EMPIRICAL EVIDENCE ON THE RELATIONSHIP BETWEEN PROXIMITY, THE FORMATION AND PERFORMANCE OF R&D COLLABORATIONS AND THE INFLUENCE OF R&D POLICY

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Deutsche Zusammenfassung

Die vorliegende Arbeit befasst sich mit den Determinanten erfolgreicher F&E-Kooperationen und dem Einfluss von Innovationspolitik auf das Entstehen dieser Kooperationen beziehungsweise die Diffusion der Ergebnisse aus diesen kooperativen Innovationstätigkeiten.

Lernen als der kumulative Aufbau von Wissen und dessen neuartige Rekombination gilt als wichtigster Inputfaktor für Innovationen und damit als fundamentale Ressource im Wettbewerb der modernen „Learning Economy" (Lundvall and Johnson 1994). Um in dem sich rapide wandelnden wirtschaftlichen Umfeld und dem stärkeren Wettbewerb zu bestehen, sind Unternehmen zunehmend darauf angewiesen, ihre Ressourcen mit anderen komplementären Akteuren zu bündeln und kontinuierlich Innovationen hervorzubringen. Hierbei hat der Zugriff auf unternehmensexternes Wissen und Informationsquellen seit den 90er Jahren signifikant an Bedeutung gewonnen (Hagedoorn 2002).

Bereits in den 80er Jahren brachte die jüngere Innovationsforschung die Erkenntnis hervor, dass Innovationen eher das Ergebnis eines interaktiven Prozesses zwischen mehreren Akteuren und selten eine Konsequenz der Anstrengungen eines einzelnen Akteurs sind (Edquist 1997). Die Generierung von neuen Ideen und deren kommerzielle Umsetzung geschehen dabei nicht entlang eines linearen Prozesses. Vielmehr ist dieser Prozess gekennzeichnet durch Feedbackschleifen, Kooperation und interaktives Lernen entlang der gesamten Prozessstufen (Freeman and Lundvall 1988, Kline und Rosenberg 1986). Diese Ergebnisse begründen die darauffolgende Entstehung der Forschungstrajektorie zu Innovationssystemen. Eine zentrale Aussage dieser relativ jungen Forschungsrichtung ist, dass die innovative Performance einer Nation, einer Region oder eines Sektors durch die Qualität des Systems von Akteuren, deren Verbindungen (Kooperationen und Interaktionen) zueinander sowie dem institutionellen Rahmen hierin bedingt ist. Die Effizienz der interaktiven Wissensgenerierung und des Wissenstransfers determinieren maßgeblich die Leistungsfähigkeit des Innovationssystems.

Diese systemische Perspektive zur Erklärung von Innovationen hat seit ihrer Entstehung auch die Forschungs- und Technologiepolitik maßgeblich geprägt. Während früher die Förderung der Innovationstätigkeiten einzelner Unternehmen im Fokus stand, wurden immer mehr Instrumente entwickelt, um das Innovationssystem als Ganzes und insbesondere die Interaktion zwischen den Akteuren zu stärken. Dies resultierte auch aus der Beobachtung, dass gemeinsame Forschung durch Ressourcenbündelung eine viel höhere Erfolgswahrscheinlichkeit hat als Einzelforschung. Die neuen systemischen Instrumente der Innovationspolitik legten dabei den Schwerpunkt verstärkt auf die Netzwerkförderung und die Förderung von Verbundvorhaben, um die Transformation von Inventionen in marktfähige Produkte zu beschleunigen.

Trotz der Prominenz des Innovationssystemansatzes in Forschung und Politik fehlt bisher ein tiefergehendes Verständnis für die Prozesse auf der Mikroebene, insbesondere des Zusammenspiels zwischen dem Entstehen der Verbindungen und dem Wissensaustausch zwischen den Akteuren. Darüber hinaus weist der Ansatz bisher einige methodische Schwierigkeiten ebenso wie konzeptionelle Unklarheiten auf. Erstens sieht sich dieser holistische Ansatz zur Erklärung von Innovationen der Herausforderung einer geeigneten Operationalisierung gegenüber. Wenn das Versagen des Systems als Rechtfertigung für Eingriffe der Innovationspolitik gesehen wird, dann bedarf es einer aussagefähigen quantitativen Evaluation der Leistungsfähigkeit dieses Systems. Damit einher geht auch die Schwierigkeit einer fundierten Bewertung der Effekte der neuen systemischen Politikansätze. Zweitens sind bisherige konzeptionelle Überlegungen und deren empirische Überprüfung eher statischer Natur. Analysen der Veränderungen der einzelnen Systemelemente im Zeitablauf sind bisher rar gesät.

