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The Bright and Dark Side of Cooperation for Regional Innovation Performance

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Abstract:
Studies analyzing the importance of intra- and inter-regional cooperation for regional innovation performance are mainly of qualitative nature and focus strongly on the positive effects that high levels of cooperation can yield. For the case of the German labor market regions and the Electrics & Electronics industry the paper provides a quantitative-empirical analysis taking into account the possibility of negative effects related to regional lock-in, lock-out, and cooperation overload situations. Using conditional nonparametric frontier techniques and cooperation behavior measures we find positive as well as substantial negative effects of cooperation with the latter being induced by excessive and unbalanced cooperation behavior.

Keywords: Regional innovation performance; cooperation; lock-out; lock-in; cooperation overload

Jel codes: R12; O18; O31

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1 Introduction

In the literature on regional innovation processes it is frequently emphasized that cooperation in general and intra-regional cooperation in particular, can foster innovation performance by triggering collective learning processes (see, e.g., Cooke et al., 1997; Asheim, 2001). It is also well known that intensive intra-regional cooperation which is not accompanied by sufficient inter-regional linkages can yield lower innovation performance (Bathelt et al., 2004). In extreme cases this can generate regional lock-in situations (Camagni, 1991). In light of this it can be argued that cooperation can have a 'bright' side in fostering actors' innovation activities. At the same time it can be characterized by a 'dark' side inducing negative effects. This 'dark' side can not only take the form of a lock-in, but there might also be situations in which actors are well embedded into inter-regional knowledge 'pipelines' but fail to develop local cooperation, i.e. they are locked-out from local networks.

There are numerous studies investigating the role of cooperation activities for regional innovation performance, which provide evidence for the positive effects of cooperation (see, e.g., Asheim and Isaksen, 2002; Boschma and ter Wal, 2007). However, the empirical picture is still mainly of qualitative nature, i.e. it is based primarily on case study research. The few existing quantitative approaches are additionally restricted in covering a limited number of regions only (see Frenkel and Schefer, 1998; Sternberg and Arndt, 2001; Oerlemans and Meeus, 2005) and find not always evidence for a conducive role of cooperation (Fritsch, 2004).

This paper contributes to the literature by providing a quantitative empirical analysis of the effects of intra-regional and inter-regional cooperation on regional innovation performance on the basis of the 270 German labor market regions and the Electrics & Electronics industry in 1999-2002. Moreover, we make use of the recently developed cooperation behavior measures by Cantner and Meder (2008) that account for the existing cooperation potential. Following critiques on the use of production function approaches by Bonaccorsi and Daraio (2006) and Broekel (2008) in this context, a robust nonparametric production frontier technique is employed. In addition to its methodological advantages, its nonparametric nature allows for an unrestricted exploration of the relationship between cooperation behavior and innovation performance.

In general, we find that 'bright' and 'dark' sides of intra- and inter-regional cooperation behavior exist. The influence on regional innovation performance shows to be curvilinear such a way that below a certain intensity level, cooperation of either kind, yields positive effects. If the level of cooperation behavior increases beyond this point the performance decreases. The results also support that to some extent intra-regional and inter-regional cooperation are complements, i.e. it requires a certain level of both for innovation performance to be fostered. This goes hand in hand with the found low innovation performance in the case of regional lock-in and lock-out situations. By this means the paper provides empirical evidence that a too strong focus on either intra- or inter-regional cooperation hampers innovation performance.

The analysis hints further at that regional lock-ins can be avoided by a supportive regional factor endowment, e.g. the presence of universities and large firms.

The paper is organized as follows. Section 2 gives an overview of the literature on cooperation and regional innovation performance. In Section 3, the empirical methodology is described in detail. The employed data on intra- and inter-regional cooperation, input factors, and innovative output are presented in Section 4. The results of the empirical analyses are described and discussed in Section 5. Section 6 concludes.

2 Cooperation and innovation

2.1 The influence of cooperation on innovation activities

In the field of economic geography, cooperation has been recognized as being a crucial element for influencing regional innovation performance. In particular, two phenomena have drawn researchers' attention: firstly, it has been shown that some regions' outstanding innovation performance can be attributed to intensive inter-firm cooperation and the existence of a location specific cooperation culture that fosters collective intra-regional learning processes (Asheim and Isaksen, 2002). This observation stimulated the vast literature on 'innovative milieus' (Aydalot and Keeble, 1985) and 'regional innovation systems' (Cooke, 1992). These strands of literature mainly conclude that higher levels of intra-regional cooperation induce higher innovation performance.

Secondly, it is argued that a strong focus of actors' cooperation activities on intra-regional partners can have negative effects. Taken to an extreme this can result in *regional lock-in* situations (Camagni, 1991).[1] Here, regional innovation performance is reduced unless access to non-regional knowledge networks provides fresh ideas helping to avoid and overcome these situations (Camagni, 1991; Asheim and Isaksen, 2002). Hence, in order to raise their innovation performance actors need to participate in "local buzz" while having simultaneously access to "global pipelines" of knowledge (Bathelt et al., 2004).

The opposite case of the lock-in situation has not drawn much attention in the literature so far. In this case, regional actors participate strongly in inter-regional knowledge exchange but fail to develop intensive intra-regional cooperation. The theoretical argument for such a situation is that it takes efforts to establish and maintain networks. Because "geographical proximity only creates a potential for interaction, without necessarily leading to dense local relations" (Isaksen, 2001, p. 110), this is irrespectively of whether the networks include regional or non-regional actors.[2] If actors are not willing or capable of realizing the efforts needed to establish and maintain their membership in regional knowledge networks they are 'locked-out' from the benefits that geographic proximity brings about for knowledge sharing and collective learning processes. Taken to an extreme in which a large

[1] In contrast to the also well-known *lock-in* described for the case of the Ruhr-Area by Grabher (1993) here the spatial dimension is at the center.

[2] This relates to the recent debate on the importance of *places* or *networks* (Castells, 1996). The importance of *places* refers to the idea that mere location, or co-location with other relevant actors, matters for firms' innovation performances. In the *network* argument it is pointed out however that interactive learning and innovation is about being member of the right network (see also Boschma and ter Wal, 2007).

number of regional actors do not participate in intra-regional networks a situation of a 'lock-out' situation can arise. Because of the missing local knowledge sharing and learning processes it can be hypothesized that regions in this situation are likely to show comparatively low innovation performance.

In addition to the missing discussion of a lock-out phenomena, the literature on cooperation and regional innovation performance builds mainly on theorizing and qualitative evidence which moreover concentrates strongly on 'extreme' positive or negative cases. There are few studies that explicitly analyze in a quantitative-empirical manner, the relationship between the level of intra-regional cooperation activities and regional innovation performance. Most of these studies rely though on data collected for a small number of regions. For example, Sternberg and Arndt (2001); Fritsch (2004) analyze eleven European regions, and Oerlemans and Meeus (2005) four regions in the Netherlands. While Sternberg and Arndt (2001) and Oerlemans and Meeus (2005) find that intra- and inter-regional cooperation is important for firms' innovation performances, the results by Fritsch (2004) do not support the hypothesis of a conducive role of cooperation for innovation activities. Though, he focuses on intra-regional cooperation only.

Thus, while there is a rich empirical literature the empirical picture on how the levels of intra- and inter-regional cooperation relate to regional innovation performance is still largely unclear. The literature suggests in general to expect 'bright' and 'dark' side effects of the level of cooperation for regional innovation performance: increasing cooperation activities can induce higher innovation performance. This can however be conditional on the actual interplay between intra- and inter-regional cooperation activities as lock-in and lock-out situations are likely to bring about comparatively low innovation performance.

2.2 An empirical challenge

What the literature on cooperation and innovation performance additionally highlights is the complexity of the relationship between the two.[3] This shows in that e.g., it is of little value to investigate intra-regional cooperation activities separately from inter-regional cooperation activities. The lock-in scenario illustrates this nicely in which it is not so much the strong intra-regional orientation that reduces innovation performance, but rather the *missing* non-regional linkages. When empirically analyzing the impact of intra-regional cooperation on innovation performance, inter-regional cooperation therefore have to be simultaneously taken into consideration (Breschi and Lissoni, 2001; Bathelt et al., 2004). The combined effect of these two types of cooperation activities on actors' innovation performances is labeled *cooperation* effect in the following. It depends in a complex way on the actors' and regions' characteristics, see Fig. 1.

