Complicating Innovative Knowledge Networks: Evidence from the FP7 (2007-2013) "space" Programme

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Abstract
This study provides theoretical argumentation for the use of multilateral proximity measures when studying tie formation in knowledge networks. This study also argues for a distinction between successful and unsuccessful collaboration when studying tie formation in knowledge networks. These theoretical arguments are tested on a sample of organisations collaborating in consortia which applied for a subsidy under the FP7 (2007-2013) "space" programme using promising exponential random graph models methodology. Evidence is found to support the claim that it is useful to study knowledge networks in a multilateral as opposed to a bilateral manner. Both organisation level and consortia level variables have significant effects on tie formation in the studied knowledge network. Evidence is also found to support the claim that it is useful to distinguish between successful and unsuccessful collaboration in knowledge networks. Variables are found to have effect on both successful and unsuccessful collaboration, raising questions about the economic value of collaboration ties in knowledge networks.

Keywords
Exponential random graph models, proximity, network analysis, space, multilateral, success

Introduction

Constant innovation is widely considered to be crucial in attaining and maintaining a competitive advantage on the global market, both for organisations themselves and the regions they operate in. In modern knowledge intensive industries, innovation has become an increasingly collaborative effort (Steensma et al., 2000; Autant-Bernard et al., 2007). It is argued that tacit knowledge (most easily communicated through face to face contact) is an important part of the innovation process. Audretsch and Feldman (1996) argue that knowledge is communicated effectively between skilled workers endowed with a high level of human capital and in close geographical proximity of one another. Many scholars have researched the effect geographical proximity of actors has on innovative collaboration, with results showing that geographical proximity has a positive effect on innovative collaboration (Boschma, 2005; Audretsch & Feldman, 1996; Jaffe et al., 1993; Maggioni et al., 2007). Geographical proximity is not the only type of proximity that affects innovative collaboration, (codified and tacit) knowledge transfer has been found to be affected by various types of non-spatial proximity as well (Boschma, 2005; Scherngell & Barber, 2009; Scherngell & Barber, 2011; Capello & Caragliu, 2018). In his influential article Proximity and Innovation: A Critical Assessment, Boschma (2005) argues that the effect of geographical proximity on innovative collaboration can never be studied in isolation, it should always be studied in combination with cognitive, organizational, social and institutional proximity if possible. Scherngell and Barber (2009) find that - although geographical proximity is a determinant of cross-region R&D collaborations - technological proximity is a larger determinant of cross-region R&D collaborations. Ertur and Koch (2011) even go as far to state "We … use it as crude proxy for socio-economic, cultural or institutional proximity" (p. 236) when discussing the use of geographical distance as a measure in economic growth theory.

In the European Union, the framework programmes (FPs from here on) facilitate innovative research and development (R&D from here on) projects by subsidizing projects in certain predetermined industries. The FPs are active for seven-year periods and have existed from 1984 to the present day. A large share of FP projects is worked on by consortia of organisations.

Ample research has been done on the impact of spatial and non-spatial proximities on collaborative R&D projects funded by different FPs (Capello & Caragliu, 2018; Balland, 2012; Scherngell & Barber, 2011; Scherngell & Barber, 2009).

FP subsidized projects are often analysed from a social network perspective because there are usually multiple organisations per project and organisations often participate in multiple projects, in other words, FP subsidized projects and the participating organisations can be seen as a knowledge network through which innovative knowledge flows. Many studies build a network of organisations that have a tie when they have collaborated on the same project. By analysing whether firms with a tie are proximate on different dimensions scholars can analyse the effect proximities have on innovative collaboration. This way of researching the impact proximities have on innovative R&D projects subsidized by FPs is rather focused on trying to explain collaborations between pairs of organisations, or dyadic ties between organisations.

By focusing on dyadic ties, studies neglect consortia formation. In this study it is proposed that, in reality, organisations form consortia together based on group level (or multilateral) characteristics instead of individual relationships with every single other organisation in the consortium. Therefore, a new way of researching the effect spatial and non-spatial proximities have on innovative knowledge networks is proposed in this paper, motivated by the assumption that consortia formation is affected by the characteristics of all the organisations within, for which empirical evidence is found in for example Uzzi (1996) and Murray (2005). Multilateral - as opposed to bilateral - conceptualizations of existing proximities are needed - and provided - to be able to approach innovative collaboration from a consortia perspective.

Next to proposing a switch from a bilateral to a multilateral perspective on innovative knowledge networks, this study also argues the importance of measures of success in innovative collaboration network studies. Often, tie formation (or dissolution) is studies in innovative knowledge networks without a measure of how successful said ties are, meaning no conclusions can be made about the economic value of said ties. Many ties that don't lead to success are arguably less economically valuable than a few ties that do lead to success, even more so when collaborations are being subsidized.

By proposing a multilateral perspective on innovative knowledge networks subsidized by the FPs and arguing the importance of success when analysing collaboration in said networks this study aims to forward both the FPs themselves via more realistic policy evaluation of the FPs and knowledge network literature in general. These ideas are empirically applied to the FP7 (2007-2013) programme "space" innovative knowledge network using promising exponential random graph methodology (Broekel et al., 2014).

This paper is structured as follows; firstly, theoretical argumentation based on existing literature is given for multilateral proximity hypotheses and the research question of this paper is stated. Secondly the data and methods used are discussed in detail. Thirdly, the empirical results are discussed. Finally, the empirical results are placed in the broader context of the literature and the limitations of this study are discussed.

Theory & research question

As discussed above, in modern knowledge intensive industries, innovation has increasingly become a collaborative effort. FP projects are a clear example of modern innovative projects often involving multilateral collaboration. For example, during FP6 the average amount of participating firms per project was 11.5 with 5.331 projects in total, during FP7 the average amount of participating firms per projects was 10.5 with 8.867 projects in total (European Commission, 2015).

However, theoretically and methodologically in the paradigm of economic geography, innovation research tends to have a dyadic perspective on innovative collaboration between firms, see Ponds et al. (2007) and Balland (2012) for example. By studying multilateral FP data from a dyadic perspective, you are coercing a dataset which has two modes (consortium and organisation) into a one mode (organisation) matrix, which has negative theoretical consequences when one does not adapt their hypotheses to this change (Borgatti & Everett, 1997). In these dyadic (or bilateral) oriented studies, consortia participation is used purely as a tie between two organisations, as opposed to consortia being theoretical entities in their own right. This is problematic when taking the arguments that organisations enter consortium relationships to gain resources from multiple organisations simultaneously as a response to their already existing relationships with other organisations (Uzzi, 1996; Elg, 2000) and that relationships contained within consortia create more value and reduce uncertainty more than multiple bilateral relationships (Murray, 2005; Harrison et al., 2001) into account. This gap between the theory and methods which are the norm (dyadic collaboration) in economic geography and which we see in reality (collaboration in consortia) can be closed by changing the way we look at spatial and non-spatial proximities between organisations and consortia. To make this theoretical step a cross-pollination is proposed between current economic geographic knowledge theory and multilaterally focused resource dependence, resource complementarity and embeddedness theory.

Consortia formation, resource dependence, resource complementarity and embeddedness theory

Three strands of literature that are suitably applicable to consortia tie formation are embeddedness literature (Uzzi, 1996; Uzzi, 1997; Granovetter, 1985), resource dependence theory (RDT) literature (Hillman et al., 2009; Pfeffer & Nowak, 1976; Pfeffer, 1987) and resource complementarity literature (Harrison et al., 2001; Lin et al., 2003; Barney et al., 2001). Embeddedness literature studies broadly argue that the structure and quality of an organisation's network defines the economic possibilities available to said organisation (Uzzi, 1996). Uzzi (1996) argues that embeddedness logic is "unique in that actors do not selfishly pursue immediate gains but concentrate on cultivating long-term cooperative relationships that have both individual and collective level benefits for learning, risk-sharing, investment, and speeding products to market" (p. 693), something which is missing in neo-economic theory. Using consortia as a means of creating individual and collective benefits for the organisations involved fits within embeddedness logic. Smith and Stevens (2010) - in line with Uzzi (1996) - argue that "embeddedness is, at its heart, an argument against the isolated dyadic relationships often portrayed by classical economic theory, where decisions are made in isolation; it is instead an argument that a more interconnected resource and social system governs organizational action" (p. 582).

