenstorf, University of Kassel, Institute of Economics and International Center of Higher Education Research (INCHER-Kassel) and Katja Guhr, Department for Structural Economics at the Halle Institute for Economic Research. We have greatly benefited from comments by the audience at the 7th EEMAE conference in 2011 in Pisa, Italy and the IIDEOS PhD colloquium in 2011 in Marburg. The latest draft of the paper was presented at the 5th EMNET Conference in 2011 in Limassol, Cyprus (Kudic et al. 2011a). I take full responsibility for any errors in this section.

[2] Section 2.5.3 provides a discussion on cooperation rationale and motives.

[3] These terms "ego network", "alliance portfolio" and "alliance constellation" are used in this paper interchangeably. For an overview and comparison of definitions and concepts, see Wassmer (2010).

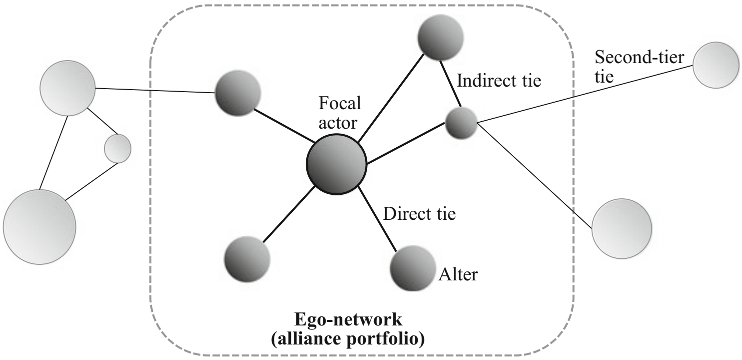

Fig. 10.1 Illustration of a typical ego network structure (Source: Kudic and Banaszak (2009, p. 9))

Figure 10.1 illustrates a typical ego network structure with one focal actor, five directly connected alters and one indirect connection (cf. Kudic and Banaszak 2009).

Earlier related work has analyzed the relationship between knowledge-intensive R&D alliances and firm innovativeness (Narula and Hagedoorn 1999; Stuart 1999; Stuart 2000) and introduced concepts explaining the identification and commercial utilization of knowledge (Cohen and Levinthal 1990) as well as disturbances in interorganizational knowledge transfer and learning processes (Simonin 1999). Moreover, scholars from various disciplines have analyzed how various dimensions of structural embeddedness in interorganizational networks (Powell et al. 1996; Rodan and Galunic 2004; Capaldo 2007) or the overall network structure itself (Schilling and Phelps 2007) affect innovativeness in the firms involved. In contrast, longitudinal empirical studies that explicitly analyze the relationship between ego network characteristics and firm innovativeness are comparably rare.[4]

One essential question that arises in this context is whether the innovativeness of firms in high-tech industries is directly affected by individual R&D cooperation events or more indirectly by structure and structural change in firm-specific ego network characteristics over time. In other words, through which transmission channels do cooperation events affect a firm's subsequent innovative performance? On the one hand it is plausible to assume that individual cooperation events directly affect firm innovativeness. On the other hand, past as well as present cooperation events determine the configuration of the focal actor's individual ego network structure over time which itself is likely to affect the firm's innovativeness. The explicit consideration of structural consequences of firm-level cooperation events raises the awareness of the existence of direct as well as indirect cooperation related innovation effects. Furthermore, Wassmer (2010, p. 162) concludes in his comprehensive review on alliance portfolios that further research based on longitudinal

[4] Most notable exceptions are: (Ahuja 2000; Baum et al. 2000; Wuyts et al. 2004).

studies is needed to understand how and why firms change the configuration of their alliance portfolios over time and how this affects a firm's performance. This dual character of individual cooperation events has been widely neglected in previous research on ego networks and constitutes the core of this investigation.

Consequently, we seek to answer the following research questions: (**I**) Do individual cooperation events (i.e. "direct effects") or rather structural ego network characteristics (i.e. "indirect effects") affect firm innovativeness over time? (**II**) How do individual cooperation events affect the structural configuration of the focal actor's ego network and which structural features affect its subsequent innovation output?

To answer these questions, we apply the longitudinal panel dataset introduced above (cf. Sect. 6.1.2). Information on type, content and funding of publicly funded R&D cooperation projects provides a solid basis for a fine-grained analysis of direct innovation effects. Structural ego network measures were calculated on a yearly basis by applying network data and quantitative network analysis methods (Wasserman and Faust 1994; Borgatti et al. 2002).[5]

10.2 Theoretical Reflections, Conceptual Framework and Hypotheses

Numerous theoretical contributions have sought to explain the nature of hybrid organizational forms and a firm's motives to cooperate in its innovation efforts (Hagedoorn 1993; Osborn and Hagedoorn 1997; Gulati 1998).[6] Some early explanations adopted the perspective of transaction cost economics (Jarillo 1988; Thorelli 1986; Williamson 1991). They interpret hybrid arrangements as strategic alliances (Borys and Jemison 1989) which are positioned between markets and hierarchies and reduce transaction costs under moderate asset specificity and frequency of disturbances (Williamson 1991, p. 292).

Other scholars have argued that hybrids have to be regarded as a unique organizational form that cannot be classified as an intermediate between markets and hierarchies (Powell 1990; Podolny and Page 1998). However, the structural forms behind these hybrids are manifold, ranging from short-term supply contracts, licensing and franchise agreements and consultancy contracts, to consortia, long-term partnerships and joint ventures (Podolny and Page 1998; Mowery et al. 1996). Previous studies on the motives for strategic alliances have shown that R&D alliances in particular provide significant cost saving potentials (Harrigan 1988; Hagedoorn 2002) and allow firms to reduce the risk inherent in R&D processes (Ohmae 1989; Hagedoorn 1993; Sivadas and Dwyer 2000). Furthermore, R&D

[5] We used standard ego network procedures implemented in UCI-Net 6.2 to calculate ego network measures (Borgatti et al. 2002).

[6] For an in-depth discussion on the motives for cooperating, see Sect. 2.5.3.

alliances provide access to new products and markets (Kogut 1991; Hagedoorn 1993), allow time to be saved by shortening the time-span between invention and market introduction (Mowery et al. 1996), and provide opportunities to internationalize business and penetrate markets abroad (Hakansson and Johanson 1988; Narula and Hagedoorn 1999). With the emergence of the knowledge-based approach in organization science (Kogut and Zander 1992; Spender and Grant 1996; Grant 1996), scholars realized the strategic importance of firm-specific knowledge resources for the competitive advantage of firms (Coff 2003). Knowledge related motives for interorganizational learning processes (Hamel et al. 1989; Hamel 1991; Khanna et al. 1998; Kale et al. 2000) as well as knowledge transfer processes (Rothaermel 2001; Grant and Baden-Fuller 2004; Buckley et al. 2009) have been analyzed from various angles in the field of alliance and network research. However, scholars have argued that "[. . .] among the various motivations for partnering, innovation is said to be a rationale of singular importance" (Bidault and Cummings 1994, p. 33).

10.2.1 R&D Alliances, Networks and Innovation Output

The relationship between knowledge transfer, R&D cooperation and firm innovativeness has been the subject of numerous case studies (Dyer and Nobeoka 2000; Ciesa and Toletti 2004; Eraydin and Aematli-Köroglu 2005; Capaldo 2007) as well as several survey-based empirical studies.

For instance, De Propris (2000) has studied the link between innovation performance and upstream as well as downstream interfirm partnerships drawing upon a unique dataset compromised of 435 firms located in the West Midlands, UK. Estimation results substantiate the importance of R&D cooperation as a driving force behind firm innovativeness. Harabi (2002) found statistically significant support for the impact of vertical R&D cooperation on firm-level innovation outcomes based on a sample of 370 small and medium sized German firms. The results indicate that informal modes of cooperation are apparently more important than formal modes. In a similar vein, Freel and Harrison (2006) investigated the impact of cooperation on firm-level innovation output. They conducted a survey-based study compromising 1,347 small firms from Northern Britain in both the manufacturing and service sectors. They report a positive correlation between product innovation success and cooperation with customers and public sector organizations.

Even though these studies provide us with important insights into the relationship between R&D partnerships and a firm's efforts to innovate, they suffer from at least three serious limitations. Firstly, the majority of survey-based cooperation studies focus on dyadic partnerships and neglect the structural dimension of the overall innovation network in which the firms under investigation are embedded. Secondly, network studies are quite sensitive with regard to network boundary misspecification and missing cooperation data. Empirical studies employing complete network data are quite rare. Finally, the majority of survey-based cooperation studies draw upon cross-sectional data and neglect the dynamic nature of cooperation activities and subsequent innovation consequences.