In this paper we are interested in the *cooperation behavior*, i.e. the cooperation culture of the re-

[3] In the following we concentrate on cooperation activities only while some of the arguments presented before referred to networks. We acknowledge though that the latter includes more than cooperative interactions. Nevertheless, cooperation are a crucial element of networks.

gional actors, which is learned and motivated by economic, but also by cultural, political, or ideological reason (Cooke et al., 1997). Hence, it is the aim to analyze the impact of inter-regional differences in the actors' cooperation behavior on regional innovation performance controlling for the existing possibilities to cooperate and innovate. Such requires the disentangling of the effects shown in Fig. 1.

So is the observed level of the *cooperation* effect, besides actors' *cooperation behavior* conditional on the regional endowment with other actors. Trivially, it needs at least additional actors in a region that can serve as potential cooperation partners. Lacking opportunities to cooperate intra-regionally, firms are forced to expand their search for cooperation partners to more geographically distant locations. In the opposite case, actors located in regions with a sufficient number of potential cooperation partners are likely to be less interested in engaging in inter-regional cooperation. This relationship between the regional potential to cooperate and the number of actually realized intra- and inter-regional cooperation is called *cooperation potential* effect in the following. According to Cantner and Meder (2008) it is mainly shaped by the technological profile of the actors located in a region. In this sense, some of the regional characteristics, e.g. the cooperation potential, are an aggregate of the actors' characteristics located in it (dashed arrow in Fig. 1). This is however only of conceptual importance. In contrast, it is crucial that in addition to the *cooperation potential* effect, the regional environment can directly influence actors' innovation activities without that necessarily cooperation come into play.

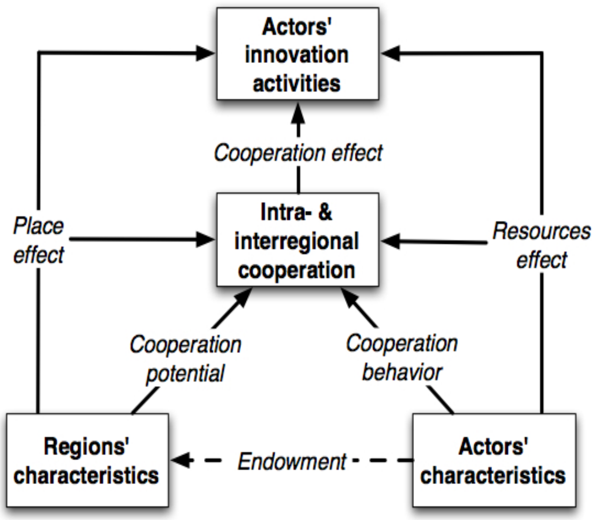

Figure 1: Effects on innovation activities

Certain firm external but regional factors can contribute to firms' innovation performances through various (non-cooperation based) mechanisms. For example, a local university can offer possibilities to share laboratories, or promotes the access to human capital. In this case, firms' innovation activities benefit from the mere co-location to the university. This reflects the *place* argument according to which (largely independently from the actors' activities) being in the right place is all that matters (see for a discussion Castells, 1996). It shows as that actors located in regions with more favorable conditions achieve higher levels of innovation performances independently of their cooperation activities. The conditions include e.g., the presence of organizations offering consulting and financial support, the existence of a well-developed science & technological infrastructure, and the availability of human capital, etc. (see, e.g., Feldman and Florida, 1994; Audretsch, 1998).

Some of these regional factors may additionally take effect on the ability of actors' to exploit the given cooperation potentials. For example, a university may function as gatekeeper and take effect on the likelihood that regional firms cooperate intra- and inter-regionally (Graf, 2007). Hence, a region's characteristics may influence actors' innovation activities directly, but also indirectly by taking effect on the exploitation of the regional cooperation potential which in turn has an impact on the innovation activities through the *cooperation* effect. As both influences do not require necessarily efforts made by actors, they are combined as *place* effect.

Lastly, it is well known that, even within the same industry, firms are heterogeneous and that this influences their likelihood to participate in cooperation and innovation activities (see, e.g., Boschma and ter Wal, 2007). In the context here, the heterogeneity of their 'absorptive capacities' is particularly relevant which determines their ability to access, absorb, and employ external knowledge (Cohen and Levinthal, 1990). In other words, actors' differ with respect to the capability to cooperate intra- and inter-regionally. In addition, they are heterogeneous regarding the resources dedicated directly to innovation activities. This in fact constitutes the most important determinant of the innovative output. The influence related to the actors' characteristics are defined as *resources* effect as they are likely to be dependent on the resources available and actually invested into the mentioned activities.

Because we want to analyze the effect of actors' cooperative behavior on their innovation performance free of existing internal and external restrictions, we need to separate it from all the other effects. Moreover, the mentioned possibilities of a 'bright' and a 'dark' side of intra- and inter-regional cooperation activities have to be taken into consideration in the empirical assessment. In the following it is shown how this can be accomplished by employing a non-parametric production frontier approach. It allows us to control for the *place* and *resources* effect. Further, by using co-operation measures that control for the *cooperation potential* effect, we can analyze the effect of actors' *cooperation behavior* on regional innovation performance.

3 Method

3.1 Nonparametric frontier analysis

Recently, it has been argued that in contrast to traditional production function approaches (e.g., regression models), applying production frontier techniques in general, and non-convex, nonparametric production frontier techniques (NNPF) in particular, is more appropriate for analyzing (regional) technology and innovation systems (Bonaccorsi and Daraio, 2006; Broekel, 2008). This is motivated by the fact that the NNPF relaxes a number of critical assumptions that are inherent to parametric production function approaches. For example, its nonparametric nature reduces the risk of mis-specification. Moreover, in this approach, the performance is not estimated on the basis of an universal pre-defined functional relationship between regional characteristics and innovation outcome. Instead, the relationship is allowed to differ between regions. Regions are also evaluated with respect to *best practice* instead of being compared to *average practice* which makes the approach more interesting for policy implications (see for an extensive treatment Broekel, 2008).

Following Broekel (2008) we employ the non-convex order-m frontier approach introduced by Cazals et al. (2002) in order to calculate regions' innovation performances. In addition, the *conditional* order-m analysis developed by Daraio and Simar (2005a,b) and extended to a multivariate scenario by Daraio and Simar (2007), is used for estimating the influence of the two types of cooperation behavior on innovation performance.

Similar to the traditional production function approaches (e.g. the knowledge production function), the starting point is that innovations do 'not fall from heaven' but are results of economic efforts. For analyzing innovation performance this implies that the innovation outcome has to be seen in relation to the efforts made into innovation activities. With respect to regional innovation performance, we differentiate between firm internal efforts, regional factors that are relevant for firms' innovation activities, as well as the aggregated innovations of regional firms. While the first two can be conceptualized as *input factors* is the latter are seen as *innovative output*.

The idea behind the NNPF approach is that a region's innovation performance is evaluated with respect to the performance of other regions. In a first step, the frontier function is estimated. This frontier consists of the *best-practice* regions given a certain level of input factors. In the NNPF *best-practice* is identified using the principle of *weak dominance*. This means that all regions are tested for whether there are regions with an equal or lower level of input factors that show higher levels of innovative output, though. All regions that dominate a specific region in this manner make a region's *reference group*.

If no dominating regions are found for a region, it becomes part of the frontier and it is declared well performing. If the *reference group* contains regions except itself, the region is located below the frontier and declared less performing. The distance to the frontier indicates its degree of (less) performance. Here, this distance (the performance measure) is represented by the vertical (euclidean) distance between the observations and the frontier. The larger the distance the less performing is a region.[4] Hence, by using this dominance principle there is no need to specify ex-ante a functional relationship between the input factors and the innovation output measures.

The described type of frontier is used in the traditional Free Disposal Hull (FDH) approach developed by Deprins et al. (1984). It is however determined by the extreme positive *best-practice* observations making the performance analysis very sensitive with respect to the existence of outliers and noise in the data (see, e.g., Wilson, 1993). This drawback has been overcome by the introduction of *robust* nonparametric frontier techniques (see for an introduction Daraio and Simar, 2007). One of the *robust* versions of the FDH approach is the order-m frontier approach developed by Cazals et al. (2002). In contrast to the FDH approach, the idea behind the order-m approach is that instead of evaluating a region's innovation performance with respect to the performance of *all* other regions, it is compared a to a randomly drawn (sub-) sample of regions showing equal or lower levels in the

[4] This view corresponds to the output-oriented type of analysis which has been argued to be most appropriate in this context by Broekel and Brenner (2007).

input factors.[5] The nonparametric frontier function becomes a *partial* frontier because not all observations are enveloped but only a sub-sample. Based on the partial frontier the evaluation of regions' innovation performance as well as the estimation of the performance scores are done as presented above.