RDT literature studies broadly argue that organisations enter inter-organisational relationships like FP consortia (or joint ventures, strategic alliances, etcetera) to reduce organisational uncertainty (of survival via economic performance) and interdependence by acquiring resources from other firms (Hillman et al., 2009; Pfeffer & Nowak, 1976; Pfeffer, 1987). Pfeffer and Nowak (1976) argue that inter-organisational relationships are undertaken either when "there are economies of scale in operation, when capital requirements are too high for a single organization to handle, and when there is a great deal of technological risk from the venture" or to "use the complementary strengths of the two organizations in developing a new product or service or entering a new market" (both p. 403). In the context of FPs, the second explanation of the logic behind inter-organisational relationships should be extended to multilateral collaboration in consortia, as follows; inter-organisational relationships are undertaken to use the complementary strengths of two or more organisations in developing a new product or service or entering a new market. Earlier RDT works argued that organisations should minimize dependence on other organisations to increase performance and thus chances of survival (Pfeffer & Nowak, 1976; Pfeffer & Salancik, 1978). However, a more recent study by Gulati and Sytch (2007) argues the opposite; higher interdependence between a group of organisations can increase performance, which is in line with the notion that higher embeddedness leads to higher performance from the embeddedness literature (at the same time, being too embedded can lead to lower performance) (Uzzi, 1996).

The logic behind an organisation joining a consortium according to resource complementarity literature is that there is value added to a focal organisation's internal resources when said organisation has access to complementary resources from the other organisations in a consortium (Harrison et al., 2001; Barney et al., 2001; Lin et al., 2003).

The assumption following the theoretical arguments above is that organisations cooperate within a FP consortium to gain resources which help said organisation to develop an innovative product or service, the resources gained from a consortium are greater than the sum of the resources gained by engaging in bilateral relationships with the same organisations.

To receive a FP subsidy, consortia must go through a selection process. This process ends with consortia either being granted a subsidy or being denied a subsidy. Being granted a subsidy is a success for and a validation of the raison d'être of a FP consortium. It is argued that spatial and non-spatial proximities affect the chances consortia and organisations have of forming both successful and unsuccessful ties.

Geographical proximity, non-spatial proximities and FP consortia

Existence or non-existence of innovative collaborations via EU framework programmes is affected (positively or negatively) by the degree of geographical, cognitive, organizational, social and institutional proximity between actors in Europe (Boschma, 2005; Scherngell & Barber, 2009; Scherngell & Barber, 2011; Balland, 2012; Capello & Caragliu, 2018). Each of these proximities has different characteristics and theoretical backgrounds. The possible theoretical complementarities between each individual proximity and the embeddedness, RDT and resource complementarity literature will be discussed.

Geographical proximity

Geographical proximity is defined by Boschma (2005) as "the spatial or physical distance between actors" (p. 69). Empirical evidence has often been found supporting the hypothesis that knowledge flows are geographically bounded (Audretsch & Feldman, 1996; Jaffe et al., 1993; Maggioni et al., 2007). Using FP data, evidence has also been found supporting the hypothesis that knowledge flows are geographically bounded (Scherngell & Barber, 2009; Scherngell & Barber, 2011; Balland, 2012; Capello & Caragliu, 2018). Scherngell and Barber (2009) find that increasing geographical distance has a negative effect on the cross-region collaboration intensity between two regions. This effect was found to be much stronger for intra-industry collaboration intensity than intra-public-research collaboration intensity. A finding which supports the idea put forward by Ponds et al. (2007) that academic collaboration is less geographically bounded than, for example, collaboration between an academic and a non-academic organization.

Traditional RDT studies often ignore spatial hypotheses (Kono et al., 1998). Kono et al. (1998) argue that interlocking (sharing of directors between firms, possibly reducing uncertainty and gaining resources between organizations within RDT logic) is spatially bounded. When reading the study by Kono et al. (1998) from a contemporary economic geographical viewpoint it seems they have found evidence supporting Ertur and Koch's (2011) notion that spatial proximity is a proxy for non-spatial proximities, as discussed in the introduction.

Using theoretical arguments from the embeddedness literature, Smith and Stevens (2010) propose that geographical proximity increases structural embeddedness between actors (in a social entrepreneurship context), stating that ties between social entrepreneurs become increasingly arms-length (less embedded) as the geographical scope of the intended social innovation increases. These arguments can be translated into a FP collaboration context, the more geographically proximate firms in a consortium are, the more structurally embedded they are, which has a positive effect on consortia success.

Following the studies discussed above, it is hypothesized that geographical proximity has a positive effect on tie formation in FP knowledge networks because organisations pursue effective and successful collaborations which are found to be more likely when actors are geographically proximate.

All consortia must specify a host institution when applying for a FP subsidy, it is fair to assume a substantial share of a consortium's work on a project will take place at the location of the host institution. Measuring the distance between organisations' location and the consortia coordinator's location can be used as a measure for geographical proximity. However, one could also argue that average distance between participating organisations is a better measure for geographical proximity from a consortia perspective.

Cognitive proximity

A certain level of cognitive proximity between actors is required for an actor receiving information to be able to communicate, understand and process said information effectively (Boschma & Lambooy, 1999; Boschma, 2005). However, too much cognitive proximity can have a negative effect on knowledge transfer. There is not much to learn from each other when two actors largely have the same knowledge base. In FP research the use of patent data as a measurement for cognitive proximity is common (Scherngell & Barber, 2009; Scherngell & Barber, 2011; Capello & Caragliu, 2018).

The economic geographical idea of cognitive proximity discussed above can be viewed from a resource complementarity perspective (Harrison et al., 2001; Harrison et al., 1991; Barney, 2001). In their 1991 article, Harrison et al. argue that organisations can create value by acquiring other firms with resources that are complementary (as opposed to purely similar) to their own. Ten years later, in 2001, Harrison et al. find evidence that organisations can create value by acquiring other firms with resources that are complementary. However, they also find evidence that organisations can create value by entering strategic alliances (like FP consortia) with organisations that possess resources complementary to their own. Strategic alliances could be an attractive alternative to acquisition because the investment and/or commitment required in a strategic alliance is less than when acquiring an organisation (Barney et al., 2001). Strategic alliances like FP consortia give firms the unique opportunity to gain access to the complementary resources of all the other participating firms, including resources that are a product of the strategic complementarity of the consortium as a whole (Harrison et al., 2001). The leading assumption then, is that organisations in a strategic alliance with complementary resources are cognitively proximate as a group. Adding to this assumption, it is hypothesised that a cognitively proximate consortium is more likely to form than a cognitively non-proximate consortium because organisations actively seek resources complementary to their own.

Scherngell and Barber (2011) measure "technological distance" by calculating how correlated the share of patents in a certain technological subclass is between two regions and then subtracting said correlation estimate from 1, "technological distance" could be seen as a measure of cognitive proximity between two regions. It is assumed that a large share of (European) patents in a technological subclass in a region is an indicator for technological specialization in said technological field in the region in question. To measure the cognitive proximity per organisation in a consortium using "technological distance" - following Scherngell and Barber (2011) - one could take the average granted patents in a technological subclass of all participating organisations in a consortium and then calculate the distance from said average per organisation. This would be a measure of cognitive proximity between organisations in a consortium on a regional scale.

Organizational proximity

Organizational proximity is defined by Boschma (2005) as "the extent to which relations are shared in an organizational arrangement" (p.65). Or in other words, the autonomy actors have within a collaboration and the control they can exert upon one another. Boschma (2005) argues that a certain amount of organizational proximity is needed "to control uncertainty and opportunism in knowledge creation within and between organizations" (p. 66). However, too much organizational proximity can create a situation in which organizations are less able to learn from one another due to lock-in and lessened flexibility. Balland (2012) uses a binary definition of organizational proximity in which two global navigation satellite system organizations are organizationally proximate when they belong to the same corporate group and organizationally non-proximate when they do not. Balland (2012) gathered this data by hand from organization websites, something which gets increasingly time consuming when studying a larger set of organizations (Balland has an N of 104 in said article). Balland (2012) proposes that two organizations are more likely to collaborate when they are organizationally proximate.