In response to these issues researchers have quite recently started to analyze the relationship between firm positioning in complex interorganizational networks and firm innovativeness based on longitudinal large-scale databases (Stuart 2000; Lee 2010; Fornahl et al. 2011).[7]

10.2.2 Ego Network Structure and Innovation Output

Over the past years the number of R&D collaborations has increased rapidly, especially in high-tech industries, (Hagedoorn 2002) and firms increasingly face the challenge of managing a portfolio of multiple collaborations simultaneously. This empirically observable fact places attention on firm-specific cooperation networks – so-called alliance portfolios or ego networks – (Wassmer 2010; Hite and Hesterly 2001) and raises several interesting and still widely unanswered research questions.

In the areas of economics, management and organization science, there are a number of excellent studies on “alliance network compositions” (Baum et al. 2000), “ego networks” (Ahuja 2000; Jarvenpaa and Majchrzak 2008; Hite and Hesterly 2001), “alliance constellations” (Das and Teng 2002; Gomes-Casseres 2003), “alliance portfolios” (George et al. 2001; Parise and Casher 2003; Hoffmann 2005, 2007; Lavie 2007; Lavie and Miller 2008) or “portfolios of interfirm agreements” (Wuyts et al. 2004). Our main interest is in the existence and the extent of additional ego network effects which are assumed to shape the focal actor’s innovative performance over time. With few exceptions, previous studies have paid comparably less attention to links between the structural ego network configuration and firm innovativeness.

For instance, Ahuja (2000) has analyzed the relationship between three aspects of a firm’s ego network characteristics – direct ties, indirect ties and structural holes – as well as subsequent firm-level innovation outcomes. The results confirm that direct and indirect ties positively affect innovation output, while also raising awareness for the negative innovation effects of structural holes. Baum and his colleagues (2000) have shown that the early innovative performance of Canadian biotech startups – measured by patent grant counts and R&D spending growth – is strongly affected by the alliance network composition of these firms at the time they are founded. Wuyts and his colleagues (2004) have analyzed the impact of different types of alliance portfolio descriptors on a firm’s incremental and radical innovations as well as on firm profitability.

[7] Schilling (2009) provides a comprehensive overview of large-scale alliance and network data databases such as “SDC”, “MERIT-CATI”, “CORE”, “RECAP”, and “BIOSCAN”.

Evidence that explains the overall advantages of alliance portfolios over dyadic cooperation linkages can be drawn from three lines of argument. Firstly, ego networks provide a risk reduction effect which goes beyond the dyadic level (Hoffmann 2007). By actively managing and controlling a portfolio of alliances, risk can be reduced by taking advantage of these risk diversification effects (Markowitz 1952). Given potentially high rates of failure in achieving risk reduction in dyadic alliances (Bleeke and Ernst 1991; Sivadas and Dwyer 2000), spreading risk over a portfolio of alliances helps firms reduce the variances in expected returns. Secondly, firms can gain cost savings by utilizing synergy effects in a portfolio of alliances (White 2005; Hoffmann 2005). Cooperation routines and standardized cooperation interfaces (Goerzen 2005), as well as alliance experience (Anand and Khanna 2000) and alliance management capabilities (Schilke and Goerzen 2010) save costs and increase the overall efficiency of a focal actor's ego network. For instance, Rothaermel and Deeds (2006) report a moderating effect of alliance experience on the relationship between a high-tech venture's R&D alliances and its new product development. Thirdly, an alliance portfolio enhances the scope of potential learning and knowledge access opportunities by providing access to multiple stocks of knowledge (Grant and Baden-Fuller 2004). Due to the heterogeneity of directly connected partners, the range of potentially accessible knowledge stocks increases. In addition, the interconnectedness of direct partners facilitates the flow of information in the narrower surroundings of the focal actor. The broader range of opportunities for knowledge access and learning, and the enhanced flow of information across partners are likely to have a positive impact on a firm's ability to innovate and gain competitive advantages (Gomes-Casseres 2003).

Most of the previously discussed arguments are directly reflected in the structural configuration of a focal actor's ego network. In other words, a focal actor's cooperative path is reflected in his past as well as present cooperation activities. Thus it is worthwhile taking a closer look at the structural features of firm-specific cooperation patterns over time in order to answer the research questions that were initially raised. Basically two distinct structural ego network dimensions can be identified in this context. On the one hand, we can analyze a firm's ego network structure with regard to features relating to the node level. This perspective refers, for instance, to the number of directly connected partners or to the heterogeneity of partners in an ego network. On the other hand, we can focus on the connectedness of partners in an ego network in order to characterize its structural features. From this point of view the various types and configurations of linkages between the actors in an ego network become relevant. In addition, ego networks are not static; they change continuously over time and shape the structural configuration of the focal actor's portfolio as well as the focal actor's subsequent innovative performance. This requires a dynamic view of networks which is provided in the following section.

10.2.3 An Evolutionary Perspective on Ego Networks

Recent reviews of overall interorganizational networks (Provan et al. 2007; Bergenholtz and Waldstrom 2011) and innovation networks (Pittaway et al. 2004; Ozman 2009) agree that the dynamic character of networks is still not understood sufficiently.[8] Changes in network structure are the result of events affecting two basic elements – nodes (i.e. organizations) and ties (i.e. R&D alliances) – of innovation networks (Doreian and Stokman 2005; Glueckler 2007). This means that an innovation network evolves as nodes enter and exit the population (i.e. changes in the number of organizations) and build and dissolve network relationships with other actors (i.e. changes in the number R&D partnerships). Structural network change can occur as a result of exogenous and endogenous factors. Determinants, mechanisms and structural change patterns as a consequence of micro-level network change processes are given a prominent role in evolutionary network studies (cf. Sects. 9.1 and 9.2). In comparison to the more general term "network dynamics" the concept of "network evolution" contains "[...] a stricter meaning that captures the idea of understanding change via some understood process" (Doreian and Stokman 2005, p. 5). However, the majority of previously conducted empirical studies on network evolution focus on the overall network level whereas research from the perspective of the focal actors is rare (Hite and Hesterly 2001). To date, only a small number of case studies (Dyer and Nobeoka 2000; Dittrich et al. 2007) have addressed the issue of how portfolios of collaborations change over time. Wassmer (2010, p. 165) concludes that "[...] little is still known on how alliance portfolio configurations change over time and what drives this evolution." In the present analysis we explicitly consider how tie formations and tie terminations of both the focal actors' cooperation activities as well as the network neighbors affect the structural configuration of ego networks and subsequent innovation outcomes.

10.2.4 Conceptual Framework: Direct and Indirect Innovation Effects

Our conceptual framework (cf. Fig. 10.2) draws upon the previously outlined theoretical considerations and seeks to substantiate the relationships between evolutionary micro-level network change processes, changes in ego network structure and firm-level innovation outcomes. The framework consists of four elements – **(I)** individual cooperation events, **(II)** ego network structure, **(III)** network environment, **(IV)** innovation outcomes – and illustrates four cooperation-related effects –

[8] Recently a number of excellent theoretical as well as empirical studies have addressed and analyzed the evolutionary change of networks. For an overview of contemporary research see Sect. 9.2.

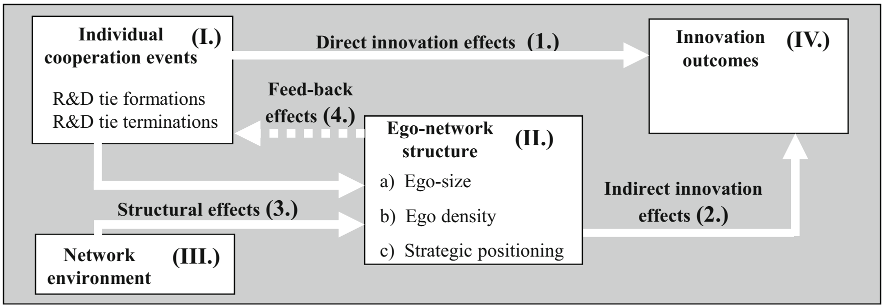

Fig. 10.2 Network change processes, ego network configuration and firm-level innovation output (Source: Author's own illustration)

(1) direct innovation effects, (2) indirect innovation effects, (3) structural effect, and (4) feed-back effects – all from a focal actor's perspective.

We start our argumentation by focusing on individual cooperation events (**I**). In this context, individual cooperation events encompass all tie formations and tie terminations on the micro-level which affect the structural configuration of the focal actor's ego network. These structural effects (3) can arise from the focal actor's own cooperation activities as well as from the cooperation activities of the focal actor's direct partners. In the first case, the size of the ego network is affected whereas in the second case the density of the focal actor's ego network is affected. In addition, the network environment (**III**) influences the ego network in at least two additional ways. Firstly, a focal actor's cooperation decisions are strongly influenced by the cooperation opportunities and restraints provided by the broader network environment. Secondly, even if an ego and its alters do not conduct any cooperation activities over a given period of time, the relative importance of its ego network changes continuously due to cooperation activities of other network actors in the broader network environment. This means that structural ego network features have to be analyzed in the context of the focal actor's broader network environment (**III**).