3.2 Analyzing the effect of cooperation on innovation performance

In order to empirically estimate the impact of certain variables, (denoted as 'external factors') on this kind of performance measure, Daraio and Simar (2005a) suggest the estimation of two different measures. The first, the *unconditional* performance measure, is calculated as described above: regions are evaluated with respect to a randomly drawn sub-sample of other regions which are characterized by equal or lower levels in the input factors.

The second measure, the *conditional* performance measure, is estimated similarly to the unconditional one. In this case the sub-sample of regions, with equal or lower levels of input factors, used for the comparison is not drawn randomly. Instead, it is drawn conditional on the values (density) of the external factors.[6] The conditional drawing is done in a way that the sample of regions by which a region's performance is evaluated is positively biased towards those regions with similar values in the external factors. In other words, the likelihood that a region is part of another region's comparison group, depends negatively on the difference between the values of the regions' external factors.

Further, the ratio between the conditional and unconditional performance measures Q_z is set into relation with the regions' values in the external factors. From this relation inference can be made on the effects of the external factors on the regional innovation performance. In a setting with two external factors analyzed at the same time, Daraio and Simar (2007) suggest to estimate three-dimensional regression plots showing the non-parametrically estimated surfaces of Q_z in dependence of the two external factors. In addition, non-parametric regressions are conducted for different sub-samples. This allows a more detailed analysis the relationship between the external factors and Q_z.

From the shape of the surfaces and curves the following inference can be made. An increasing regression surface (curve) indicates a positive influence, while a decreasing surface (curve) hints at a negative impact. In this paper, the intra-regional and inter-regional cooperation behavior are defined as two external factors that take effect on the regions' innovation performances.

The performance analyses are conducted separately for each year. However, the subsequent analyses of the influences of the two cooperation types are conducted on the basis of the pooled yearly performance measures. Hence, in the plots, and the estimated regressions, each region is represented

[5] The sub-sample's size has to be specified by the researcher and is denoted by m, giving the name to the procedure. We follow Bonaccorsi et al. (2005) in setting the level of robustness to below ten percent, i.e. ten percent of the units are outside the frontier. Given 258 valid observations this is true for $m = 70$.

[6] For the estimation of the probability we use the truncated gaussian kernel as well as the bandwidth selection method for multivariate cases given in Daraio and Simar (2007).

as many times as years are considered.[7] The motivation for this is that by using the pooled ratios the impact of short term change (statistical noise) is reduced.[8] Moreover, the robustness of the nonparametric regressions used to illustrate potential trends in the data is increased.

From a methodological point of view such an endeavor is appropriate if the underlying mechanisms determining a region's innovation performance do not change significantly in the considered time period. This implies that the way in which intra- and inter-regional cooperation take effect on regional innovation performance does not change at large within a couple of years. The theories on cooperation give little reason for why this would be the case, see Section 2.

3.3 The definition of the regional innovation performance

While this approach seems to be very conclusive an open issue is the definition of the *input factors*. The problem is that the very nature of R&D processes makes the exact identification of the set of relevant input factors impossible (Broekel and Brenner, 2007). For example, there may be regions in which the local university is an active intermediate in innovation processes. In other regions it can play a rather passive role. Should the university then be considered as a general input factor and be taken into account when evaluating regions' innovation performance? At the same time is the outcome of the performance analyses strongly dependent on the choice of the input factors.

In this paper we make a 'virtue out of a necessity' by following Broekel and Brenner (2007) emphasizing that "different approaches measure different things, and measuring innovation performance in different ways provides us with additional information about the causes of the different performances" (p. 12). More precise, we estimate the impact of intra- and inter-regional cooperation behavior as previously described. This is however done using two different definitions of the set of input factors in the performance analysis. In the first case, the *firm-oriented* analysis, only firm internal innovation efforts are defined as input factors. In the second case, the *region-oriented* analysis, in addition to the firm internal innovation efforts a number of regional factors are considered as input factors.

The idea behind it is that in both analyses it is controlled for the *cooperation potential* effect through the construction of the later introduced cooperation behavior measures. In the analysis focusing firm internal resources only (*firm-orientation*), the *resources* effect is taken into consideration while it is not accounted for the *place* effect. In the *region-oriented* analysis both effects, *resources* and *place* are controlled for because firm internal as well as external factors are part of the input factor set. Hence, if the way the two types of cooperation behavior variables influence regional innovation performance changes in case the input factor set is extended with the regional factors, i.e. if we

[7] In this paper this corresponds to four times because the performances are estimated for the years 1999-2002, see Section 4.

[8] Indeed, the two later introduced cooperation behavior measures show considerable variance between the years: from year to year they are weakly correlated, the correlation coefficients are in all cases smaller than $r = 0.25^{***}$ (Pearson's correlation coefficient). This indicates the presence of short term noise in their empirical estimation which is likely to be caused by variance in the employed patent data.

control additionally for the *place* effect, this change can be attributed to the effect of *place*. Or in other words, in this case the influence of the *cooperation* effect is conditional on the *place* effect. If no change is observed, it can be inferred that the regional characteristics (*place*), except for the *cooperation potential* effect, do not influence the extent to which cooperation behavior is relevant for actors' innovation performances.

In this way we test only for the relevance of the *place* effect because in contrast to the *resource* and *cooperation potential* effect, its role can be questioned. As the discussion about the importance of *place* and *network* highlights, there are substantial arguments for that large parts of the influence attributed to *place* are actually a result of firms' participation in local (or non-local) networks. Nevertheless, it can still play a role because *place* can not only directly influence actors' innovation activities. It has been argued above that it is is also likely to have an indirect impact on the extent to which the intra- and inter-regional cooperation potential is exploited, see Section 2.

In addition to this, the estimation of two analyses with two different input factor sets functions as robustness check whether the obtained results are sensitive to varying definitions of this set. In case the results differ substantially in the interpretation we have to keep in mind that they are conditional on the definition of the input factor set.

4 The employed data

4.1 Data on patent applications and R&D

The 270 German labor market regions are chosen as units of analysis, because they seem to fit best to the theoretical arguments of a regional dimension of knowledge sharing and innovation processes (see, e.g., Broekel and Binder, 2007).[9] As it is common in innovation research, the output of innovation activities is approximated by patent applications. The data on patent applications for the years 1999-2003 are published by the *Deutsches Patent- und Markenamt (German Patent Office)* in Greif and Schmiedl (2002) and Greif et al. (2006) (called *Patentatlas* in the following). The applications by public research institutes, e.g., universities and research societies (e.g. Max Planck Society) as well as the patent applications by private inventors are not included because our data on R&D employment covers only industrial R&D.

The data on R&D employees is obtained from the German labor market statistic. Following Bade (1987) the R&D personnel is defined as the sum of the occupational groups: agrarian engineers (032), engineers (60), physicists, chemists, mathematicians (61) and other natural scientists (883). The R&D personnel is organized according to the NACE classification. In order to match it with the patent application that are organized in 31 technological fields in the *Patentatlas* we rely upon the concordance developed by Broekel (2007).

In this paper we take up the point made by Oerlemans and Meeus (2005) and account for sectoral

[9] We use the up-to-date definition of labor market regions in contrast to the older definition used in Greif and Schmiedl (2002) and Greif et al. (2006).

differences by conducting an industry-specific analysis for the Electrics & Electronics (ELEC) industry. Its definition with respect to the considered technological fields and NACE industries is presented in Table 5. For this industry patenting represents an important property rights protection mechanism (Arundel and Kabla, 1998). This ensures that the innovation output measure captures most, or at least a significant share of, innovations in this industry.

In this paper the patent applications of the five technological fields assigned to ELEC by Broekel (2007) are summed resulting in a single innovation output measure. This is motivated by the existence of a great number of zeros in most of these fields which can bias the results. Furthermore, we consider a time lag of one year to the R&D employment data (see on this Fritsch and Slavtchev, 2007, p. 4).[10]

On the side of the R&D employees one of the three relevant two-digit NACE industries (DL30, DL31, DL32) is characterized by a large number of zero values. Out of 270 labor market regions DL30 shows 147 zero values in 1999. We therefore add this industry's R&D employees to that industry with which it is correlated the highest. In this case this is DL32 ($r = 0.72^{***}$).[11] After excluding those regions which still show no R&D employment in DL32_DL30 (sum of DL32 and DL30) and DL31, this leaves 258 valid observations. The exclusion is necessary because performance analyses are improper in case of zero inputs.[12].