From the resource dependence literature, Kono et al. (1998) study interlocking (sharing of directors between firms, as discussed above) between organizations. Interlocking can be seen as a way in which organizations can increase organizational proximity, although the findings of Kono et al. (1998) don't fully support this claim. From an embeddedness perspective one would argue that two organisations with high organisational proximity have a highly embedded relationship, something which has a positive effect on organisation performance (Uzzi, 1997). From a resource complementarity perspective - and following the notion that organisations can acquire or merge with other firms to acquire resources complementary to their own, making the two organisations involved organisationally proximate - one would expect acquisition of an organisation to have a positive effect on organisational success (Lockett & Thompson, 2001). It is hypothesised (although the evidence in the RDT literature is ambiguous) then, that higher organizational proximity has a positive effect on tie formation between organisations and consortia subsidized under FP7 because organisations seek to minimize the uncertainty within collaborations.

Following Balland's (2012) operationalization of organizational proximity - and from a consortia perspective - one calculates the amount of different mother firms in a consortium when trying to measure organisational proximity. For example, a consortium of nine firms which all fall under three mother firms will be more organizationally proximate than a consortium of nine firms of which three fall under one mother firm and the remaining six are individual firms not in a corporate group.

Social proximity

Social proximity is defined by Boschma (2005) as "socially embedded relations between agents at the micro-level" (p. 67), using embeddedness literature from Uzzi, Granovetter and Polanyi as references. Social proximity is a measure of the individual trust, friendship and familiarity between individuals from different organisations. In other words, organisations which have a large overlap in their employees' social networks are highly socially proximate. The higher this individual trust, friendship and familiarity between the employees of a group of organisations the more likely they are to successfully collaborate. Adjei et al. (2016) support this social proximity hypothesis by finding that the amount of family members (a proxy for social proximity) in an organisation is positively related to organisational success.

The theoretical roots of social embeddedness of collaborating organisations mainly stem from the embeddedness literature (Uzzi, 1996; Uzzi 1997; Boschma, 2005). From the embeddedness literature one would expect that a group of firms that are highly socially embedded - and thus have a high degree of social proximity - to have higher chances of being successful as a consortium. It is hypothesized then, that higher social proximity has a positive effect on tie formation between organisations and consortia subsidized under FP7 because organisations seek effective and successful collaborations which are more likely in consortia with socially proximate participating organisations.

Seeing as the FP datasets don't contain data on the personal social networks of employees, little research has been done on this micro-level definition of social proximity in the FP literature. Balland (2012) attempts to address this problem by using distance within a constructed social network (created using data from FP projects) as an indicator for social proximity. He argues that social proximity increases as the geodesic distance (distance between two actors within a network) decreases between two organizations, based on the assumption that geodesic distance in a social network of organisations is a proxy for social proximity (Balland, 2012). Although this way of measuring social proximity can seem problematic (just because two organisations collaborated with the same organisation doesn't mean they themselves are socially close per se) it is fair to assume that on average firms with a lower geodesic distance are more proximate socially when taking the social side of business; conferences, informal meetings, presentations, etcetera into account.

Institutional proximity: cultural habits and values

Institutional proximity is defined by Boschma (2005) as having two dimensions; 1) sharing cultural habits and values and 2) sharing institutional rules and systems. Boschma (2005) argues that having similar cultural habits and values (think of a common language, common ideas about work ethic, shared habits, etcetera) provides a solid basis for innovative collaboration. Capello and Caragliu (2018) - from the FP literature - discuss "interregional social Proximity" (p. 20) - which falls into the second dimension of institutional proximity discussed above stating that "the sharing of similar social values among regions facilitates interactions, and most importantly, reduces transaction costs" (p. 20). They find that interregional social proximity (or shared cultural habits and values) have a positive effect on knowledge network tie formation subsidized under the 5th FP. Capello and Caragliu (2018) measure "interregional social proximity" by aggregating European Social Survey (ESS) results on cultural habits and values to the regional level, the similarity in these aggregated results between regions is used as an indicator for their interregional social proximity.

A study by Steensma et al. (2000) - which uses an RDT perspective - finds that national culture traits influence technology alliance formation. In other words, certain cultural traits (uncertainty avoidance, masculinity and individualism) from a focal organisations country of origin influence the likelihood that a focal firm will pursue collaboration in a technological alliance (like FP consortia). Sirmon and Lane (2004) discuss studies that find contradictory evidence on the effect of difference in national culture between organisations within an alliance on alliance performance. In line with Boschma (2005) and Capello and Caragliu (2018) - but keeping in mind the contradictory studies discussed by Sirmon and Lane (2004) - it is hypothesised that higher institutional proximity via cultural habits and values has a positive effect on tie formation between organisations and consortia subsidized under FP7 because organisations seek effective and successful collaborations which are more likely in consortia with less cultural distance on average.

When measuring institutional proximity via cultural habits and values within consortia, one is interested in the similarity or dissimilarity of cultural habits and values (of the different regions firms are situated in) present in the consortium. Following Capello and Caragliu (2018) as discussed above, the similarity or dissimilarity of cultural habits and values can be measured by using aggregated ESS results. These results can be used on a group level by analysing whether tie formation is more likely between organisations - within consortia - that are less culturally distant (or more institutionally proximate) on average.

Institutional proximity: rules and systems, the knowledge triangle & the triple helix

The second dimension of institutional proximity is focused on the formal set of institutional rules and systems (Boschma, 2005). Triple helix literature is a useful tool for studying this second type of institutional proximity because it is used for investigating collaboration between different formal institutions, these institutions being government, universities (education) and firms (industry) (Ranga & Etzkowitz, 2013). As Ponds et al. (2007) state: "Scientific research and the research for industrial innovation are conducted within different socio-economic structures" (p. 426). The triple helix framework argues that innovative research and education can be produced most effectively when all three helices (government, education and industry) collaborate intensively on innovative projects (Ranga & Etzkowitz, 2013). Part of the strategy put in place by the European commission in 2010 for the upcoming century was strengthening the "knowledge triangle" by promoting knowledge partnerships between education, business research and innovation (Soriano & Mulatero, 2010). In essence this knowledge triangle bears a lot of resemblance to the triple helix framework discussed above, whereby government (in this case the EU) work together closely with universities and firms to produce innovative research and education (Ranga & Etzkowitz, 2013). Balland (2012) finds evidence for his hypothesis that organizations are more likely to collaborate in an R&D project when they have the same institutional form (within the triple helix definition). In line with this, Luo and Deng (2009) - from a strand of management literature on strategic alliances - find evidence for their hypothesis that the percentage of similar partners in a focal firm's portfolio of consortia is curvilinearly related to the focal firm's rate of innovation. In other words, having more similar organisations within consortia a focal firm collaborates in leads to a higher rate of innovation up until a certain point where consortia are too similar to one another which leads to a negative effect on a focal firm's rate of innovation. Triple helix literature however, argues that the most innovative projects have participants from all three institutional forms working together (Ranga & Etzkowitz, 2013). These two theoretical arguments can be combined.
It is hypothesised then, that organisation A is more likely to collaborate on a project containing organisation B which shares the same institutional type according to the triple helix definition than any other project where this isn't the case, because similar organisations lead to higher rates of innovation. At the same time, organisation A (government) is more likely to successfully collaborate on a project containing organisation C (private for-profit industry) and organisation D (education) than any other project where this isn't the case because all three helices of the triple helix are present in said project, which also leads to higher rates of innovation.

Research question and hypotheses

Although there are theoretical grounds for testing all of the propositions proposed above, limitations have caused the selection of four hypotheses for testing. Many of the hypotheses above need specific data to be tested, when the data is not present in a satisfactory way it is best to leave them to be tested when the data at hand is satisfactory.

Taking the theoretical arguments given above and the limitations of the data at hand into consideration, the following research question and hypotheses have been formulated for this study:

RQ: What are the effects of multilateral (spatial and non-spatial) proximities on formation of ties between consortia and organisations under the FP7 "space" programme?

H1: Both FP7 "space" consortia and organisation level proximity measures have an effect on tie formation.

H2: Higher geographical proximity (average distance from coordinator location) between FP7 "space" consortia and FP7 "space" organisations has a positive effect on tie formation.

H3: Higher organizational proximity (less independent organisations) within FP7 "space" consortia has a positive effect on tie formation.

H4: Higher institutional proximity within FP7 "space" consortia (higher participation of unique triple helix institutional forms) has a positive effect on tie formation.