Now we turn our attention to the relationship between individual cooperation events (**I**) and firm-level innovation outcomes (**IV**). As outlined above, this direct innovation effect (1) has been the subject of a large number of empirical studies. The findings of these studies substantiate the assumption that cooperation events are positively related to firm-level innovation outcomes. However, especially in the case of publicly funded R&D cooperation projects, it is unclear whether it is the cooperation itself or, whether it is in fact the amount of funding received which affects firm innovativeness at a later point in time. To account for this issue we divide the direct cooperation-related drivers behind firm innovativeness into a "cooperation effect" and a "funding effect".

Firm-specific cooperation activities have an additional, more indirect innovation effect by shaping the focal actor's ego network structure. Theoretical arguments on risk diversification, synergy and cost-savings in alliance portfolios substantiate the assumption that an alliance portfolio is more than the sum of its parts. Thus, we argue that each cooperation event (**I**) affects the structural configuration of a focal actor's ego network structure (**II**) and exerts an indirect innovation effect (2) which is assumed to be related to firm-level innovation outcomes (**IV**) at a later point in time. We include three structural ego network dimensions – "ego size", "ego density" and "strategic positioning" – in our conceptual framework in order to capture a wide range of portfolio characteristics. Ego network size refers to the number of directly connected partners of a focal actor and the ego itself whereas ego network density captures the connectedness of the partners involved. In addition, firms act strategically in constructing their network (Dyer and Singh 1998; Gulati et al. 2000) and choose those network partners whose characteristics comply with their specific innovation process requirements. Consequently we include a structural component ("ego density") and strategic component ("strategic positioning") in our framework.

Finally, the dotted feedback line (4) illustrates the inter-temporal relationship between past and current cooperation events. The sum of all previously conducted tie formations and tie terminations of a focal actor itself and its closer network environment constitutes its individual ego network structure. New cooperation decisions are based on previous cooperation experiences and are determined by considerations of how new linkages fit into existing webs of linkages (Gulati and Gargiulo 1999). In other words, cooperation decisions are path-dependent. Some authors have argued that existing network structures are resistant to change. For instance, Kim and his colleagues (2006) have proposed a theoretical "network inertia" framework that explains the organizational resistance to changing interorganizational network ties as well as difficulties that an organization faces when it attempts to dissolve old relationships and form new network ties. In contrast, other authors have argued that firm strategies and actions can disrupt existing network paths (Glueckler 2007). Both, however, agree that a longitudinal setting is required to appropriately account for the inter-temporal dimension of structural ego network change patterns.

The deduction of testable hypotheses in the following section concentrates on the drivers as well as interrelationships between direct innovation effects (1) and indirect innovation effects (2) in our framework.

10.2.5 Hypotheses on Cooperation-Related Innovation Effects

Does R&D cooperation affect firm innovativeness, and if so, what are the rationales behind this assumption? The answer to at least the second part of this question was provided quite early by scholars (Alic 1990; Hagedoorn 1993). Due to the science-based character of the German laser industry (Grupp 2000) we refer to knowledge-related arguments to substantiate our first set of hypotheses. There are two streams of literature – the "knowledge acquiring approach" and the "knowledge accessing approach" which can be distinguished in this context (Al-Laham and Kudic 2008). The distinction is based on the underlying processes of knowledge generation (or "exploration") and knowledge application (or "exploitation") among partners in strategic alliances (Grant and Baden-Fuller 2004, p. 61).

According to the first approach, alliances can be regarded as "vehicles of learning" (Grant and Baden-Fuller 2004, p. 64) which allow a firm to share a particular part of its knowledge bases and exchange implicit stock of knowledge across firm boundaries. The firm's ability to "[. . .] recognize the value of new, external information, assimilate it, and apply it to commercial ends [. . .]" (Cohen and Levinthal 1990, p. 128) is of paramount importance for organizational as well as interorganizational learning processes. Since the introduction of the initial concept of "absorptive capacity", several scholars have contributed to a concretization of the concept itself (Van Den Bosch et al. 1999; Zahra and George 2002) and to a reconceptualization from a firm-level construct to a learning dyadic level concept (Lane and Lubatkin 1998; Lane et al. 2001). In addition, the establishment of mutual trust between partners (Lui 2009) has been recognized as a key factor in successful interorganizational learning processes in order to avoid learning races (Amburgey et al. 1996) or tensions between alliance partners (Das and Teng 2000) which can result in alliance instabilities or terminations (Park and Russo 1996; Inkpen and Beamish 1997).

The second approach suggests that firms cooperate in order to gain access to complementary stocks of knowledge (Grant and Baden-Fuller 2004) without necessarily internalizing the partner's skills (Doz and Hamel 1997). In other words, a knowledge accessing strategy focuses on the use of the partner's rich experience without acquiring any specific skills (Lui 2009). Grant and Baden-Fuller (2004, p. 69) argue in their "knowledge accessing" framework that the efficiency of knowledge integration through alliances can be superior compared to markets or hierarchies where products require a broad range of different types of knowledge. Firms do not necessarily have to generate new stocks of knowledge within the boundaries of the firm. Instead, they can collaborate with other firms or public research organizations to gain access to complementary stocks of explicit knowledge. However, several problems can occur during the interorganizational knowledge transfer processes. Simonin (1999) has introduced the concept of "causal ambiguity" and empirically analyzed the determinants affecting knowledge transfer processes in strategic alliances.

In summary, both knowledge acquiring as well as knowledge assessing strategies can significantly flexibilize and improve the firm's knowledge base – a necessary precondition for subsequent innovation processes. Broekel and Graf (2011, p. 6) argue that publicly funded R&D projects provide strong incentives for sharing knowledge and for innovating due to the regulative framework to which all cooperation partners involved have to agree. To test the empirical relationship between direct cooperation events and innovation output, we look at the two types of publicly funded R&D cooperation projects separately. Nationally funded cooperation projects predominantly address cooperation attempts among German firms and organizations. In contrast, supra-national cooperation projects are based on the notion of supporting pan-European research and development activities. Based on our previous considerations we can formulate the following two hypotheses:

H1a The annual number of nationally funded cooperation projects ("Foerderkatalog") is positively related to a firm's innovative performance at subsequent points in time.

H1b The annual number of supra-nationally funded cooperation projects ("CORDIS") is positively related to a firm's innovative performance at subsequent points in time.

Next we turn our attention to the structural dimension of individual cooperation events. The appropriate choice and establishment of R&D cooperation projects can increase the structural efficiency of an existing ego network. As outlined above, firms choose new partners based on strategic considerations (Dyer and Singh 1998; Gulati et al. 2000) which comply with their specific innovation process requirements. The rationale behind the establishment of a cooperative relationship is not necessarily direct access to the partner's resource pool. Instead the focal actor's intention may be to reduce its dependence on brokers by establishing alternative knowledge channels to strategically relevant actors or groups of actors. In other words, focal actors choose cooperation partners for strategic reasons in order to secure their network position, to complement their existing ego network structures and to increase efficiency. Consequently, tie formations and tie terminations may induce an additional structural effect (i.e. indirect innovation effect) by reshaping the configuration of the ego network. These individual cooperation events contribute to firm-specific innovation processes by filling "structural gaps" in existing ego networks. Thus, not only the "cooperation-specific" effect but also the superior "ego network-specific" effect is likely to determine firm innovativeness. In other words, it is plausible to assume that an additional innovation effect occurs which is caused by the focal actor's ego network structure. This implies that the several facets of the focal firm's ego network structure potentially affect the firm's innovativeness.

To test the empirical relationship between network structure and innovation output, we look separately at the distinct structural dimensions characterizing the ego network topology. The size of an ego network may affect the focal actor's innovativeness for a variety of reasons. As outlined above, collaborative arrangements provide access to new and complementary stocks of knowledge (Rothaermel 2001; Grant and Baden-Fuller 2004). This, however, is also of vital importance in portfolio settings. The more direct linkages there are in a portfolio, the broader the range of potentially accessible complementary knowledge stocks. Scholars have argued that a firm's ability to access new knowledge from external sources becomes itself a more relevant source for competitive success than the present stock of knowledge within the firm (Decarolis and Deeds 1999). Basically the same argument applies to knowledge-acquiring strategies. In addition, saving time, which can be achieved through cooperation, becomes increasingly important in science-based industries. Mowery and his colleagues (1996, p. 79) argue that the perceived shortening of product life-cycles increases the competitive pressure on firms in technology-intensive industries. They conclude that the rapid penetration of foreign markets becomes increasingly important, a goal which can be more easily achieved through alliances. These arguments become important, especially in an alliance portfolio context, as multiple collaborative R&D endeavors with diverse heterogeneous partners increase the accessibility to various types of knowledge stocks or learning opportunities and accelerate the development of new ideas and products. These arguments substantiate our next hypothesis:

H2a The greater the size of a focal actor's ego network, the higher its subsequent innovative performance.