As has already been mentioned above, in the firm-oriented analysis, apart from firms' R&D employees, no further regional input factors are considered. It is conducted with a single innovation output variable, the sum of patent applications of ELEC, and two input factors DL31 and DL32_DL30.

4.2 Regional factor endowment

For the region-oriented analysis in addition to ELEC's R&D employment, we consider regional factors are commonly argued to take effect on firms' innovation activities. At the same time some of them may however also contribute to the *cooperation* effect in that they influence the level to which the intra- and inter-regional cooperation potential is exploited, see Section 2.

The first factors influencing firms' innovation activities need to be located in the same region as the innovative actor in order to become effective. In contrast, we also consider factors which impacts are to a lesser extent regionally bounded. In their case, firms might benefit from the presence of these factors in neighboring regions. In addition to firms' R&D employees that are considered as input factors in both analyses, nine firm-external input factors are additionally included in the region-oriented analysis.

In a common fashion urbanization advantages are approximated by the population density (POP_DEN). Among others the benefits of urbanization can show as rich local labor markets, well developed infrastructure, strong local demand, as well as the presence of private and public research

[10] We also used a two years time lag but the results did not change significantly.

[11] Pearson's correlation coefficient is used.

[12] Remember that in the firm-oriented analysis only the R&D employees are considered as input factors.

facilities (Burger et al., 2007). In particular, with respect to the latter, urbanization is likely to take effect on the structure and importance of local cooperation. The local demand, public financial situation, and economic activity in the region is taken into account by considering the gross domestic product (GDP) per capita. It may also account for the possibilities of the local authorities to start and maintain policy initiatives aiming at increasing the interactions of local actors.

Furthermore, the literature highlights the importance of business services for innovation and cooperation activities (see, e.g., Feldman and Florida, 1994) so that the variable SERVICE has been added. It represents the employees in industry KA74 (according to WZ03) in a region. We compute the influence of SERVICE by using the 'production structure specialization index' (PS) (see Feldman and Audretsch, 1999). The index (PS) is made symmetric as proposed by Laursen (1998) in a different context, by calculating $\frac{PS-1}{PS+1}+1$. This index ranges from 0 to $+2$ with one indicating average specialization.

The potential impact of the share of employees with high qualifications (EMP_HIGH) is also considered because it is an often used measure for the quality of local human capital (Weibert, 1999) and the presence of high-tech industries that may offer valuable cooperation possibilities.

An industry specific variable (ELEC_PS) accounts for the specialization of a region with respect to ELEC. Industrial agglomeration is, among others, argued to stimulate knowledge spill-overs and exchange which in turn fosters innovation performance (Greunz, 2004).It is approximated by the PS of the employees of ELEC which is also made symmetric as described above. It enters the analysis as variable ELEC_PS. In order to account for similar effects that however stem from the absolute regional employment of ELEC, we include it as EMPL_ELEC (see Brenner, 2004).

In order to account for the effects of the presence of large firms in ELEC, the average firm size (SIZE) is included. In this paper, the role large or multinational firms play as 'gatekeepers' is particularly relevant as they are more likely to be embedded into networks spanning regional boundaries (Graf, 2007).

These seven input factors are argued to influence only firms located in the same region. In contrast, the effects of the following input factors are argued to be regionally less bounded. This regards in particular knowledge spill-overs from public research facilities that are sensitive to, but not 'bounded' by, geographic distance. As these effects are not exclusively cooperation related they need to be taken into consideration in the estimation. We include variables that account for the geographic mobility of university students because this seems to capture most of the direct spillovers between research institutes and firms' innovation activities (Faggian and McCann, 2006). In the context of this paper, particularly the university graduates of engineering (GRAD_ENG) and natural sciences & math (GRAD_NAT) are relevant. After obtaining their degree a certain share of them leaves the region in which they studied and move to other regions. Hence the receiving regions benefit from the knowledge created in universities' host regions that 'spills-over'. In the statistics the graduates are assigned to the host regions only. Following the procedure proposed by Broekel and Brenner (2007), the numbers of graduates are distributed across the regions such that a region's probability to obtain another regions' graduates depends positively on its population and negatively on the geographic distance between the regions. Further, a certain share of the graduates from a university stays in the region. The parameters of a hyperbolic function used for estimating the probabilities are fitted by a maximum likelihood calculation, using geographic coordinates and population counts for the German five digit postal code areas as well as empirical findings from Legler et al. (2001) on the mobility of graduates. This means that with increasing geographic distance the likelihood to move decreases hyperbolically. Table 4 summarizes the distribution parameters. To control for size effects regarding a region's industry endowment, the distributed graduate counts enter the analysis as ratios a region's total employment.

In order to avoid including variables which are statistically redundant, i.e. highly correlated, we check the input factors' correlation structure. In case that two or more variables are correlated with $r = 0.8$ (Spearman rank correlation) or above, the variables with less theoretical relevance are excluded.[13] Applying this rule, seven variables enter the analysis as input factors: the two R&D employee variables (DL32_DL30 and DL31); average firm size (SIZE), gross domestic product (GDP), the share of highly qualified employees (EMP_HIGH), the spatially distributed graduates of engineering faculties (GRAD_ENG), and a region's specialization in business services (SERVICE).[14] The variables GDP is kept instead of POP_DEN; DL31 for EMPL_ELEC; GRAD_ENG for GRAD_NAT; SIZE for ELEC_PS. Tables 8 and 9 in the Appendix show the corresponding correlation coefficients. Table 6 summarize the variables and Table 7 illustrates the selection.

In the nonparametric performance analysis the selected variables enter simply as additional input factors.

4.3 Two cooperation behavior measures

As pointed out in Section 2 our main concern in this study is on actors' *cooperation behavior* and its impact on regional innovation performance. This requires that we control for the *cooperation potential* effect meaning that regions in which a multitude of actors are located that can potentially serve as cooperation partners, are likely to show higher numbers of realized intra-regional cooperation. It is to some extent a 'size' effect regarding the cooperation opportunities that exist to cooperate intra-regionally. However, this does not say that the actors are more intra-regionally cooperative than actors located in regions that are characterized by fewer potential cooperation partners. Similar applies to the level of inter-regional cooperation partners with which more cooperation can be expected when the number of actors in a region is large.

In order to avoid this bias we make use of the cooperation behavior measure that has been developed recently by Cantner and Meder (2008). The measure is characterized by the absence of this

[13] The threshold of $r = 0.8$ seems to be well fitting in this context because the number of variables is moderately but sufficiently reduced. Robustness checks have been conducted showing that the results are not sensitive with respect to the inclusion of variables that are correlated with 0.8 or above with already considered variables.

[14] Following (Bonaccorsi and Daraio, 2007) we add 0.001 to the input factors as well as to the innovation outputs. This avoids distortion in the estimation but does not influence the results.

cooperation potential effect because in its construction it is controlled for the existing technological opportunities to cooperate. Hence, it represents actors' "real" cooperative behavior abstracted from external restrictions and opportunities to cooperate. However, lacking data on the quality, i.e. intensity, of the cooperation we observe only cooperation counts. It is acknowledged though that the quality of the cooperation is a crucial aspect as well.

Data on cooperation are obtained from German patent data published in the German "Patentblatt". More precisely, a cooperation is defined as a co-application of a patent, i.e. two organizations that jointly apply for a patent within the IPCs classes assigned to ELEC.[15]

The methodology includes three steps. First, the general cooperation propensity of ELEC is calculated by the dividing the total number of collaborations by the total number of innovations within this industry. In a second step, the patents are assigned to the labor market regions according to the inventor principle. It reflects the regions' industry-specific technological endowment. Next, the number of cooperation is calculated that can be expected within a region according to this technological endowment. The expectation is estimated by the multiplication of the number of innovations in ELEC (technological endowment) and the cooperation propensity of ELEC which has been calculated in step one. This can be regarded as the *cooperation potential*, i.e the number of cooperation that can be expected given the number of cooperation possibilities and average cooperation behavior. In the final step, for each region the number of expected cooperation is divided by the number of observed cooperation. The idea is that in the case of expected and observed cooperation measures being equal, this indicates that the regional actors' cooperation behavior is influenced by technological patterns alone as the cooperation level corresponds to the national average.

Regions in which no cooperation are observed, and given their technological profile, no cooperation can be expected, are treated the same as regions with no observed cooperation but for which positive levels of cooperation are expected. Empirically, both regions are indicated by zero values as we assume in both cases a similar relationship between cooperation activities and regional innovation performance (see for an extensive description of the methodology Cantner and Meder, 2008).[16]

The resulting index I is made symmetric by $\frac{I-1}{I+1} + 1$. This allows an easier interpretation as well as more meaningful graphical representation. Hence, a value of one implies a cooperation behavior that corresponds to what can be expected given the technological structure of the region. Lower values indicated cooperation behavior below the expected level and values above one the opposite.