Data and Methods

Sample and network

The FP7 data used in this study contains consortia of "space-based science" organisations that both did and did not successfully receive a subsidy between 2007 and 2013 under the FP7 topic "space". The use of FP data in knowledge network studies is commonplace (For example; Capello & Caragliu, 2018; Balland, 2012; Scherngell & Barber, 2011).
For every organisation there is relevant information on: organisation name, organisation type, organisation role per consortium they participate in, organisation location, organisation SME status, organisation independence status, etcetera. For every consortium there is relevant information on: consortium name, consortium objective, consortium participant names, consortium participants amount, consortium intended duration, etcetera. Most organisations in the sample are situated in EU member states, however, associated non-EU organisations were allowed to collaborate in FP7 "space" consortia as well (Hazir & Autant-Bernard, 2012). The sample used in this study consists of 2818 unique organisations and 659 unique consortia.

The data contains two modes when viewed as a social network; one being organisations and the other being consortia. As argued above, this study will make use of the natural two mode network structure as opposed a converted one mode network structure. Focal firm A's participation in consortium B registers as a tie between A and B, with every organisation participating in consortium B having a tie to said consortium. Focal firm A has ties to every consortium it partakes in, for example consortium B and C. The ties between organisations and consortia are unweighted, meaning ties can't have different values, they simply do or don't exist based on consortia participation.

In this study two networks are analysed, in both networks the total population of organisations in identical, in network S (Successful) only successful consortia are present and in network U (Unsuccessful) only unsuccessful consortia are present. In tables 1 & 2 you can see descriptions of the size of network S and network U. In figures 1 & 2 you can see a visual representation of network S and network U.

Exponential random graph models

Exponential random graph models are stochastic social network models that account for the presence and absence of ties in an observed network (Broekel et al., 2014; Lusher et al., 2013). An underlying assumption of exponential graph modelling is that any observed network is just one manifestation of an unknown amount of hypothetically possible networks with the same characteristics. Exponential graph models estimate the effects that observed network parameters (for example; node level variables a researcher feeds into the model) have on the existence of the observed network as opposed to simulated random networks. Exponential random graph models are well suited to knowledge network research because they don't contain assumptions regarding independence of observations, meaning knowledge networks (which don't total independence of observations because nodes are linked in a network) can be researched without violating assumptions regarding independence of observations like one would when using - for example - a logistic regression (Hazir & Autant-Bernard, 2012). The parameters in an exponential random graph model are most accurately estimated using Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMCMLE), for a detailed explanation see Snijders (2002). Wang et al. (2009) find evidence supporting the use of MCMCMLE to accurately estimate exponential random graph model parameters in bipartite social networks. Thus, in this study, two mode exponential random graph models are used to research the FP7 "space" knowledge network.

Two exponential random graph models are used in this study, both with the same population of organisations but differing populations of consortia, thus making a distinction between successful (consortium received subsidy) and unsuccessful (consortium did not receive subsidy) networks. In the first exponential graph model, only the successful collaborations of organisations within consortia are present (network S), the model estimates the effects that the observed network parameters have on the exist-

Table 1: Network S size

Number of organisations:	2818
Number of consortia:	200
Number of ties:	1987
Number of possible ties:	563600
Network density:	0.0035

Table 2: Network U size

Number of organisations:	2818
Number of consortia:	459
Number of ties:	3917
Number of possible ties:	1293462
Network density:	0.0030

Figure 1: Network S (green circle = organisation, pink diamond = consortium)

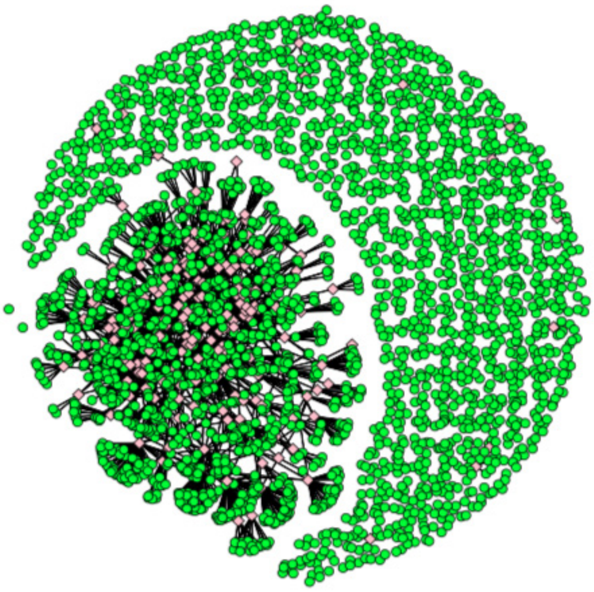
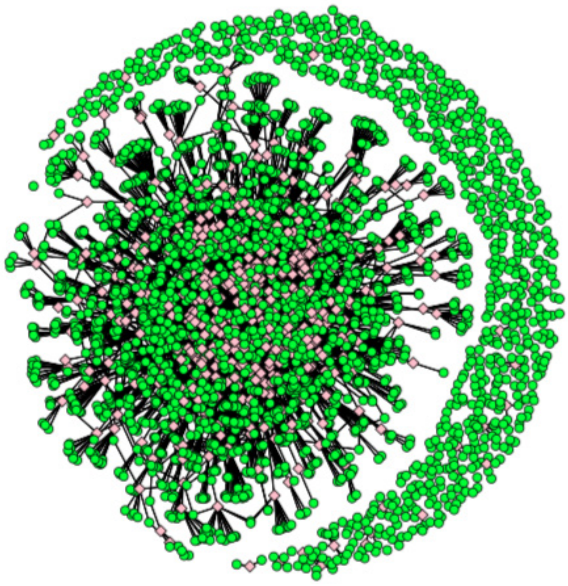


Figure 2: Network U (green circle = organisation, pink diamond = consortium)



ence of the observed successful network as opposed to hypothetical simulated networks. In the second exponential graph model, only the unsuccessful collaborations of organisations within consortia are present (network U), the model will estimate the effects that the observed network parameters have on the existence of the observed unsuccessful network as opposed to hypothetical simulated networks. By running both a successful and an unsuccessful exponential random graph model it is possible to infer differences that spatial and non-spatial proximities have on successful and unsuccessful tie formation in the FP7 "space" knowledge network.

The variables added to the exponential random graph model are operationalizations of spatial and non-spatial proximities and are used to test the hypotheses stated in the theory section above. While all variables that are relevant to the context of this study are discussed on a theoretical level, not all variables could be satisfactorily operationalized within the FP7 "space" data. The variables that could be satisfactorily translated from the theory are discussed below. Next to the variables for testing the stated hypotheses, control variables have been added to the exponential random graph model. Variables in this study fall under three categories; organisation level variables, consortia level variables and network level variables.

Organisation level variables

There are three organisational level variables present in the exponential random graph model, organisation level variables reflect a characteristic of an organisation.

Geographical distance: The first organisation level variable is geographical distance of focal organisation A to the coordinator of consortia B - in which organisation A participates - on the national level. This variable is used to test hypothesis 1, the effect of geographical proximity on the existence of successful ties between organisations and consortia. Geographical distance in kilometres between organisation A and consortia B was calculated using the CEPII distance measures discussed by Mayer and Zignago (2011) which are freely available online.

SME: The second organisation level variable is a measure of whether focal organisation A falls in the category small- and medium-sized enterprise or not. This variable is a control variable. A binary measure-

Table 3: Descriptive statistics for organisational and consortia level variables (network S & U)

Variable	Min.	Max.	Mean	S.D.
Geographical distance	0	18128	1392.609	2086.404
SME status	0	1	0.241	0.428
Independent status	0	1	0.530	0.499
Unique institutional forms	1	3	2.646	0.538
Project duration	3	180	34.266	8.098
Partners per consortia	1	69	12.638	11.819

ment of whether a firm falls in the category small- and medium-sized enterprise is present in the data.

Independent: The final organisation level variable is a measure of whether focal organisation A is an independent firm or whether focal organisation A is a sister or daughter firm to another firm in the data. A binary definition of whether a firm is independent or not is present in the data.

Consortia level variables

There are three consortia level variables present in the exponential random graph model, consortia level variables reflect a characteristic of a consortium.

Unique institutional forms: The first consortia level variable is a measure of the amount of institutional forms (three being a full triple helix configuration) in focal consortium B by counting the amount of unique institutional forms in focal consortium B. This variable is used to test hypothesis 4, the effect of higher institutional proximity (higher participation of unique institutional forms) on the existence of tie formation between organisations and consortia. This variable is calculated using the amount of unique institutional forms in focal consortium B, when the amount of unique institutional forms is three a triple helix is present in focal consortium B.