As outlined above, in addition to node-related ego network features such as size we can distinguish between dimensions that are structurally and strategically oriented, i.e. degree of connectedness and brokerage positions. The degree of connectedness in an ego network is related to the extent to which firms gain innovation experience by being well connected to other firms or public research organizations. According to closure theory a high degree of connectedness increases the visibility of network actors (Coleman 1988). Furthermore, a high number of linkages in a densely connected ego network lower the risk of dependence on other organizations due to the existence of redundant ties and optional knowledge channels to relevant partners. Moreover, in highly connected networks, firms gain access to various types of potentially decisive stocks of explicit as well as implicit (or tacit) knowledge. This increases the scope of the firm's potentially available complementary knowledge stock and increases the firm's flexibility. These considerations lead to the following prediction[9]:

H2b The higher the degree of connectedness in a focal actor's ego network, the greater its subsequent innovative performance.

A central debate in alliance and network literature occurs around Coleman's "closure theory". Burt's (1992) "structural hole" theory highlights the importance of strategic positions and brokerage activities of actors in sparsely connected networks. Recent theoretical and empirical studies (Rowley et al. 2000; Burt 2005) indicate that these two perspectives are not mutually exclusive. We follow Burt's line of argument with regard to our last hypothesis. According to this perspective it is not so much a high degree of connectedness but rather the occupation of strategically relevant network positions that is decisive. Actors

[9] Even though we argue in this paper that the connectedness of an actor exerts a positive effect on innovation output, one has to keep contrary lines of argument in mind. For instance, Uzzi (1997) proposes that the effects of network embeddedness may become negative with an increasing level of connectedness.

connecting a large number of otherwise unconnected actors – so-called "brokers" – occupy such positions. Referring to this argument and keeping in mind our ego network perspective, we put forward the following argument: like brokers in overall networks, we can identify strategically decisive actors in ego networks who mediate the majority of the relationships between the other ego network actors. "When 'ego' is tied to a large number of 'alters' who themselves are not tied to one another, then ego has a network rich in structural holes" (Podolny 2001, p. 34). These positions are beneficial for several reasons. Brokers can facilitate, control or prevent the flow of knowledge into an ego network to a large extent by bridging structural holes in existing network structures. They are in a position that allows them to bring together firms as well as other organizations. Consequently we formulate our last hypothesis as follows:

H-2c Focal actors that occupy a brokerage position show a higher innovative performance at a later point in time.

10.3 Data, Methods and Variable Specification

10.3.1 Applied Data Sources

The analytical part of this book is based on three main data sources: patent data, industry data and network data. [10]

We use patent data to construct indicators reflecting the innovative performance at the firm level. A lot has been written about the empirical challenges of measuring innovation processes. Despite the methodological constraints related to the use of patents to measure innovation performance (Patel and Pavitt 1995), patent indicators are commonly used in analyzing innovation processes (Jaffe 1989; Jaffe et al. 1993). Raw data was taken from the EPO Worldwide Statistical Database. DEPATISnet (the German Patent and Trade Mark Office's online database) and ESPACEnet (European Patent Office database) were used to check results for integrity and consistency. Our database includes patent applications as well as patents granted by the German Patent Office and by the European Patent Office.[11]

Industry data came from a proprietary dataset containing the entire population of German laser source manufacturers between 1969 and 2005 (Buenstorf 2007). Based on this initial dataset we used additional data sources to gather information about firm entries and exits after 2005. For the purpose of this paper we chose the

[10] Fo an in-depth description of applied data sources and data gathering procedures, see Sect. 4.2.

[11] Identifying patent grants is a difficult task. We used the "patent first granted" flag (PatStat) in combination with the variable "publn_kind" to identify all granted patents.

business-unit or firm level. We ended up with an industry dataset encompassing 233 laser source manufacturers over the entire period under observation. In addition, we identified 145 universities and public research organizations with laser related activities by using the methodical procedure described below.

Network data came from two official databases on publicly funded R&D collaboration projects. The first source was the Foerderkatalog database provided by the German Federal State, which contains information on a total of more than 110,000 completed or ongoing subsidized research projects and provides detailed information on the starting point, duration, funding and characteristic features of the project partners involved. This data source has quite recently been used by other researchers to gather network data (Fornahl et al. 2011; Broekel and Graf 2011). The publicly funded research projects are subsidized by five German federal ministries. In total, we were able to identify, for the entire population of 233 German laser source manufacturers, 417 R&D projects with up to 33 project partners from various industry sectors, non-profit research organizations and universities. The second raw data source was an extract from the *CORDIS* project database which includes a complete collection of R&D projects for all German companies which were funded by the European Commission between 1990 and 2010. Data on EU Framework programs has also been used by other researchers to construct R&D networks (Cassi et al. 2008; Protogerou et al. 2010; Scherngell and Barber 2011). In total, this database extract consisted of a project dataset with over 31,000 project files and an organization dataset with over 57,100 German organizations and roughly 194,000 international project partners. Based on this raw data, we identified 155 R&D projects with up to 53 project partners for the entire sample of German laser source manufacturers. Finally, both cooperation data sources were used to construct interorganizational innovation networks on a yearly basis.

We used both data sources on publicly funded projects because the German national funding paradigm differs in several ways from the supra-nationally oriented funding paradigm of the European Union. For instance, a comparison of *Foerderkatalog and CORDIS* data shows a much higher heterogeneity of projects in terms of partner nationality, number of project partners and funding received (Kudic et al. 2011b). In addition, other researchers have pointed out that supra-national projects have a much higher involvement of public research organizations (Scherngell and Barber 2011; Broekel and Graf 2011, p. 5).

Using information about publicly funded research projects to construct R&D networks raises potentially grave selectivity concerns. It is conceivable – and indeed desirable from a societal perspective – that funding decisions reflect the heterogeneous quality of applicants. In our empirical setting, this concern seems to be of limited salience for several reasons.[12] Another potential concern is that publicly funded R&D projects primarily affect innovation outcomes through their resource effects. We checked for the resource effects by including funding as a control variable in our empirical analysis.

[12] A detail discussion of potential selection biases is provided in Sect. 4.2.3.

10.3.2 The Data Preparation Process

The empirical analysis is based on the full population of German laser source manufacturers between 1990 and 2010 – an unbalanced panel of 233 firms with a total of 2,645 firm years. Over the entire observation period we had an average of 11.08 observations per firm. Annual counts of patent grants and applications were used as the measure of innovation output, with a 2 year lag structure accounting for the time required to arrive at patentable innovations.

To construct the R&D network we had to identify all laser-related public research organizations (PROs). Two complementary methods were applied to obtain a complete list of all PROs involved (cf. Sect. 4.2.1). We started with the "expanding selection method" according to Doreian and Woodard (1992). Using the initial list of 233 laser source manufacturers we added to our extended ID-list all non-profit research organizations and universities active in the field of laser research as long as these organizations established two or more links to at least one firm on our initial list. In contrast to the "snowball sampling method" (Frank 2005) we did not immediately include organizations with just one link in our sample. Instead, we checked in each of these cases whether the identified public research organization was active in the field of laser research or not. In total we identified 138 laser-related public research organizations. This procedure, however, has a serious limitation. All laser-related PROs that did not cooperate with LSMs in the period under observation were systematically ignored. Thus, we applied a second methodological approach to complement our sample. Based on a bibliometric analysis we identified all of the organizations that published laser papers in conference proceedings or academic journals over the past two decades. Raw data for this analysis, provided by the LASSSIE project consortium (Albrecht et al. 2011), was used and supplemented by searches for laser-related publications listed in the ISI Web of Knowledge database. Thus we were able to generate a complete list of all PROs that have published at least one paper in the field of laser research. By comparing and consolidating the results of these two data gathering methods we ended up with a final list of 145 laser active PROs for the time spanning between 1990 and 2010. Finally, entry and exit dates and addresses were retrieved for all identified PROs in the dataset.

In a second step we broke down the overall network into 21 time-distinctive network layers, one network for each year. Each network layer is based on a symmetric undirected and binary adjacency matrix (Wasserman and Faust 1994) whereas the number of rows or columns was determined by the number of active laser source manufacturing firms in a given year. The decomposition of multi-partner R&D cooperation projects into dyadic network linkages is based on the assumption that all partners involved have linkages to one another (cf. Sect. 5.2).

This converted dataset allowed us to capture and quantify structural network characteristics over time and to account for several key network variables – especially ego network measures – that may influence the innovative performance of laser source manufacturing firms during the period under observation. We used standard ego network procedures implemented in UCI-Net 6.2 to calculate ego network measures (Borgatti et al. 2002).

For the patent data gathering process we used the names of the firms in the sample and assigned a patent to a firm if its name appeared as an applicant and if either applicant or inventor had a German address. We also traced changes in corporate names and legal status, as well as organizational changes and the establishment of spin-offs to allocate annual patent counts to each company.