The intra-regional cooperation activities measure (CoopIntra) is constructed on the base of cooperation of the inventors being located within the same region but are part of different organizations. In case of inter-regional cooperation activities (CoopInter), cooperation are indicated by the inventors being located in different German regions. The latter implies that in this paper inter-regional cooperation behavior refers to national cooperation. International cooperation are not considered because

[15] Note furthermore that the cooperation behavior measures are constructed from patent data while the innovation output measures are obtained from patent applications.

[16] We also estimated the results when assigning a value of one to those regions that are not expected to show cooperation. The results proofed to be not sensible to this, though.

of too many zero values in the resulting measure.[17] At this stage it is also not discriminated between the industries the cooperation partners belong to which is certainly an issue for future research. Because the cooperation behavior measures are based on patent data, we consider a time lag of one year with the input factors, i.e. the cooperation behavior measures for the year 1999 are based on the patent data of 2000.

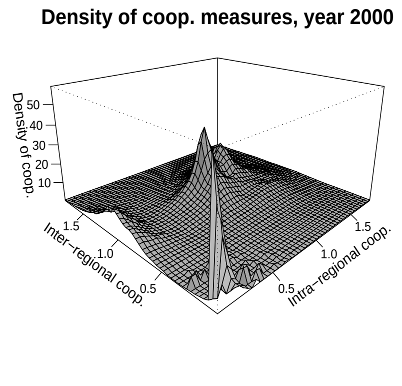

Figure 2: Density of coop. measures

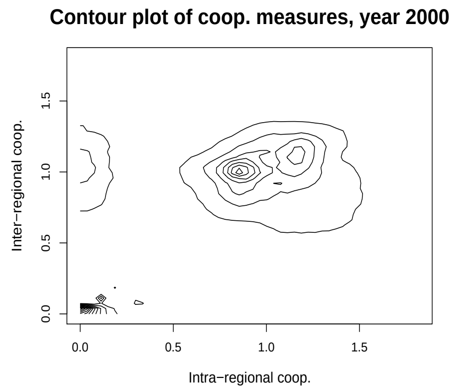

Figure 3: Contour of coop. measures

Surprisingly, intra- and inter-regional cooperation behavior measures are only weakly correlated ($r = 0.01^{***}$). We can only speculate that this is a result of that actors' intra- and inter-regional cooperation behavior are independent of each other, i.e. their cooperation attitude is not independent of the cooperation partner's geographic location. This deserves clearly more research.

The low correlation is also illustrated in Fig. 2 and 3 showing the density of the two cooperation behavior measures as well as the corresponding contour plot.[18] In addition, both measures' histograms are included in the Appendix, see top left graphs in Fig. 10 and 11. The plots illustrate that the mass of observations are characterized by values around one in CoopIntra as well as in CoopInter. There is also a significant mass with zero values in both measures. In addition, a considerable number of observations shows close to zero or zero values in CoopIntra and values of one or close to one, in CoopInter. The latter ones are regions with comparatively low R&D employment in ELEC. This is not surprising because lacking regional alternatives, firms located in such regions need to cross regional boundaries in order to find cooperation partners.

We also observe a weak correlations with the innovation output measures which is simply a result of the way the cooperation behavior measures are constructed. As the cooperation potential is determined by the number of patents applications in a region, it is naturally strongly correlated to the number of patent applications. Hence, when controlling for the *cooperation potential* we simultaneously lower the correlation with the innovative output. For the pooled data of 1999-2002, the correlation between the two cooperation behavior measures and the numbers of patent applications in ELEC (PAT) is just $r = 0.29^{***}$ for CoopIntra and $r = 0.08^{***}$ in the case of CoopInter. This

[17] This is certainly an interesting aspect for further research.

[18] For the estimating the density we used the truncated gaussian kernel proposed by Daraio and Simar (2007).

explains also the low correlation of CoopIntra and CoopInter with the variables approximating the regions' input factor endowment as these are positively correlated to the innovative output, see Table 9 in the Appendix. The low correlation between the variables approximating the input factors and the cooperation behavior suggests however to expect a relatively low relevance of the first for the effect of the letter on innovation performance, i.e. a low impact of *place* effect on the shape of the *cooperation* effect.

5 Results

5.1 Stability and presentation of results

At this point, the employed nonparametric frontier analysis does not allow to estimate the significance of the relationship between the cooperation behavior measures and regional innovation performance, i.e. confidence intervals can not be calculated for Q_z.[19] Hence, it is necessary to take a look at the numbers of observations backing the estimated relationships. The histograms for the two cooperation variables can be found in the Appendix in the top left corner of Fig. 10 and 11. They show that in both cases only few observation have values between 0 and 0.5 as well as larger than 1.5. We refrain from interpreting these areas. However, while we cannot discuss the interior of the interval]0,0.5] due to too few observations, there are many observations on both sides of this interval's borders. Though, the relationship can be analyzed with respect to differences between regions with zero values and those with values larger than 0.5, i.e., whether a positive or negative influence on innovation performance exists when the levels of cooperation behavior 'jump' from 0 to above 0.5.

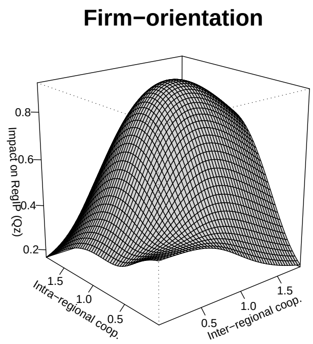

Figure 4: Surface of Qz, firm-orient.

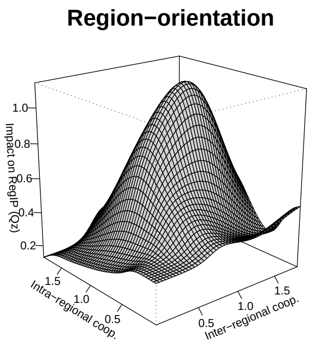

Figure 5: Surface of Qz, region-orient.

Figures 4 and 5 show the relationship between the levels of intra- and inter-regional cooperation

[19] Several robustness checks have been conducted, though, showing the stability of the results. For example, it has been checked that regions with identical unconditional and conditional performance scores do not cause some of the observed patterns.

behavior and regional innovation performance for the firm-oriented analysis and the region-oriented analysis, respectively. While the three-dimensional plots illustrate nicely the simultaneous effect of both types of cooperation behavior on regional innovation performance a more detailed view at the results can be obtained by slicing the three-dimensional surfaces into six parts which then can be represented in two-dimensional plots. Following Daraio and Simar (2007) the results are divided the into six sub-samples on the basis of their CoopIntra and CoopInter values.[20] The first sub-sample consisting of the 33 percent of observations with the smallest values in CoopIntra (low levels of intra-regional cooperation behavior). The second covers the 33 percent with the largest values in CoopIntra (high levels of intra-regional cooperation behavior). The third represents the 33 percent in between (medium levels of intra-regional cooperation behavior). In a similar manner the observations are divided according to their values of CoopInter giving us three additional samples for low, medium, and high levels of inter-regional cooperation behavior. For the three sub-samples that are defined on the basis of the CoopInter values, the obtained Q_z values are nonparametrically regressed on the corresponding CoopIntra values. Accordingly, the procedure is done in case of the sub-samples defined by the values of CoopInter. The resulting regressions are shown for the firm-oriented analysis in Fig. 6 and 8. Those for the region-oriented analysis in Fig. 7 and 9).[21] In the plots the dashed regression curve indicates the relationship of the considered cooperation measure for low levels, the solid line for medium levels and the dotted line for high levels of the cooperation type that is not used for defining the sub-sample.[22]

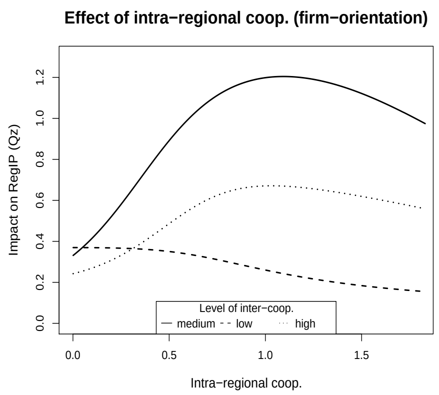

Figure 6: CoopIntra, firm-orient.