Project duration: The second consortia level variable the duration of the FP7 "space" project focal consortium B is working on in months. This variable is a control variable. A measure of the duration of projects in months is present in the data.

Partners per consortia: The third consortia level variable is the amount of organisations participating in focal consortium B. This variable is also a control variable. This variable is constructed by calculating the amount of organisations participating in consortia.

Network level variables

There are three network level variables present in the exponential random graph model, network level variables reflect a structural characteristic of the network as a whole.

Edges: The first network level variable is the amount of edges in the observed network, this variable should always be included in an exponential random graph model and has similarities to the intercept in a regression model (Broekel & Hartog, 2013). The edges variable is calculated by the exponential random graph model when handed the FP7 "space" network data.

Concurrent nodes: The second and third network level variables are networks statistics equal to the amount of nodes in the network with a degree of 2 or higher also known as the concurrent node count (Morris et al., 2008). This variable is added to the model for both modes, organisations and consortia. These variables are control variables. The concurrent node count variables are calculated by the exponential random graph model when handed the FP7 "space" network data.

Empirical results

The results of the models of network S and U can be seen in tables 4 and 5. Both models converge properly, which is important for reliable exponential random graph model results (Broekel & Hartog, 2013). Both models show horizontal parameter traces which can been seen in the appendix 2 & 3. The goodness of fit summary for both models can be found in the appendix 1, the model for network S fits the sample better than the model for network U.

In the model for network S, support is found for hypotheses 1 & 4. In the model for network U, support is found for hypotheses 1, 3 & 4. It is useful to look at the overall trend of MCMCMLE estimates before analysing the results one by one. As discussed in the theory and hypothesized in hypothesis 1, both organisation level and consortia level measures of proximity have significant effects on tie formation in the models for network S and U. However, all consortia level variables have a significant effect on tie formation in both models as opposed to the organ-

Table 4: Exponential random graph model estimates for network S

Variable	Estimate	Std. error
Organisation level		
Geographical distance	6.089*	2.636
SME status	-3.949	1.006
Independent status	9.635	1.037
Consortia level		
Unique institutional forms	1.814***	8.385
Project duration	-3.314***	7.861
Partners per consortia	-6.829**	2.601
Network level		
Edges	-1.093***	2.712
Concurrent nodes organisations	9.825***	8.859
Concurrent nodes consortia	-3.314***	1.158
Null deviance	781316 on 563600 degrees of freedom	
Residual deviance	2606 on 563591 degrees of freedom	
AIC	2624	
BIC	2725	

Note: *** p<.001, ** p<.01, * p<.05

Table 5: Exponential random graph model estimates for network U

Variable	Estimate	Std. error
Organisation level		
Geographical distance	1.447	1.247
SME status	7.293	3.594
Independent status	-1.145**	4.245
Consortia level		
Unique institutional forms	1.613***	3.587
Project duration	-9.649***	2.764
Partners per consortia	-1.674**	6.440
Network level		
Edges	-6.989***	1.296
Concurrent nodes organisations	1.539***	4.781
Concurrent nodes consortia	-2.924	5.846
Null deviance	1855624 on 1338550 degrees of freedom	
Residual deviance	13340 on 1338541 degrees of freedom	
AIC	13358	
BIC	13467	

Note: *** p<.001, ** p<.01, * p<.05

isation level variables where only one variable has a significant effect on tie formation per model (distance in network S and independence in network U).

Organisation level

In network S, geographical distance between participating organisations and consortia coordinators (hypothesis 1) has a significant positive effect on successful tie formation (6.089, p<.05), a result which goes against many empirical studies (Scherngell & Barber, 2009; Broekel & Hartog, 2013; Audretsch & Feldman, 1996; Jaffe et al., 1993; Maggioni et al., 2007). In network U, geographical distance between participating organisations and consortia coordinators (hypothesis 1) does not have a significant effect on unsuccessful tie formation.

Whether an organisation is independent or not (hypothesis 2) does not have a significant effect on successful tie formation in network S. In network U, independence of organisations has a significant negative effect on unsuccessful tie formation (-1.145, p<.01). This implies that independence of organisations (higher organisational proximity) is characterised by less unsuccessful links. Partial support for hypothesis 2 is found.

In network S, whether an organisation is counted as an SME or not does not have a significant effect on successful tie formation. In network U this is also the case. This implies that the size of an organisation doesn't have an effect on how often said organisation collaborates.

Consortia level

In network S, the amount of unique institutional forms within consortia (hypothesis 4) has a significant positive effect on successful tie formation (1.814, p<.001), supporting hypothesis 4. This result implies that a triple helix configuration in consortia leads to more successful ties between said consortia and organisations. In network U, the increase of triple helix institutional forms within consortia (hypothesis 4) has a significant positive effect on unsuccessful tie formation (1.613, p<.001), supporting hypothesis 4. The fact that positive estimates for increase of unique triple helix institutional forms were found in both network S and U raises the point whether more or larger collaborations are always positive in economic sense when ignoring the successfulness of said collaborations.

The intended duration in months of FP7 "space" consortia has a significant negative effect on successful tie formation in network S (-3.314, p<.001). In network U, the intended duration of FP7 "space" consortia also has a significant negative effect on unsuccessful tie formation (-9.649, p<.001). This implies either that organisations that plan to work together for longer would rather keep their consortia smaller or less organisations are interested in committing themselves to a longer collaboration.

The amount of partners in FP7 "space" consortia has a significant negative effect on successful tie formation in network S (-6.829, p<.01). In network U, the amount of partners in FP7 "space" consortia also has a negative significant effect on successful tie formation (-1.674, p<.01). This implies that organisations are less likely to collaborate in a consortium as the size of said consortium increases.

Network level

In both network S and U, the edges statistic has a significant negative effect on tie formation (-1.093, p<.001; -6.989, p<.001). This means that both in the successful and the unsuccessful network, networks with a higher amount of edges are less likely.

In network S, the concurrent node count for mode 1 (organisations) is significant and positive, meaning that organisations with concurrent ties are relatively more likely to occur (9.825, p<.001). For mode 2 (consortia), the effect is significant and negative (-3.314, p<.001), meaning that consortia with concurrent ties are relatively less likely to occur in network S. In network U, the concurrent node count for mode 1 is also significant and positive (1.539, p<.001). The effect for mode 2 is also significant and negative in network U (-2.924, p<.001).

Conclusion & discussion

The main aim of this study is twofold, firstly; to bring bilateral proximity measures to a multilateral level in a theoretically sound manner. By using a mix of proximity, embeddedness, resource dependence and resource-based view literature, geographical, cognitive, organizational, social and institutional (both forms) proximity were translated from bilaterally focussed to multilaterally focussed testable hypotheses. However, due to data technical reasons and to keep this study concise only a selection of stated hypotheses were tested. Future studies could (and should if possible) focus on testing all stated multilateral proximity hypotheses (Boschma, 2005).

Secondly; to make a distinction between successful and unsuccessful collaboration in knowledge networks. These objectives were applied to and empirically tested on a successful (S) and an unsuccessful (U) knowledge network in the FP7 "space" programme using exponential random graph models. Full support was found for hypotheses 1 & 4, partial support was found for hypothesis 3 and no support was found for hypothesis 2, the hypotheses and the corresponding results will be discussed in this order. Hypothesis 1 stated that both FP7 "space" consortia and organisation level proximity measures would have an effect on tie formation, which was the case for both models. Especially the highly significant consortia level effects in both models illustrate the importance of analysing networks in a multilateral (or bipartite) manner. Coercing a network that is naturally bipartite into a one mode network and then handing organisations group level attributes can result in an oversimplification of knowledge networks (Borgatti & Everett, 1997). To investigate the difference between two mode models and coerced one mode models, future studies could perform a side by side comparison of the two methods.