10.3.3 Variable Specification

In previous studies, both patent applications and grants were used as innovation proxies (Powell et al. 1996; Ahuja 2000; Jaffe et al. 1993). We decided in favor of patent grants *[pgcnt]* because they indicate the actual securitization of a patent. In other words, we chose a more restrictive innovation indicator for the purpose of this empirical section. In addition, we used patent application *[pacnt]* as an additional innovation proxy to cross-check our results and ensure robustness of our findings. Application counts are frequently used in innovation studies as this reflects the earliest point in time that research was completed (Jaffe et al. 1993). A 1 and 2 year time lag structure was applied in line with previous research in this area.

The key explanatory variables are two types of cooperation counts and three basic ego network measures (cf. Sect. 5.2.2). On the one hand, we measured firm-specific cooperation propensity with two cooperation count measures based on the *Foerderkatalog* data *[coopcnt_fk]* and *CORDIS* data *[coopcnt_c]*, respectively, as well as a combined cooperation count indicator *[coopcnt_fkc]* consisting of the sum of both. On the other hand we applied three structural ego network indicators. We used procedures implemented in UCI-Net 6.2 (Borgatti et al. 2002) to generate our ego network variables. We repeated this procedure for each year under observation. The first measure is a size variable *[ego_size]*. It is defined by the number of actors (alters) that are directly connected to the focal actor (ego). The second ego network measure is a density variable *[ego_density]*. This variable is defined as the number of de facto ties at a given point in time divided by the number of pairs, multiplied by a factor of 100.[13] The third ego network variable is a normalized ego network

[13] The number of pairs of alters in an ego network is a measure for the maximum connectedness, i.e. potential ties that can be realized, of the ego network.

brokerage indicator *[ego_nbroke]*. This measure captures the number of times a focal actor of an ego network lies on the shortest path between two alters, normalized by the number of brokerage opportunities, which is a function of ego network size (Borgatti et al. 2002).

For firm-level control variables, we include a linear firm age measure *[firmage]* as well as a squared term *[firmage_sq]*. To account for overall network effects we include two types of network level control variables. The first variable captures the size of the overall network *[nw_size]* defined as the proportion of firms with at least one dyadic partnership in a given year. The second variable measures the connectedness of the overall network *[nw_density]* calculated by using the standard network density procedure implemented in UCI-Net 6.2 (Borgatti et al. 2002). In addition, we include annual time-dummies to control for inter-temporal effects. We included a set of year dummies *[yr97-yr08]* to account for year-specific effects in our estimations. Finally, we include a cooperation funding *[coopfund_fkc]* variable in our model. The funding received is measured in 1,000 euros.

Table 10.1 provides an overview of the variables and corresponding definitions on the left-hand side. Summary statistics for the dependent and independent variables are displayed on the right. Table 10.2 presents the correlation matrix for all variables used.

Table 10.1 Descriptive statistics – cooperation events and ego network characteristics

Variable	Variable definition	Summary statistics				
		Obs.	Mean	Std. dev.	Min	Max
Endogenous variables						
pacnt	Patent applications (annual count)	2,645	2.662004	17.43323	0	366
pgcnt	Patent grants (annual count)	2,645	0.339130	1.635554	0	28
Control variables						
firmage	Age of the firm	2,645	8.055955	6.800477	0	43
firmage_sq	Age of the firm, squared	2,645	111.1274	177.8146	0	1,849
nw_size	Network size	2,645	0.381853	0.060200	0.240506	0.472393
nw_density	Network density	2,645	0.088119	0.069955	0.037300	0.440500
yr97	=1, if year = 1997	2,645	0.04272	0.20227	0	1
yr98	=1, if year = 1998	2,645	0.04499	0.27322	0	1
yr99	=1, if year = 1999	2,645	0.05217	0.22241	0	1
yr00	=1, if year = 2000	2,645	0.05252	0.22318	0	1
yr01	=1, if year = 2001	2,645	0.05861	0.23492	0	1
yr02	=1, if year = 2002	2,645	0.06049	0.23844	0	1
yr03	=1, if year = 2003	2,645	0.06049	0.23844	0	1
yr04	=1, if year = 2004	2,645	0.06201	0.24131	0	1
yr05	=1, if year = 2005	2,645	0.06351	0.24393	0	1
yr06	=1, if year = 2006	2,645	0.06162	0.24052	0	1
yr07	=1, if year = 2007	2,645	0.06049	0.22384	0	1
yr08	=1, if year = 2008	2,645	0.06163	0.24051	0	1
Cooperation count variables						
coopcnt_c	Count of CORDIS cooperation projects	2,645	0.06578	0.322242	0	4
coopcnt_fk	Count of Foerderkatalog cooperation projects	2,645	0.21921	0.632911	0	8
coopcnt_fkc	Count of both types of cooperation projects	2,645	0.27599	0.774139	0	8

(continued)

Table 10.1 (continued)

Variable	Variable definition	Summary statistics				
		Obs.	Mean	Std. dev.	Min	Max
Ego network variables						
ego_size	Ego network size	2,645	2.46992	5.25304	0	41
ego_density	Ego network density	2,645	13.89213	25.73445	0	100
ego_nbroke	Normalized ego network brokerage	2,645	24.8449	67.4958	0	65.09

Source: Author's own calculations

Table 10.2 Correlation matrix – cooperation events and ego network characteristics

	pgcnt	pacnt	nw_size	nw_density	firm_age	firmage_sq	coopfund_fkc	coopcnt_c	coopcnt_fk	coopcnt_fkc	ego_size	ego_density	ego_nbroke
pgcnt	1.0000												
pacnt	0.6506	1.0000											
nw_size	0.0670	0.0448	1.0000										
nw_density	−0.0831	−0.0529	−0.6576	1.0000									
firmage	0.0106	−0.0566	0.2138	−0.2007	1.0000								
firmage_sq	−0.0046	−0.0455	0.1609	−0.1451	0.9275	1.0000							
coopfund_fkc	0.3114	0.3922	0.0146	−0.0144	−0.0279	−0.0100	1.0000						
coopcnt_c	0.2310	0.1754	0.0234	−0.0175	0.0193	0.0266	0.3144	1.0000					
coopcnt_fk	0.2157	0.2208	0.0420	−0.0132	0.0027	0.0200	0.4651	0.2326	1.0000				
coopcnt_fkc	0.2725	0.2535	0.0441	−0.0181	0.0102	0.0274	0.5112	0.6064	0.9144	1.0000			
ego_size	0.3170	0.2732	0.0313	−0.0071	0.1101	0.1306	0.3393	0.3217	0.6128	0.6349	1.0000		
ego_density	0.0542	0.0908	0.1265	−0.0724	0.0654	0.0754	0.0783	0.0661	0.2496	0.2316	0.4129	1.0000	
ego_nbroke	0.2733	0.2352	0.0959	−0.1032	0.1149	0.1244	0.2875	0.2442	0.4740	0.4892	0.6607	0.2035	1.0000

Source: Author’s own calculations

10.4 Empirical Analysis: Model Specification and Results

In this paper we use panel count data techniques to test our hypotheses.[14] In general, the use of fixed effects models provides some important advantages. Most importantly, the fixed effects estimator is unbiased as it includes dummy variables for the different intercepts and is more robust against selection bias problems than the random effects estimator (Kennedy 2003, p. 304). However, fixed effects models also have two considerable drawbacks. Firstly, all time-invariant explanatory variables are thrown out because the estimation procedure fails to estimate a slope coefficient for variables that do not vary within an individual unit (Kennedy 2003, p. 304). Secondly, using only within-variation leads to less efficient estimates and the model loses its explanatory power (Cameron and Trivedi 2009, p. 259). The random effects model compensates for some of these disadvantages. On the one hand random effects estimators make better use of the information values of patent data and generate efficient estimates with higher explanatory power. In addition, random effects estimators can generate coefficient estimates of both time-variant as well as time-invariant explanatory variables (Kennedy 2003, p. 307). The major drawback of the random effects model is that correlations between the error term and the explanatory variables generate biased estimates (Kennedy 2003, p. 306). In other words, the random effects estimator generates potentially inconsistent results when the model assumptions are violated.

10.4.1 Empirical Model Specification

As our endogenous variable accepts only nonnegative integer values, we chose a count data model specification for the purpose of this analysis.[15] Following Ahuja (2000) and Stuart (2000) we estimated panel count models and adopted the following estimation strategy to test our hypotheses. First we estimated panel Poisson models in order to obtain an initial idea of the relationship between cooperation counts, network positioning measures and firm-specific patenting activity. As our endogenous variables exhibited strong over-dispersion, we then turned to a negative binomial model specification with random effects. This generalization of the Poisson model allows for overdispersion by including an individual, unobserved effect into the conditional mean (Schilling and Phelps 2007, p. 1119). In the next step we estimated both fixed effects and random effects models.[16] We

[14] We used STATA 10.1 (Stata 2007), a standard software package for statistical data analysis.