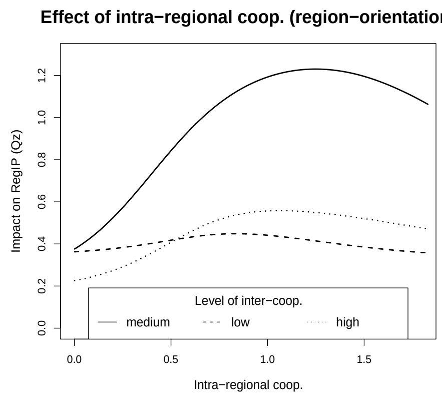

Figure 7: CoopIntra, region-orient.

5.2 The influence of cooperation behavior

What the surfaces and curves show is that, in contrast to the (not industry specific) findings by Fritsch (2004), cooperation behavior plays a role for the regional innovation performance, at least in the case

[20] While Daraio and Simar (2007) use quartiles in the context of the paper a division into thirds seems to be more appropriate.

[21] Note that in the two-dimensional plots the turning points may depart from the one in the three-dimensional surfaces. However, the two-dimensional plots represent only supportive but not definitive illustrations.

[22] The histograms for each of the six sub-samples are shown in Fig. 10 and 11 allowing for basic robustness checks.

of the German Electrics & Electronics industry. Even more so, evidence for the ‘bright’ and ‘dark’ side arguments are found: irrespectively of the definition of the considered input factor set (firm or region-oriented analysis) the obtained relationship between intra- and inter-regional cooperation behavior with innovation performance takes the form of a bump. With increasing levels of intra- or inter-regional cooperation the surfaces and curves turn upward indicating positive effects, while when exceeding a certain turning point their slope becomes negative and points at the existence of negative effects. Or in other words, up to a certain level cooperation behavior fosters innovation performance. Cooperation behavior exceeding this level yields negative effects, though. This holds in all situations except when level of either intra- or inter-regional cooperation behavior is low.

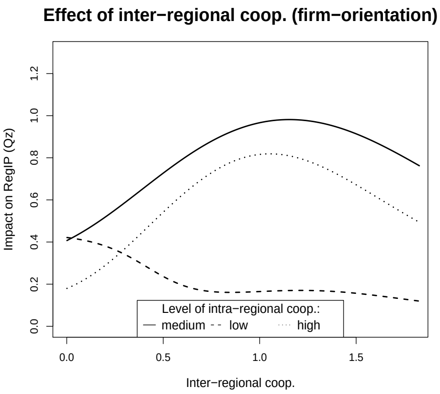

Figure 8: CoopInter, firm-orient.

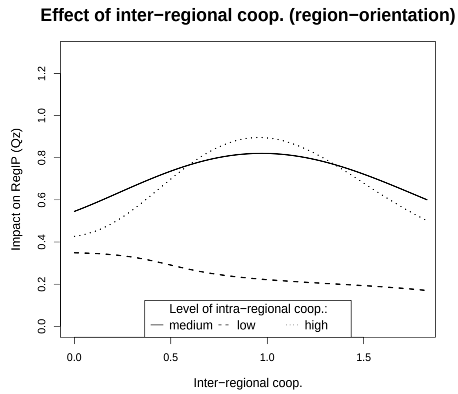

Figure 9: CoopInter, region-orient.

The analyses provides quantitative empirical evidence for the importance of intra- and inter-regional cooperation behavior for firms’ innovation performances and confirms that increasing cooperation stimulates regional innovation performance (bright side). However, the rather over-positive view on higher levels of cooperation which is sometimes found in literature on the ‘innovative milieus’ or ‘regional innovation systems’ can clearly be rejected. To the contrary, the results suggest the existence of a dark side in form of a *cooperation overload*, i.e. excessive intra- and inter-regional cooperation behavior hampers regional innovation performance. Such can be caused by missing rivalry which is crucial for the motivation of firms to innovate (Porter, 1990). In addition, in this situation firms’ may over invest into establishing and maintaining cooperation and eventually suffer from ‘free riding’ (Cassiman and Veugelers, 2002) or ‘learning races’ (Faems et al., 2005).

	Min.	**Max.**	**Mean**	**Median**	**TP** firm*	**TP** regional*
$CoopIntra_{t-1}$	0.001	1.81	0.78	0.90	1.33	1.25
$CoopInter_{t-1}$	0.001	1.82	0.87	0.96	1.18	1.03
* According to the maximum value of surfaces of Q_z in Fig. 4 and 5.						

Table 1: Descriptives of cooperation behaviors’ impact

The turning point beyond which intensified cooperation behavior reduces innovation performance is interesting in itself. In case of CoopIntra it is considerably larger than one, while in case of CoopInter it is just somewhat larger than one, see Table 1. In Section 4.3 it was argued that the cooperation behavior measures signal the degree to which actors exploit the intra-regional and inter-regional cooperation potential. With respect to the difference in the levels of intra- and inter-regional cooperation behavior at the turning point it can be inferred that to some extent the intra-regional cooperation potential can be exploited to a higher degree than the inter-regional cooperation potential without that firms suffer from negative effects. An explanation for this can be that geographic proximity entails a higher visibility of the cooperation partners activities which can make free riding more difficult. Similarly, geographic proximity can stimulate the development of social proximity (Boschma, 2005) which reduces the risk of free riding as well. "Co-location and visibility generate potentials for efficient interpersonal translation of important news and information between the cluster actors and firms ..." (Bathelt et al., 2004, p. 39). Hence, certain advances of geographic proximity seem to compensate parts of the negative effects resulting from too intense intra-regional cooperation behavior.

In addition to the *cooperation overload*, two other scenarios give rise to a 'dark side' of cooperation for regional innovation performance: the *lock-in* and the *lock-out*. In Fig. 6 the regression curves for the three levels of inter-regional cooperation behavior and increasing levels of intra-regional cooperation behavior shows a monotonic decreasing trend. This implies that low innovation performances cannot be raised by increasing the level of intra-regional cooperation when inter-regional cooperation are comparatively rare. This corresponds to the idea of a *lock-in* situation in which too many intra-regional cooperation take place but region external linkages are missing. Our analyses show that the lock-in is not a singular phenomena but seems to occur frequently.

We can also confirm empirically the situation of a *lock-out*: in Fig. 8 the curve for low levels of intra-regional cooperation and increasing levels of inter-regional cooperation is monotonically decreasing as well. Thus, increasing inter-regional cooperation cannot substitute missing intra-regional cooperation.

This observation suggests that if the level of at least one of the two types of behavior is below the turning point, intra- and inter-regional cooperation are complements, i.e. they foster innovation performance only in combination.[23] Hence, firms have to establish certain contacts outside the region while at the same time they need to be part of intra-regional networks. Or in the terminology of Bathelt et al. (2004), firms need to participate in the "local buzz" and have simultaneously access to the "global pipelines" of knowledge. A sole orientation on one of the two hampers innovation performance and entails the danger of being locked-in or locked-out. Again, this is only true in situations in which at least one type of cooperation is below the turning point. There is no indication that one of the two types of cooperation is more beneficial for firms' innovation activities than the other (see on this Gertler, 2003; Bathelt et al., 2004). In the light of this we can speculated that e.g. 'innovative milieus' are not characterized by the highest or extreme levels of intra-regional cooperation

[23] Note however that the curves in Fig. 8 and 9 (low intra-regional cooperation) are supported by few observations in the interval]0,0.7], see top right histogram in Fig. 10 in the Appendix.

but rather by a performance maximizing balance of intra- and inter-regional cooperation behavior as well as non-cooperative innovation activities.

		Intra-regional cooperation behavior		
		low	**medium**	**high**
Inter-regional cooperation behavior	**low**	isolation (-)	A (-)	lock-in (-)
	medium	B (-)	balanced coop. (+)	C (+)
	high	lock-out (-)	D (+)	cooperation overload (-)
(+) indicates positive, and (-) negative effects on regional innovation performance				

Table 2: Effects of intra- and inter-regional cooperation

The overview table 2 summarizes the results. Its rows depict the levels of intra- and its columns the levels of the two types of inter-regional cooperation behavior. The nine cells represent the different stylized situations that can exist in a region with respect to the two behaviors. For each situation the corresponding impact on the regional innovation performance is given in parenthesis. In the table, the extreme situations correspond to a lock-in (high CoopIntra and low CoopInter) and to a lock-out (low CoopIntra and high CoopInter). The middle position accounts for balanced (average) cooperation behavior as in this case both cooperation measures are close to the national average. The four situations in between are represented by **A**, **B**, **C**, and **D**.