Hypothesis 4 stated that higher institutional proximity (unique institutional forms) within FP7 "space" consortia would have a positive effect on tie formation in both models of network S & network U. As discussed briefly in the results, the exclusion of some measure of value in knowledge network collaboration hypotheses can lead to hypothesis 4 - similar hypotheses are often used in knowledge network studies - to find support both in a network that is successful in receiving a subsidy (often studied) and in a network that is not successful in receiving a subsidy (less often studied). This calls into question the economically productive nature often attributed to - for example - triple helix collaboration (or other proximate collaboration forms) when it has a positive effect on the formation of ties that can be seen as successful and unsuccessful. In a more general sense, organisation and consortia characteristics that have a positive effect on tie formation (or collaboration) in innovative knowledge networks should not blindly receive subsidies without questioning whether the characteristic at hand increases successful or unsuccessful tie formation between - for example - consortia and organisations.

Hypothesis 3 stated that higher organizational proximity (less independent organisations) within FP7 "space" consortia would have a positive effect on tie formation. Support for hypothesis 3 was only found in the model for network U. This means that organisations that are legally tied to another FP7 "space" organisation are more likely to form unsuccessful ties than organisations that are not. This result goes against Uzzi's influential article "The Sources and Consequences of Embeddedness for the Economic Performance of Organizations: The Network Effect", which argues that the more embedded ties a focal organisation has (up until a certain point) the higher the economic effectiveness of said organisation (Uzzi, 1996).

Hypothesis 2 stated that higher geographical proximity (average distance from coordinator location) between FP7 "space" consortia and FP7 "space" organisations would have a positive effect on tie formation. The absence of support for hypothesis 2 is striking due to the sheer amount of studies in which this hypothesis finds support (for example; Scherngell & Barber, 2009; Broekel & Hartog, 2013; Audretsch & Feldman, 1996; Jaffe et al., 1993; Maggioni et al., 2007). A possible explanation could be one of the conditions FP7 "space" consortia must satisfy, stating that there must be at least three organisations from different member states present in a consortium (Hazir & Autant-Bernard, 2012) thus artificially increasing the distance across which collaborations take place.

This study contains several limitations. Firstly, due to limitations in the data, not all hypotheses stated in the theory section could be tested. In future research, if scholars have access to broader data, scholars could (and if possible, should) test and then refine all multilateral proximity hypotheses (Boschma, 2005). Secondly, because the FP7 "space" programme is a manifestation of policy trying to achieve cross-border collaboration and strengthening of "space-based science" organisations, the results found aren't in a vacuum where policy is non-existent, and thus have to be interpreted within this context. Thirdly, the data used to measure geographical distance was at the country level, in an ideal situation one would use a finer level measurement of geographical distance, NUTS3 (the current smallest geographical unit in the European NUTS classification) for example.

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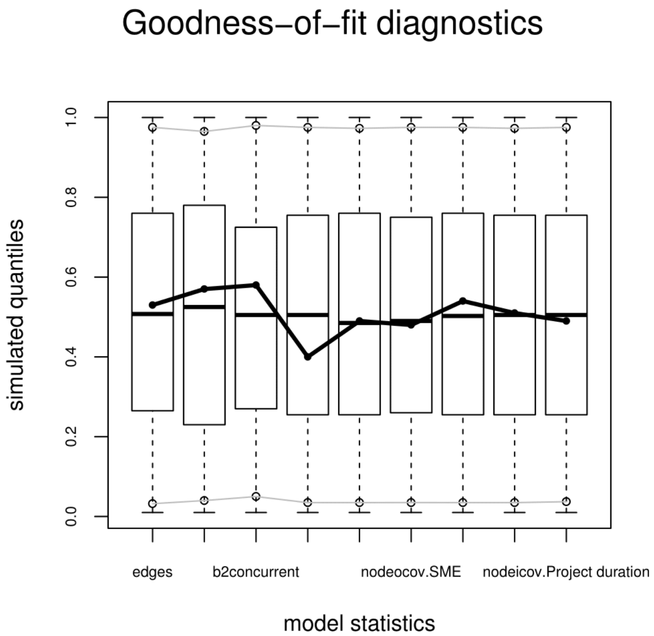
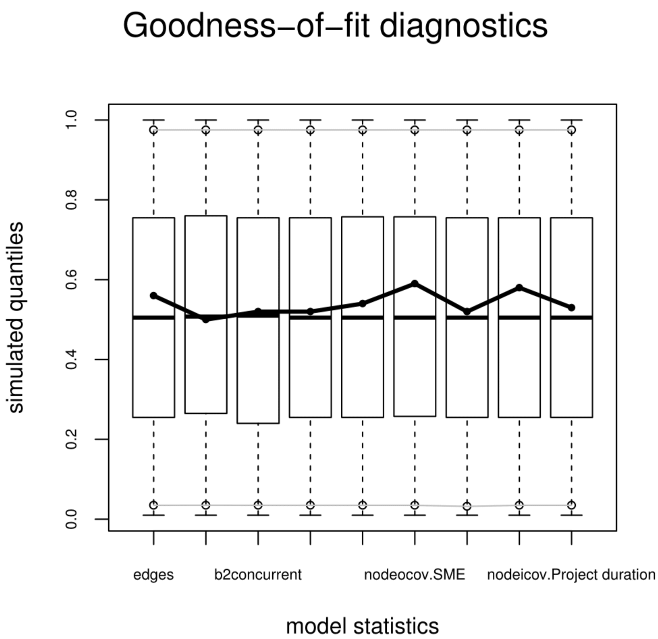
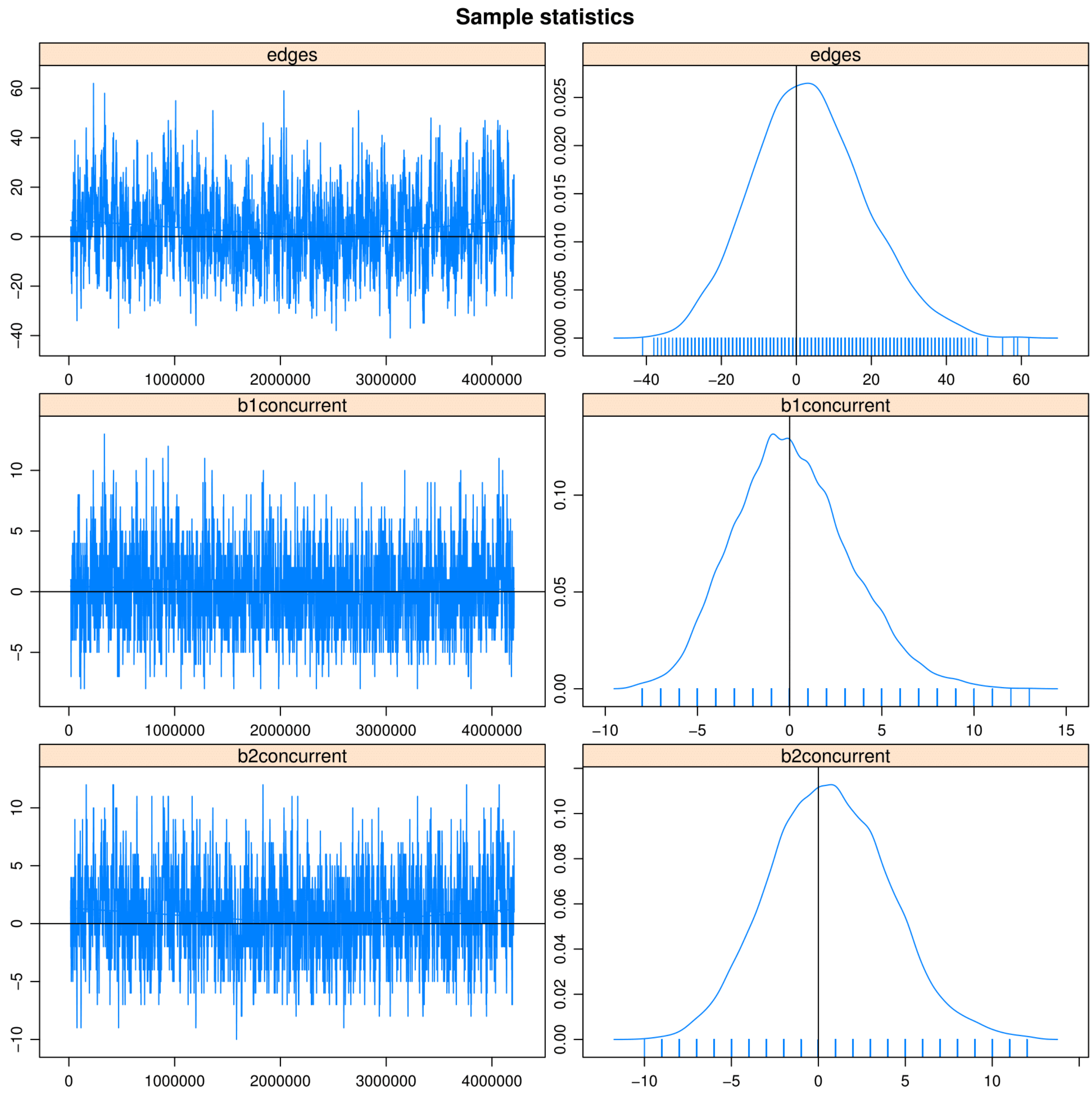
Appendix