[15] For an in-depth discussion of panel data count models, see Sect. 6.1.2.

[16] The main difference between the estimation techniques is that fixed effects models allows for correlations to be made between the unobserved individual effect and the included explanatory variables whereas random effects models require the unobserved individual effect and the explanatory variables to be uncorrelated (Greene 2003, p. 293).

used the Standard Hausman Test (1978) to decide which results to interpret.[17] Finally, we ran several consistency checks to ensure robustness of the reported results. We used several time lags for the estimations. Additionally, we used patent applications in some cases as an additional innovation measure to ensure the results.

10.4.2 Estimation Results

Tables 10.3, 10.4, 10.5, and 10.6 report the estimation results for patent grants based on a panel negative binomial model with both fixed effects and random effects estimation techniques. The tables are organized as follows. The baseline model (i.e. BL Model) consists of a set of time dummies, two firm age variables, two network control variables and a funding variable. Models I–III address direct cooperation effects and Models IV–VI report ego network effects. The last three models (i.e. Model VII–IX) provide the results for the fully specified models. Fixed effects as well as random effects estimates are reported for both patent grants with a lag of $t = 1$ and patent grants with a lag of $t = 2$. Results are reported under consideration of Standard Hausman Test results and interpreted on the basis of the fully specified models.

We start the discussion with Tables 10.3 and 10.4 which illustrate the estimation results for patent grants with a time lag of 2 years. The baseline model (cf. Table 10.3, BL Model) provides fixed effects estimation results for a set of time dummies, two firm age variables, two network control variables and a funding variable. The time dummies show positive and significant effects for the time period from 1998 to 2007. Models I–III (Table 10.3) address direct cooperation effects. The fixed effects model reveals no significant effects for *CORDIS [coopcnt_c]* or *Foerderkatalog [coopcnt_fk]*. The last cooperation count model (cf. Table 10.3, Model III) addresses combined cooperation counts *[coopcnt_fkc]*. Fixed effects estimates are significant at the 0.1 level indicating a moderate relatedness between combined cooperation counts and firm innovativeness. Models IV–VI (Table 10.3) address structural ego network effects. The ego size variable *[ego_size]* as well as the ego brokerage variable *[ego_nbroke]* show highly significant and positive coefficients at the 0.01 level for the fixed effects model. Surprisingly, network density *[ego_density]* shows no significant effect (cf. Table 10.3, Model V). Finally, we turn our attention to the fully specified models (cf. Table 10.3, Models VII–IX). The results are consistent with the previously reported findings on

[17] The basic idea of the Standard Hausman specification test is to test the null hypothesis that the unobserved effect is uncorrelated with the explanatory variables (Greene 2003, p. 301). If the null hypothesis cannot be rejected, both fixed effects estimates as well as random effects estimates are consistent and the model of choice is the random effects model due to its higher explanatory power. Under the alternative, random effects and fixed effects estimators diverge and it is argued that the latter model is the appropriate choice (Cameron and Trivedi 2009, p. 260).

Table 10.3 Estimation results – cooperation events and ego network characteristics; panel data count model, patent grants, time lag (t – 2): fixed effects

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
yr97	.28301388	.27134911	.33328969	.33802164	.23259319	.25011823	.25915583	.24418028	.2869446	.3046047
yr98	.63349169	.63238627	.69985957	.7092334	.56353661	.65428546	.55159163	.56265345	.69367349	.62658734
yr99	.82586662**	.88061534***	.86092359***	.90019169***	.87293139***	.82059957**	.75845013**	.9056236***	.88917565***	.85159569**
yr00	.95342567***	.99923104***	.98786659***	1.0216749***	1.0312264***	.96580641***	.90642038***	1.0555268***	1.0232238***	.99003889***
yr01	.92004125**	.98326257***	.93150456**	.97397866***	1.0491278***	.92587801**	.82002215**	1.0825001***	.98419502***	.90722633**
yr02	.84997207**	.93087144**	.8529483**	.90519472**	1.0329185**	.84339954**	.85076682**	1.0781388***	.91179799**	.94296864**
yr03	.97198301**	1.0752515***	.98363511**	1.0516739***	1.1652561***	.97673664**	.90963022**	1.2198901***	1.0686577***	1.0209909**
yr04	1.0875851**	1.1864142**	1.073296**	1.1348294**	1.2989609**	1.0902405**	1.0001675**	1.3523733***	1.1584861**	1.0958454**
yr05	1.347883***	1.4177135***	1.3216201***	1.3624504***	1.5210474***	1.3623725***	1.1419374**	1.5569011***	1.3886375***	1.2125097***
yr06	1.1220418**	1.205549***	1.165116**	1.2248344***	1.3246384***	1.1330364**	.93178546*	1.3671364***	1.2250648***	1.0651463**
yr07	.95981367*	1.0862809**	.99180778**	1.0777645**	1.1370854**	.95285036*	.76052249	1.2115581**	1.0747211**	.93667485*
yr08	.67159305	.77197143	.70824405	.77595561	.83052698	.68624225	.50677561	.8836538	.78164193	.64574211
nw_size	.90263709	.98554392	.32529304	.30542586	1.045863	.62072613	1.0811379	1.0960311	.33799293	.66379718
nw_density	−3.001253	−2.735748	−3.321225	−3.172295	−2.579785	−3.150222	−2.721877	−2.428528	−3.096249	−2.75881
firmage	.01604764	.01039181	.02262534	.02010696	.00761643	.01785	.03356662	.00449849	.01887192	.03180792
firmage_sq	−.0015182	−.00142676	−.00164884	−.00161259	−.00092361	−.00148828	−.00169563	−.00090271	−.001519	−.00170399
coopfund_fkc	−5.63E-06	−.00001184	−.00001427	−.00001984	−.0000115	−1.10E-06	−.00001693	−.00001494	−.0000143	−.00003011
coopcnt_c		.14257143						.07254601	.13064184	.11665961
coopcnt_fk			.086562					−.00420153	.06514561	.06454571
coopcnt_fkc				.0953059*						
ego_size					.03505361***			.03404157***		
ego_density						.00430862			.00377074	
ego_nbroke							.01321065***			.01233842***
_cons	−.01708228	−.10815625	.10310738	.05881304	−.44521632	−.02884002	−.2722868	−.4810172	−.03998001	−.22026722
chi^2	52.509824	55.411193	54.147803	56.250292	66.074274	54.534457	61.149145	67.531997	58.406049	64.025971
ll	−642.8041	−641.8139	−641.9164	−641.1722	−635.854	−641.6564	−639.0199	−635.575	−640.2322	−637.7467
aic	1,321.6081	1,321.6279	1,321.8327	1,320.3444	1,309.708	1,321.3127	1,316.0398	1,313.15	1,322.4643	1,317.4935
bic	1,409.1377	1,414.0203	1,414.2251	1,412.7368	1,402.1004	1,413.7051	1,408.4322	1,415.2679	1,424.5822	1,419.6114
N	956	956	956	956	956	956	956	956	956	956

Legend: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Source: Author's own calculations

Table 10.4 Estimation results – cooperation events and ego network characteristics; panel data count model, patent grants, time lag (t − 2): random effects