The table illustrates nicely the opportunities and dangers that a movement from one situation (cell) to another can bring about. For example, regional authorities might be interested in escaping a situation in which firms participate in comparatively few intra- and inter-regional cooperation (*isolation*) causing low innovation performance. The authorities then might initiate a program to stimulate intra-regional cooperation activities. While they might be successful in fostering intra-regional cooperation activities the region moves from cell *isolation* to cell **A**, or even to cell *lock-in* and regional innovation performance does not increase but might even decrease. Thus, it is crucial to know in the first place in which particular situation a region is and which cooperation type is underdeveloped.

5.3 The impact of the resource endowment

We argued in Section 3.3 that by comparing the results of the firm-oriented and region-oriented analyses insights on the relevance of the *place* effect for the importance of cooperation activities can be gained. While the input factor set of the region-oriented analysis includes additional regional factors, the corresponding three-dimensional plot is not too much different from that of the firm-oriented analysis, Fig. 5. The same holds when comparing the two-dimensional plots, Figures 6 with 8 and Figures 7 with 9. It has been discussed in Section 3.3 that this tells us two things: first, the results are fairly robust with respect to the choice of the considered input factors. Second, the *place* effect is only weakly relevant for the impact of cooperation behavior on regional innovation performance (*cooperation* effect). This meets our expectations on the basis of the observed low correlations between cooperation measures and the regional factors in Section 4.

In a specific situation however, the *place* effect seems to have some relevance. In Fig. 7 the curve for low CoopInter and increasing CoopIntra in the region-oriented analysis is almost a horizontal line. This behavior is not observed in the corresponding curve in the firm-oriented analysis (Fig. 6). The missing decreasing trend in the region-oriented analysis indicates that the consideration of the regional factors levels out the negative effect of high intra-regional but constantly low inter-regional cooperation behavior.

This is particularly interesting in the extreme situation of a regional *lock in* as this implies that the latter is related to an insufficient endowment with the considered regional factors. Or put differently, the bad performance in a lock-in situation can not only be attributed to missing inter-regional linkages but also to an underdeveloped regional factor endowment regarding the presence of universities, highly qualified human capital, large firms, etc. Reasons for this may be found in that in regions with no universities or large firms, their function as gatekeepers is missing which can explain the scarcity of external linkages (Graf, 2007). This is supported by the negative (even though weak) correlation between GRAD_ENG and CoopInter, see Table 9. The positive correlation between GDP and CoopInter, as well as between the share of highly qualified employees EMP_HIGH and CoopInter can be interpreted as that regions that are economically not very well developed may attract less inter-regional cooperation offers. Hence, we can speculate that the missing of inter-regional linkages in a lock-in situation is to some extent a result of an in this respect non supportive regional environment. This is certainly a point that needs to be analyzed in more detail in the future. It has to be emphasized though that this observation is supported by a low number of observations (see the top right histograms in Fig. 10 in the Appendix).

6 Conclusion

On the basis of the 270 German regions and the Electrics & Electronics industry it was empirically confirmed that cooperation behavior plays a role for regional innovation performance. Thereby a gap was filled as most studies on this issue are of qualitatively nature (see, e.g., Boschma and ter Wal, 2007) or cover only small samples of regions (see, e.g., Sternberg and Arndt, 2001). However, in contrast to the often highlighted positive role of high levels of cooperation for regional innovation performance, for which we also found evidence, the main result was that there exists a substantial 'dark' side of cooperation. In particular, it was shown that excessive cooperation behavior can result in a *cooperation overload*, i.e. too much cooperation hampers innovation performance. Strikingly, this phenomenon is characterized by high levels of intra- as well as inter-regional cooperation behavior. Hence, it seems to be related to the general cooperative attitude of the actors. In this case, the negative effects for innovation performance can be caused by lacking rivalry between firms which is though to be crucial for their motivation to innovate (Porter, 1990). The latter remains however speculative at the moment.

It has been shown in the paper that below a certain level both increasing intra- as well as inter-regional cooperation foster regional innovation performance. In addition, the analysis clearly revealed the complementary nature of the two types of cooperation. On the one hand this supports the idea of 'local buzz' and 'global pipelines' by Bathelt et al. (2004), i.e the need of firms to participate simultaneously in local as well as non-local knowledge networks. On the other hand it is shown however that too extensive cooperation behavior hampers innovation performance. This is particularly highlighted by the indication of the existence of regional lock-in and lock-out situations. These situations go hand in hand with low innovation performance. Thus, the type of regional lock-in suggested by Camagni (1991) as a situation in which cooperation mainly takes place between intra-regional actors which lack inter-regional linkages, is supported by the qualitative evidence in this paper. The opposite case, the regional lock-out, was proposed as a situation in which actors participate strongly in cooperation spanning regional boundaries but fail to develop intra-regional cooperation. For both regional lock-in as well as lock-out empirical evidence was provided suggesting that they are not singular phenomena and that generally they go hand in hand with low regional innovation performance.

Another interesting outcome was that the presence of universities and large firms in a region as well as a well-developed regional economy help to avoid lock-in situations and the low innovation performance this generates. Likely, these factors determine the attractiveness of regional actors as potential cooperation partners for non-regional actors and the foster the initiation of non-regional cooperation.

In general, the results refute the purely positive effects of cooperation on regional innovation performance. The empirical evidence provided here highlights the 'dark' side of cooperation. In particular, it is crucial to analyze carefully whether actors in a region lack intra- or inter-regional cooperation before initiating support for either of them because false incentives for cooperative behavior may induce *cooperation overload* situations. However, support for the type of cooperation that is already comparatively well-developed in a region can entail regional *lock-in* and *lock-out* situations which can yield even lower innovation performance.

In this paper we focused on the German Electrics & Electronics industry. Hence, our results remain restricted in their generality. Clearly, analyses have to be extended to include more industries in the future. Preferably, these investigations should take a more dynamic perspective as the importance of cooperation behavior may vary between the different stages of the regions' and industries' life-cycles. Even more, the cooperation behavior was defined quantitatively, ignoring the qualitative side. It matters however with whom one cooperates, e.g. how related the cooperation partners' knowledge bases are (Boschma and Iammarino, 2007). Taking this into account would certainly help to better understand the 'bright' and 'dark' side of cooperation for regional innovation performance.

7 Tables & Figures

Distance	$< 50km$ #	$50 < 200km$ #	Share 1999	Share 2000
GRAD_ENG (university)	48.8%	29.8%	41.6%	40.7%
GRAD_ENG (tc)	42.3%	35.5%	58.4%	59.3%
GRAD_NAT (university)	61.2%	14.9.9%	89.7%	89.8%
GRAD_NAT* (tc)	45.4%	36.0%	10.3%	10.2%
* No data available, the shares of all technical graduates taken together are used. # Data based on Legler et al. (2001) but adjusted for inner Germany mobility				

Table 3: Graduates Mobility

	Empirical values		Estimation		
Spill-over source	$< 50km$	$200km <$	$< 50km$	$200km <$	α
GRAD_ENG	45,1%	33,1%	44.70%	34.35%	1.4851
GRAD_NAT	60.0%	17.0%	56.34%	29.29%	1.6358
Estimation based on sum of 1999 and 2000 data.					

Table 4: Range of spill-overs of graduates, hyperbolic distribution

Technological fields *	NACE industries**
TF27, TF28, TF29, TF30, TF31	DL31, DL32, DL30
* As defined in Greif and Schmiedl (2002) ** According to the GIC DESTATIS (2002)	

Table 5: Definition of the Electrics & Electronics industry according to Broekel (2007)

Variable	Description
PAT	Sum of patent applications of
	TF27, TF28, TF29 ,TF30, TF31 in Greif and Schmiedl (2002); Greif et al. (2006)
DL_31	R&D employees of DL31
DL_32_30	Sum of R&D employees of industries DL32, DL30
POP_DEN	Inhabitants per $kilometer^2$ land area
GDP	Gross domestic product per inhabitant
SERVICE	Production structure specialization index of
	WZ03' category 74: 'other business activities' (business services) industry
EMP_HIGH	Share of employees with high qualification
ELEC_PS	Production structure specialization index (PS) of RD_ELEC)
EMPL_ELEC	Absolute regional employment of ELEC
GRAD_ENG	Distributed engineering graduates per employee
GRAD_NAT	Distributed natural and science graduates per employee
All shares refer to total employment	

Table 6: Variables, estimation base, and sources

Variable	Firm-level orientation	Regional orientation
Innovation output measures		
PAT_t	$\times$	$\times$
Input factors		
$DL32\_30_{t-1}$	$\times$	$\times$
$DL31_{t-1}$	$\times$	$\times$
$SIZE_{t-1}$		$\times$
$EMPL\_ELEC_{t-1}$		$-$
EMP_HIGH_{t-1}		$\times$
GDP_{t-1}		$\times$
$ELEC\_PS_{t-1}$		$-$
POP_DEN_{t-1}		$-$
$SERVICE_{t-1}$		$\times$
$GRAD\_ENG_{t-1}$		$\times$
$GRAD\_NAT_{t-1}$		$-$
$\times$ Indicates inclusion, $-$ exclusion because of correlation.		