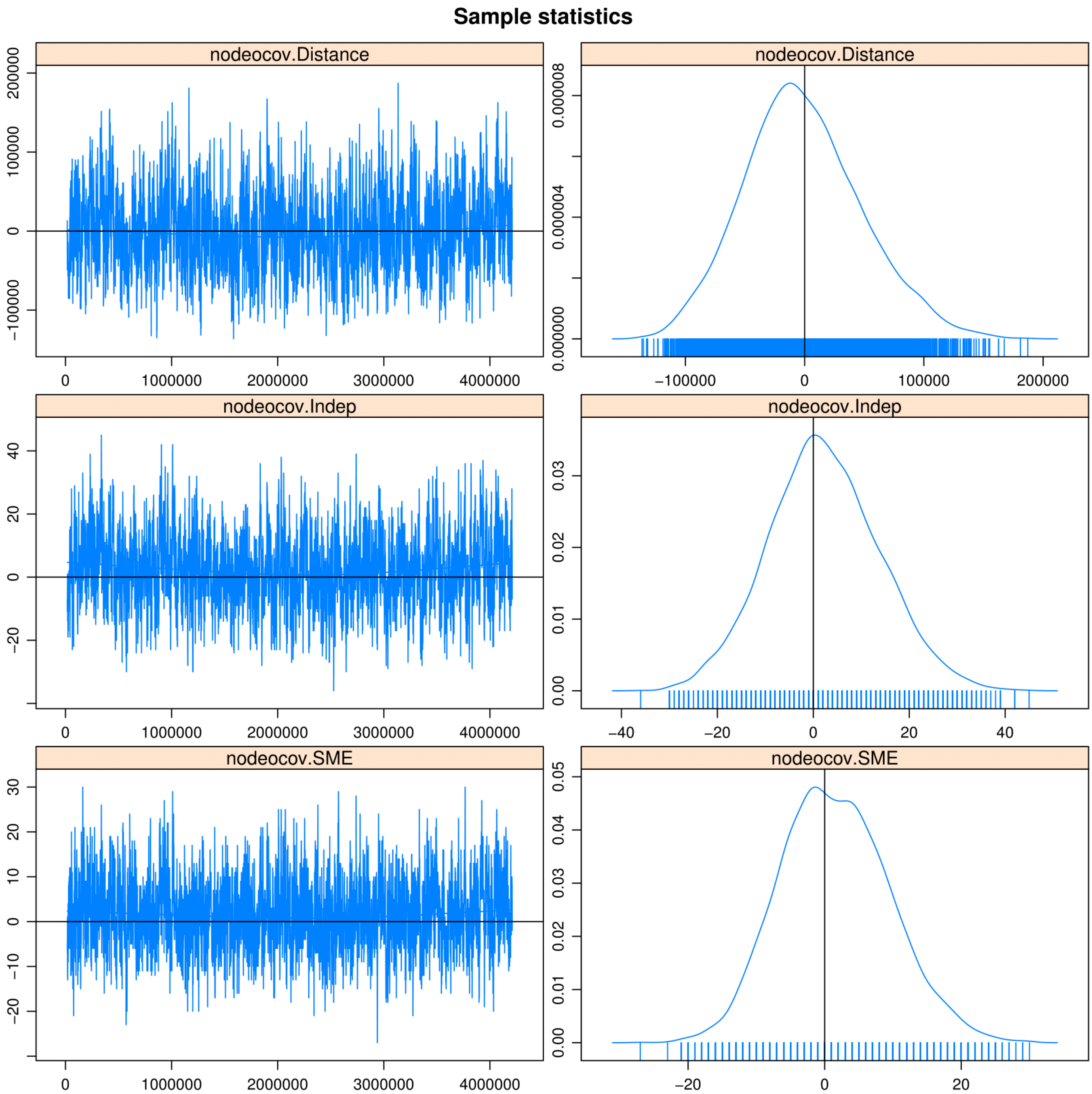
Appendix 1: Goodness of fit diagnostics network S (left) & network U (right)





Appendix 2: Parameter traces Network S

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100000
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0.000000
0.000004
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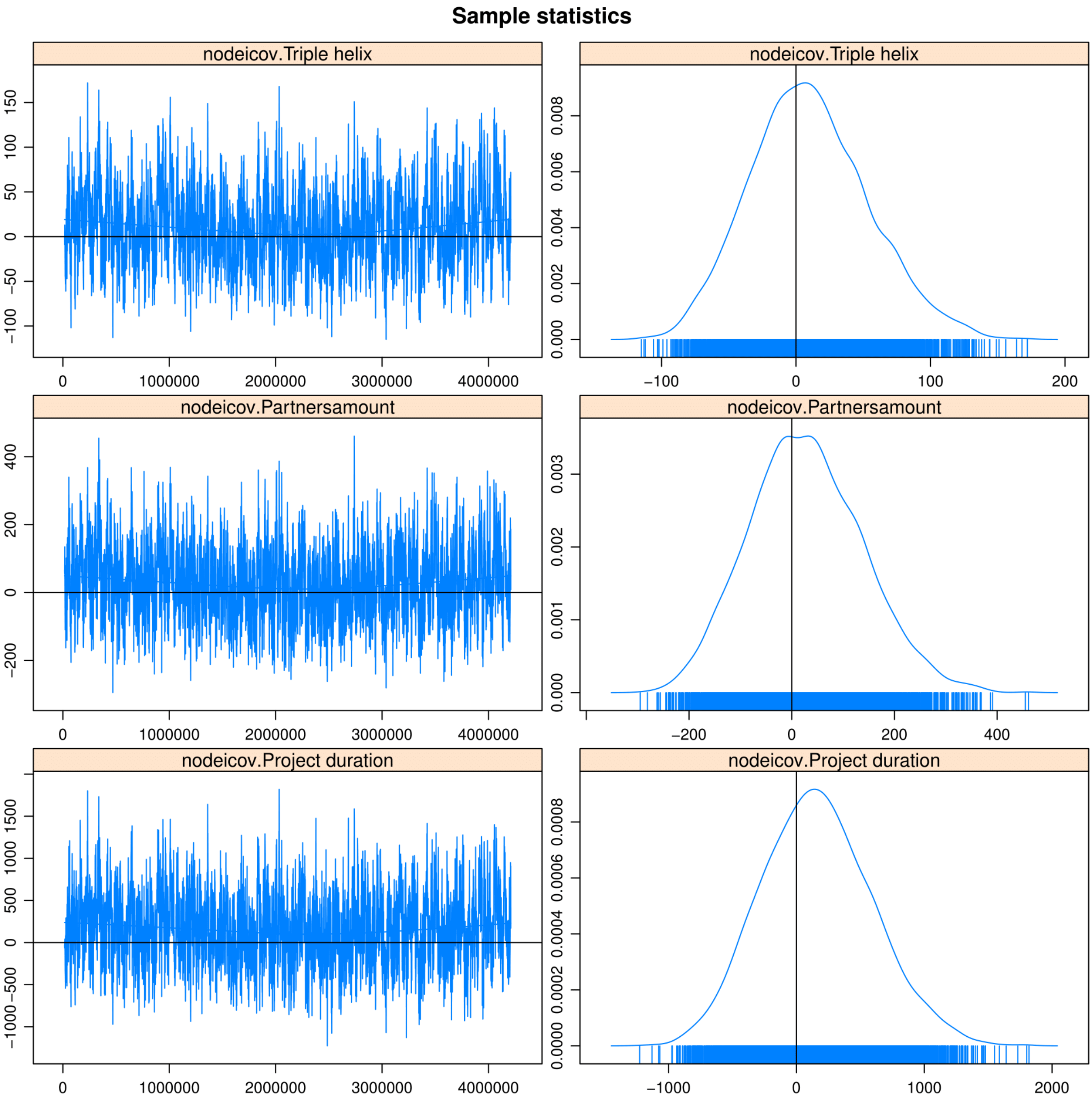
0.05
30
10
−10