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
yr97	.28958433	.26156408	.40949314	.40041785	.22462128	.24614093	.27302751	.26437514	.35062709	.37382097
yr98	.72302556	.71322182	.89548873*	.8820191*	.65197964	.74708038	.63789276	.71806691	.864066**	.81086855
yr99	.82907701***	.88984488***	.92798811***	.96839459***	.91596182***	.82506891***	.78335293**	.97467178***	.94276367***	.93589088***
yr00	.95077403***	.99707042***	1.0482623***	1.0775272***	1.0974957***	.97550928***	.94377903***	1.1409193***	1.0774213***	1.0793283***
yr01	.83181421**	.89915129***	.88611249***	.9367763***	1.0347635***	.85001325**	.76243324**	1.071034***	.93900536***	.89332907***
yr02	.72281924**	.81511353**	.77725397**	.8452026**	1.0035318***	.72687333**	.78666605**	1.0530985***	.83581661**	.92121655***
yr03	.89798708**	1.0097849***	.9719612***	1.0539452***	1.1863558***	.91524701**	.87845921**	1.2431772***	1.0524818***	1.0358243***
yr04	.95081279**	1.0549921**	.97754627**	1.0552204**	1.2689355***	.97050824**	.91898499**	1.3064586***	1.062301**	1.042154**
yr05	1.240967***	1.2969524***	1.2479777***	1.2807483***	1.5089173***	1.2696625***	1.0600288***	1.5215934***	1.2907343***	1.1484343***
yr06	1.0399992***	1.116053***	1.1898283***	1.2422235***	1.3446564***	1.064106***	.87002448**	1.401828***	1.2267438***	1.0893737***
yr07	.89268594**	1.0224223**	1.0264416**	1.120329**	1.1708172***	.89241509**	.7213689**	1.2676747***	1.0863207**	.99479006**
yr08	.62559058	.7195015	.7772816	.83709645	.88454814*	.64516148	.51333118	.95571482*	.81283373	.73222948
nw_size	−.12371274	−.01476782	−1.3205184	−1.1774041	.09392536	−.41114889	.24700993	−.22673423	−1.174295	−.73962207
nw_density	−3.1861801	−2.8161108	−3.7008682	−3.3468854	−2.7453617	−3.3526623	−2.9368624	−2.7026842	−3.4065215	−3.0772957
firmage	.01972481	.01581655	.02832724	.02586692	.00514208	.02206826	.03293266	.00686375	.02719964	.03414089
firmage_sq	−.00094217	−.00084522	−.00114572	−.00108107	−.0002293	−.00098127	−.00121826	−.00031047	−.00108934	−.00124884
coopfund_fkc	.0000103	2.89E-06	−5.78E-06	−.00001274	1.25E-06	.00001542	−5.25E-06	−6.41E-06	−6.53E-06	−.00002515
coopcnt_c		.20296094**						.08820682	.17173138*	.14649198
coopcnt_fk			.17515551***					.03174681	.14507879**	.12989886**
coopcnt_fkc				.16547723***						
ego_size					.04775071***			.04409843***		
ego_density						.00596513**			.00490688*	
ego_nbroke							.0181826***			.01599729***
_cons	.20849708	.07200637	.43883649	.31596308	−.3642751	.17140244	−.14703416	−.29658238	.22780358	.02877153
ln_r_cons	.79957613***	.82964915***	.82943021***	.84928918***	.91174454***	.80721387***	.83048072***	.92259594***	.85348863***	.87566941***
ln_s_cons	−1.4847918***	−1.4648625***	−1.4145574***	−1.4039554***	−1.3271212***	−1.4583187***	−1.3972224***	−1.3214073***	−1.3894995***	−1.3526565***
chi^2	54.440312	60.435554	61.91168	67.27798	84.718806	59.268746	72.699885	86.973403	70.893299	81.056876

(continued)

Table 10.4 (continued)

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
ll	−1,037.63	−1,035.5521	−1,033.8359	−1,032.3531	−1,023.0145	−1,035.117	−1,030.0798	−1,022.4587	−1,030.6775	−1,026.5078
aic	2,115.2599	2,113.1042	2,109.6717	2,106.7062	2,088.0291	2,112.234	2,102.1595	2,090.9174	2,107.3551	2,099.0156
bic	2,228.9923	2,232.5233	2,229.0908	2,226.1253	2,207.4289	2,231.6337	2,221.5593	2,221.6886	2,238.1263	2,229.7867
N	2,179	2,179	2,179	2,179	2,177	2,177	2,177	2,177	2,177	2,177

Legend: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Source: Author's own calculations

Table 10.5 Robustness check – cooperation events and ego network characteristics; panel data count model, patent grants, time lag (t – 1): fixed effects

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
yr97	.68785935*	.66294073	.74171482*	.72638156*	.6754754*	.69253539*	.87113862**	.67944759*	.7380029*	.89218256**
yr98	1.1279063**	1.090248**	1.2345816**	1.197073**	1.1529394**	1.1258483**	1.2607989**	1.1585452**	1.2073965**	1.341176***
yr99	.61629188**	.63616725**	.62699145**	.64986356**	.61403569**	.61773981**	.65599545**	.62534616**	.64955633**	.69013901***
yr00	.84741821***	.85623162***	.87221792***	.87942742***	.88632774***	.84600484***	.85838016***	.89262562***	.87780939***	.89305845***
yr01	.22683027	.24861631	.19232501	.21743036	.24204418	.22795257	.17979738	.24470296	.2124664	.18003816
yr02	−.22577387	−.18664191	−.28803614	−.24488059	−.14145878	−.22494196	−.15822143	−.13762631	−.2565136	−.18553153
yr03	−.40210607	−.35731528	−.46965221	−.41903848	−.33126601	−.40147874	−.35362227	−.3263149	−.43293813	−.38143208
yr04	−.69302719	−.65073261	−.82785045	−.77720869	−.68068334	−.69169004	−.69602363	−.68326859	−.79496528	−.77552661
yr05	−.17803578	−.15739976	−.29019569	−.26237468	−.11706538	−.17914557	−.24835379	−.1233949	−.27781723	−.31295593
yr06	.32909289	.33850187	.30519773	.31727216	.38580388	.32540284	.2603632	.38326797	.3063161	.25760356
yr07	.15369194	.18051145	.13103061	.16074346	.20540014	.15516037	.0998801	.21096708	.15682981	.11545088
yr08	.43233178*	.42533845*	.42750285*	.42036388*	.43745154*	.43104303*	.42595142*	.43239495*	.41925132*	.41762267*
nw_size	−10.819289**	−10.505499**	−12.204879**	−11.830165**	−12.057715**	−10.771181**	−11.51977**	−12.107176**	−11.912055**	−12.478111***
nw_density	−17.409863**	−17.033061**	−18.769641***	−18.244603***	−16.773439**	−17.384798**	−15.70962**	−16.789017**	−18.424683***	−16.611578**
firmage	.10819177***	.10748294***	.11637332***	.11580378***	.12233203***	.10790828***	.13292805***	.12373452***	.1158048***	.13944415***
firmage_sq	−.00237513	−.00226284	−.00234645	−.00222562	−.00110621	−.00238232	−.00211179	−.00111539	−.00226306	−.00206684
coopfund_fkc	−.00001606	−.00001958	−.00003609	−.0000395	−.00003263	−.00001662	−.00003245	−.00003508	−.00004154	−.00005128
coopcnt_c		.10273775						.03039635	.09064787	.07093859
coopcnt_fk			.12046422*					.00820148	.12122404*	.08743728
coopcnt_fkc				.11098304**						
ego_size					.04274911***			.04191475***		
ego_density						−.00068882			−.0013467	
ego_nbroke							.01687165***			.01573293***
_cons	5.5180797**	5.3313742**	6.0586559**	5.8412712**	5.5225411**	5.5160388**	5.3467067**	5.5313789**	5.9226843**	5.7184145**
chi^2	67.746283	68.216716	71.267474	71.333738	87.241417	67.821444	81.283363	86.98889	71.599599	82.397879

(continued)

Table 10.5 (continued)

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
ll	−687.9207	−687.4949	−686.126	−685.8197	−676.8627	−687.8914	−681.5634	−676.8159	−685.6867	−680.3578
aic	1,411.8413	1,412.9898	1,410.2521	1,409.6394	1,391.7255	1,413.7827	1,401.1267	1,395.6319	1,413.3734	1,402.7156
bic	1,501.2807	1,507.3979	1,504.6602	1,504.0476	1,486.1336	1,508.1909	1,495.5349	1,499.9777	1,517.7193	1,507.0615
N	1,063	1,063	1,063	1,063	1,063	1,063	1,063	1,063	1,063	1,063

Legend: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Source: Author's own calculations

Table 10.6 Robustness check – cooperation events and ego network characteristics; panel data count model, patent grants, time lag (t − 1): random effects