Table 7: Variables and their employment

	DL32_DL30	DL31	EMPL_ELEC	ELEC_PS	POP_DEN	DistriNAT	DistriENG
DL32_DL30	1***	0.48***	0.75***	0.62***	0.5***	−0.05*	−0.12***
DL31	0.48***	1***	0.83***	0.73***	0.44***	−0.1***	−0.16***
EMPL_ELEC	0.75***	0.83***	1***	0.84***	0.59***	−0.12***	−0.2***
ELEC_PS	0.62***	0.73***	0.84***	1***	0.23***	0.02	0.01
POP_DEN	0.5***	0.44***	0.59***	0.23***	1***	−0.21***	−0.32***
DistriNAT	−0.05*	−0.1***	−0.12***	0.02	−0.21***	1***	0.8***
DistriENG	−0.12***	−0.16***	−0.2***	0.01	−0.32***	0.8***	1***
GDP	0.45***	0.45***	0.58***	0.25***	0.81***	−0.08***	−0.16***
EMP_High	0.38***	0.33***	0.43***	0.08***	0.77***	−0.21***	−0.31***
Service	0.11***	0.02	0.09***	0.02	0.29***	−0.12***	−0.13***
Firm size	0.53***	0.65***	0.78***	0.85***	0.26***	−0.02	−0.05*
$CoopIntra_{t-1}$	0.22***	0.17***	0.23***	0.14***	0.2***	0.06**	0.02
$CoopInter_{t-1}$	0.07***	0.06**	0.1***	0.05*	0.17***	−0.02	−0.06**

Table 8: Pearson's correlation coefficients I

	GDP	EMP_High	Service	SIZE	$CoopIntra_{t-1}$	$CoopInter_{t-1}$
DL32_DL30	0.45***	0.38***	0.11***	0.53***	0.22***	0.07***
DL31	0.45***	0.33***	0.02	0.65***	0.17***	0.06**
EMPL_ELEC	0.58***	0.43***	0.09***	0.78***	0.23***	0.1***
ELEC_PS	0.25***	0.08***	0.02	0.85***	0.14***	0.05*
POP_DEN	0.81***	0.77***	0.29***	0.26***	0.2***	0.17***
DistriNAT	−0.08***	−0.21***	−0.12***	−0.02	0.06**	−0.02
DistriENG	−0.16***	−0.31***	−0.13***	−0.05*	0.02	−0.06**
GDP	1***	0.68***	0.22***	0.32***	0.2***	0.11***
EMP_High	0.68***	1***	0.19***	0.08***	0.11***	0.16***
Service	0.22***	0.19***	1***	0.05*	0.06**	0.03
Firm size	0.32***	0.08***	0.05*	1***	0.12***	0.02
$CoopIntra_{t-1}$	0.2***	0.11***	0.06**	0.12***	1***	0.08***
$CoopInter_{t-1}$	0.11***	0.16***	0.03	0.02	0.08***	1***

Table 9: Pearson's correlation coefficients II

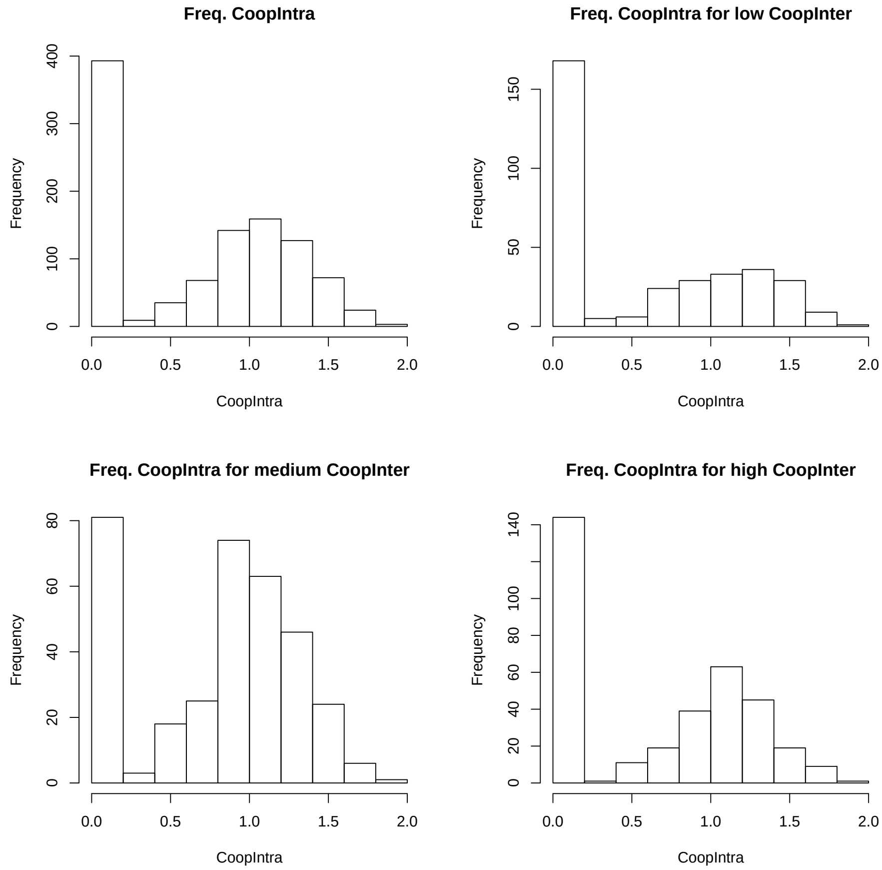

Figure 10: Histograms of CoopIntra

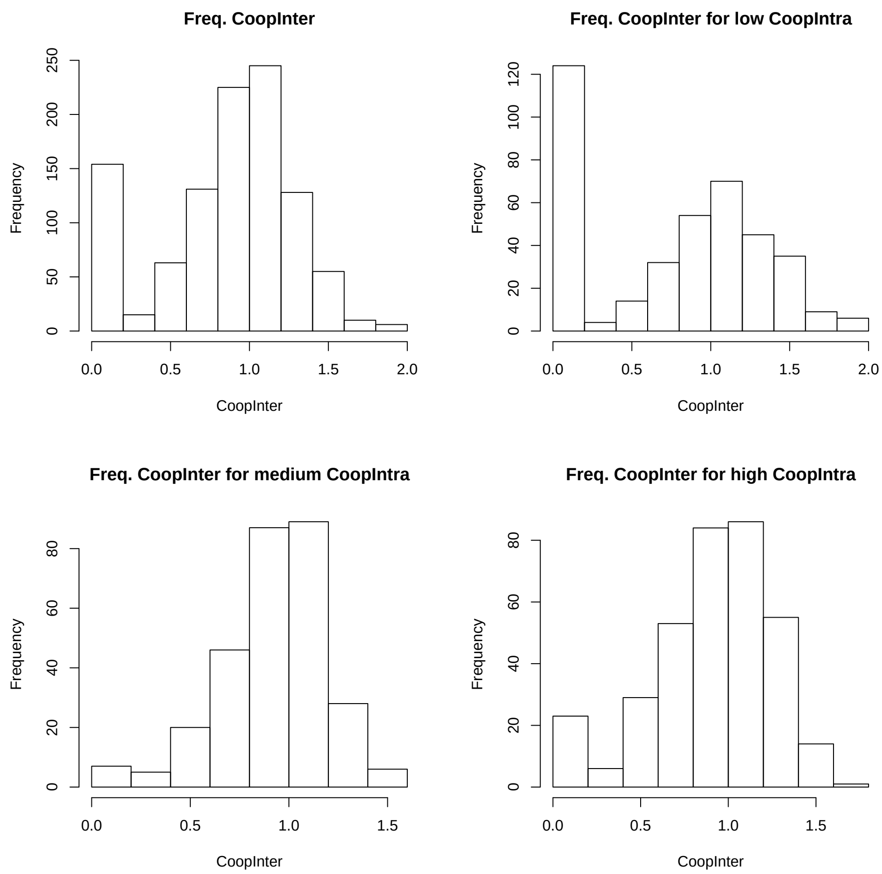

Figure 11: Histograms of CoopInter

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