Sample statistics
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nodeicov.Triple helix
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nodeicov.Project duration
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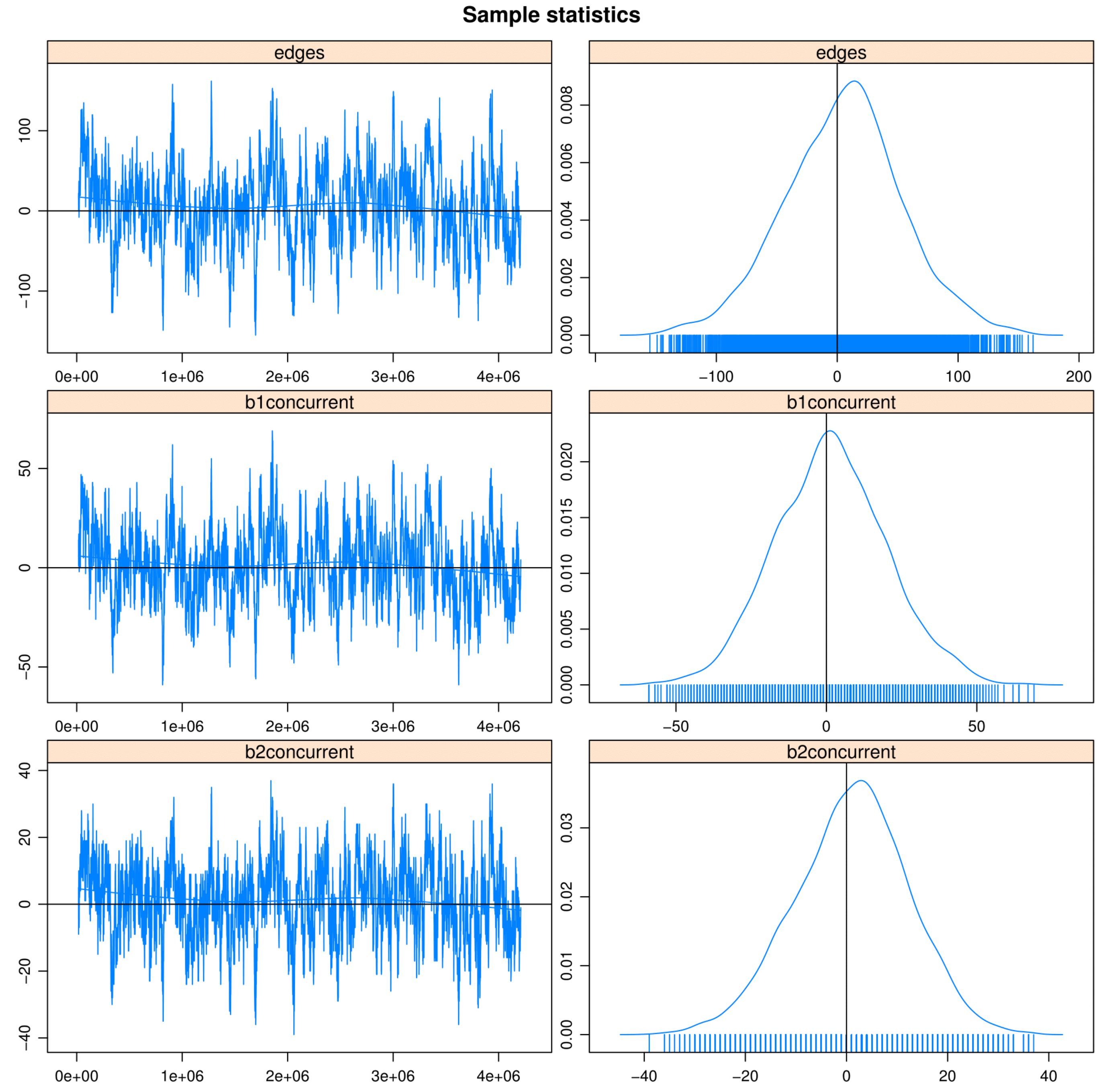
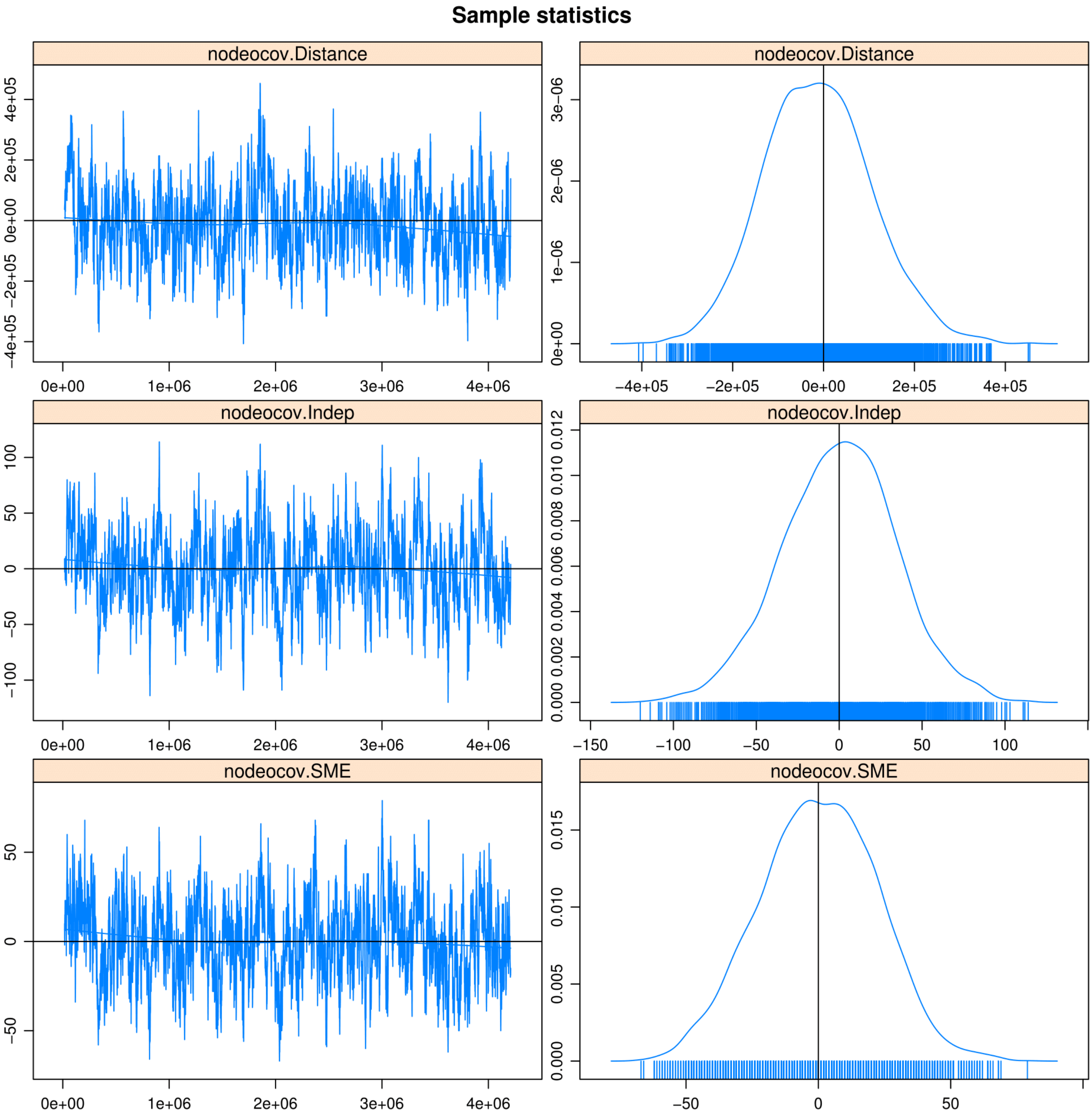
1000
2000

Appendix 3: Parameter traces Network U

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3e+06
4e+06
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−2e+05
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2e+05
4e+05
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−100
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0.010
0.015

Sample statistics