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
yr97	.46324924	.40007221	.50604133	.46998198	.29400179	.4505134	.52573381	.2957748	.4713754	.52550231
yr98	.89284237*	.81495246*	1.0094595**	.9408987*	.74367303	.89233824*	.87920164*	.72602959	.94854238*	.94793599**
yr99	.61120188**	.64617483**	.6327672**	.66529358**	.62902407**	.60877572**	.64562722**	.64497679**	.6617576**	.69362867***
yr00	.90011859***	.91932571***	.96036612***	.97340323***	1.0223323***	.90548414***	.93522689***	1.0306877***	.97565071***	.9972492***
yr01	.30508782	.35439181	.27663257	.32587166	.40339144	.30743574	.31199899	.41252192	.32292195	.3340893
yr02	−.21379731	−.13330299	−.26707914	−.19457355	−.04157813	−.211843	−.08333328	−.02591321	−.20106005	−.08751152
yr03	−.35717163	−.27470625	−.42681579	−.34932546	−.23750035	−.35553922	−.2721566	−.22154065	−.35612416	−.28789802
yr04	−.61165042	−.52957056	−.77196361	−.69117413	−.52427483	−.60949472	−.5452333	−.51478462	−.69970397	−.62491829
yr05	−.13659284	−.10159446	−.27286589	−.23641331	−.02795895	−.13150452	−.16901561	−.03261082	−.23939201	−.23869546
yr06	.37005431	.38796475	.35983868	.38037001	.47571513	.37911672	.31452759	.47093128	.38169832	.33173044
yr07	.18871255	.23819118	.18055139	.22660797	.27929432	.18763892	.14666464	.29181355	.2220858	.19573344
yr08	.43894939*	.42518311*	.44609622*	.43230737*	.44698795*	.44038243*	.42527008*	.43338907*	.43374551*	.42197885*
nw_size	−9.6061159*	−8.9198244*	−11.258832**	−10.572557**	−9.6574063*	−9.659645*	−9.2507536*	−9.5466639*	−10.674452**	−10.214994*
nw_density	−18.879345**	−18.373738**	−21.149769***	−20.536506***	−20.458121***	−18.934135**	−17.853806**	−20.43898**	−20.642559***	−19.378541***
firmage	.0768271**	.07463565**	.08392102**	.08225298**	.0637425*	.07727288**	.08744924**	.0645004	.08266315**	.09054553***
firmage_sq	−.00215862*	−.00206355	−.00225022*	−.00218002*	−.00112079	−.00216901*	−.0022373*	−.00114604	−.00219021*	−.00224674*
coopfund_fkc	−2.43E-07	−6.56E-06	−.0000241	−.00003033	−.00002091	8.53E-07	−.00002042	−.00002358	−.00002977	−.00004263
coopcnt_c		.17767547*						.05606854	.1482401	.10678382
coopcnt_fk			.17407617***					.00336744	.16471489***	.11765017*
coopcnt_fkc				.160997***						
ego_size					.05132971***			.05022702***		
ego_density						0.00144519			.00051321	
ego_nbroke							.01955928***			.01717148***
_cons	5.226859*	4.8656738*	5.8961892**	5.542724**	4.9745992*	5.2151074*	4.729544*	4.9195327*	5.5786573**	5.1408288*
ln_r_cons	.77643775***	.79111548***	.79492294***	.80543569***	.87561503***	.77952532***	.8029451***	.87810292***	.80648061***	.82384172***
ln_s_cons	−1.4661876***	−1.4447477***	−1.4163338***	−1.4030847***	−1.3109938***	−1.4584033***	−1.385512***	−1.3080685***	−1.4001969***	−1.3599306***
chi^2	65.795584	68.225196	72.497399	73.98586	97.423975	66.038451	87.174111	97.482609	74.049408	89.786435

(continued)

Table 10.6 (continued)

Variable	Estimation results									
	BL model	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
ll	−1,097.0172	−1,095.6135	−1,093.0796	−1,092.1249	−1,079.1377	−1,096.8302	−1,087.6593	−1,078.9803	−1,092.0537	−1,085.2273
aic	2,234.0344	2,233.2271	2,228.1592	2,226.2498	2,200.2755	2,235.6604	2,217.3186	2,203.9606	2,230.1073	2,216.4545
bic	2,349.7986	2,354.7795	2,349.7116	2,347.8022	2,321.8105	2,357.1954	2,338.8536	2,337.0704	2,363.2171	2,349.5643
N	2,412	2,412	2,412	2,412	2,410	2,410	2,410	2,410	2,410	2,410

Legend: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$
Source: Author's own calculations

cooperation count (Models I–III) and ego networks (Model IV–VI). The effects for ego network size and ego network brokerage remain robust in Models VII and IX (Table 10.3) whereas no effect could be identified for ego network density in Model VIII (Table 10.3) based on fixed effect estimation.

However, a look at the results of the random effects model (cf. Table 10.4) reveals a slightly different picture. Estimation results for both cooperation count measures as well as ego network measures are positive and highly significant in nearly all model specifications. In other words, the previously reported findings are supported by random effects models. These estimation results, however, have to be interpreted with caution bearing in mind the results of the Hausman Test.

In order to check the robustness and consistency of these initial findings we estimated all previously discussed models again with a time lag of 1 year (cf. Tables 10.5 and 10.6).[18] Table 10.5 reports results for fixed effects estimation techniques whereas Table 10.6 provides results based on random effects estimators. Just as before, Models I–III (cf. Table 10.6) address direct cooperation effects. This specification confirms the previously reported combined cooperation count effect *[coopcnt_fkc]* with an increased 0.05 significance level. Moreover, we can now observe an additional direct cooperation for nationally funded cooperation projects *[coopcnt_fk]* at the 0.1 significance level.

The results for the ego network effects (cf. Table 10.5, Model IV–VI) are fully consistent with our previous findings (cf. Table 10.3, Model IV–VI). Again, ego size (cf. Table 10.5, Model IV) as well as the ego brokerage variable (cf. Table 10.5, Model VI) show highly positive and significant coefficients at the 0.01 level and no network-density effects (cf. Table 10.5, Model V). The fully specified models (cf. Table 10.5, Model VII–IX) reconfirm our previous ego network results and reveal at the same time some interesting additional insights with regard to individual cooperation effects. The effects for ego network size *[ego_size]*, and ego network brokerage *[ego_nbroke]* remain robust (cf. Table 10.5, Model VII and IX) and ego network density *[ego_density]* still shows no significant effect (cf. Table 10.6, Model VIII). Surprisingly, now the nationally funded cooperation counts *[coopcnt_fk]* are directly related to firm-level innovation output, but the estimates are only marginally significant at the 10 % level (cf. Table 10.6, Model VII). A look at the fully specified random effects model (cf. Table 10.6, Model VII–IX) confirms this finding. Model VII (Table 10.6) reports a highly significant coefficient for nationally funded cooperation counts at the 0.01 significance level and no effect for ego network density.

What do these results tell us about our previously formulated hypotheses? Hypotheses H1a and H1b suggest that both nationally (i.e. Foerderkatalog counts) and supra-nationally funded (i.e. CORDIS counts) collaborations are positively related to firm innovativeness. Our results show that nationally funded cooperation projects are positively related to innovation output in three out of four fully

[18] Additional robustness checks have been conducted by using patent application data. Most of the results confirm the reported findings. All estimations are available upon request.

specified models (Model VII, in: Tables 10.4, 10.5, and 10.6). Thus we find at least modest support for Hypothesis H1a. In addition, these findings support our initial conjecture that individual cooperation effects diminish at least partially when considering structural ego network effects at the same time.

Now we turn to Hypothesis H1b. Based on our previously discussed estimation results we have to reject Hypothesis H1b. Moreover, it is interesting to note that none of the models (cf. Tables 10.3, 10.4, 10.5, and 10.6) reveal significant coefficient estimates for funding. In other words, it is not the funding effect but rather the cooperation itself that is related to firm-level innovativeness. Hypothesis H2a suggests that the size of an ego network is positively related to firm-level innovation output. Estimation results provide strong support for Hypothesis H2a, predicting that innovation output is positively related to a firm's number of direct linkages to other laser source manufacturers or public research organizations with laser-related activities. Likewise our estimation results provide strong support for Hypothesis H2c suggesting that brokerage positions in ego networks are positively related to subsequent firm-level innovation outcomes. Surprisingly, estimation results provide no support for Hypothesis H2b.

In summary, it turns out that the estimation models confirm the existence of direct innovation effects of individual cooperation events as long as portfolio characteristics are ignored. These effects partially diminish when ego network characteristics are taken into consideration at the same time (cf. comparison of Model VIII, Tables 10.3 and 10.5). Funding plays a subordinate role in the innovative performance of the firms under investigation. In contrast to the ego network size and brokerage, the ego network density proves to be of subordinate importance for firms in their attempts to innovate.

10.5 Discussion and Implications

This analysis was motivated by a goal to broaden our understanding of the relationship between individual cooperation events, ego network structures and firm level innovation output in the German laser industry. Our research in this area is still in an early stage. We started the analysis by taking a closer look at individual cooperation events of laser manufacturing firms.

The results of our analysis imply that the initialization of new collaborative arrangements seems to be an important driver behind a firm's innovation performance. Participation in new R&D projects with multiple profit and non-profit organizations broadens the scope of potentially accessible knowledge stocks. At the same time this increases the diversity of the knowledge base of focal firms. The subsequent impact of newly initialized R&D collaboration projects on innovation output is in line with theoretical reasoning from a knowledge-based perspective as outlined above. Surprisingly, this result only applies to nationally funded projects whereas the supra-nationally funded cooperation projects end up showing no significant effects. Furthermore, our findings relativize the argument that a firm's innovative performance is affected more by public funding than the cooperation activities themselves. With regard to the structural configuration of a firm's ego network it becomes obvious that the size of the ego network does matter. The findings for ego size suggest that the number of direct connections between the focal actor and ego network alters are especially decisive in terms of innovation output. This result is consistent with the initial findings as the diversity of potentially accessible knowledge stocks increases with the size of the ego network. Surprisingly, we found no support for ego network density. In other words, the existence of ties among alters seems to be less important for firm-level innovation outcome in the German laser industry innovation network. Finally, it turns out that the ego network brokerage has significant coefficient estimates. In other words, there is a positive and significant relationship between ego network brokerage and a firm's patenting activity. Thus, the strategic positioning of focal actors and their ability to mediate and control knowledge flows between other pairs of ego network actors appears to be of vital importance for their innovative performance.

The limitations of our empirical analysis (cf. Sect. 13.2) and our strategy to solve these issues (cf. Sect. 14.2) is subject to discussion in the final chapter of this study.

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