Aus diesem Grund liegt der Fokus dieser Arbeit auf einer detaillierten, empirischen Studie des Entstehens beziehungsweise der dynamischen Entwicklung der Verbindungen zwischen den innovativen Akteuren, der Qualität der Verbindungen in Bezug auf Wissenstransfer und Output und den Möglichkeiten der Einflussnahme durch die Politik. Um diese Interrelationen ganzheitlich zu beleuchten, ist die Arbeit in zwei Hauptteile gegliedert. In einem ersten Teil (Kapitel 2 und 3) werden wesentliche Determinanten empirisch untersucht, die das Entstehen beziehungsweise das Fortbestehen der Verbindungen zwischen innovativen Akteuren erklären. Speziell werden hier die dynamische Entwicklung von bilateralen, innovativen Kooperationen (Kapitel 2) und die Auswirkung öffentlicher Förderung hierauf untersucht (Kapitel 3).

Man kann zwar annehmen, dass die Akteure ex-ante antizipieren, welche Verbindung am erfolgversprechendsten für das Hervorbringen von Innovationen ist und diese auch eingehen, jedoch ist die Bildung einer Forschungskooperation allein kein Indiz für deren garantierten Erfolg. Um jedoch angemessene Implikationen für die Politik abzuleiten, bedarf es einer qualitativen Aussage über die Leistungsfähigkeit der angestoßenen Verbindungen. Die vorangegangene empirische Forschung hat gezeigt, dass die Faktoren zur Bildung von Forschungskooperationen nicht automatisch deren Erfolg bedingen.

Aus diesem Grund beschäftigt sich die Arbeit in einem zweiten Teil mit der Frage nach den Erfolgsfaktoren von Forschungskooperationen. Dabei konzentriert sich die Analyse einerseits auf einen Faktor, der von der Politik immer noch als zentral für das Gelingen von Kooperationen angesehen wird: die regionale Nähe zwischen den Kooperationspartnern (Kapitel 4). Dabei ist der positive Zusammenhang zwischen Innovation und regionaler Nähe von innovativen Akteuren bisher nicht eindeutig belegt beziehungsweise stark umstritten. Daher wird untersucht, ob Kooperationen mit lokalen Nachbarn erfolgreicher verlaufen als von Akteuren, die eine größere geografische Distanz überwinden müssen. Ein weiterer Aspekt für erfolgreiche Forschungsprojekte ist die Diffusion und damit der Austausch von Forschungsergebnissen. In Kapitel 5 wird untersucht, welchen Einfluss öffentliche Forschungsförderung auf die Ergebnisdiffusion von Forschungsprojekten hat. Auch hier ist der Fokus auf Nähe: die Nähe zwischen Wissensproduzenten und Wissensanwendern. Speziell wird analysiert, ob ein Zusammenhang zwischen öffentlich Förderung und Interdisziplinarität in der Anwendung der Forschungsergebnisse besteht. Mit anderen Worten, ob der Wissenstransfer aus öffentlich geförderten Projekten in kognitiv entferntere Bereiche gelingt.

Nach einem einleitenden Kapitel, welches die Thematik der Arbeit motiviert und die Anknüpfungspunkte zur relevanten Literatur darstellt, beschäftigt sich Kapitel 2 mit der Erklärung innovativer Kooperationen und deren Langlebigkeit. Als gewichtige Determinante innovativer Kooperationen hat sich die Ähnlichkeit von Kooperationspartnern erwiesen. Es wurde nachgewiesen, dass Akteure, die sich in verschiedenen Aspekten ähnlich sind, eine höhere Wahrscheinlichkeit haben, gemeinsame Forschung zu betreiben als unähnliche Akteure. In diesem Zusammenhang wurden fünf Dimensionen von Nähe konkretisiert, welche die Innovationswahrscheinlichkeit in Kooperationen beeinflussen. Es hat sich herauskristallisiert, dass vor allem technologische sowie soziale Nähe als bedeutend für das Hervorbringen von Innovationen sind. Obwohl die konstituierende Wirkung von Nähe in verschiedenen Dimensionen auf Innovationskooperationen bisher umfassend untersucht wurde, sind Langzeiteffekte, auch aufgrund der Verfügbarkeit von relationalen Längsschnittdaten, bisher nicht klar. Auch ist nicht eindeutig geklärt, in welchem Zusammenhang diese Nähedimensionen zueinander stehen beziehungsweise ob die Dimensionen in einer komplementären oder substitutiven Beziehung stehen. Bisher hat sich soziale Nähe durch den Aufbau von Vertrauen und die Kontrolle von ungewollten Wissensabflüssen als bindender Faktor für Langzeitkooperationen erwiesen. Im spezifischen Kontext von Innovationskooperationen spielt jedoch die Neuheit und Komplementarität des Wissens der Partner eine entscheidende Rolle. Wiederholte Kooperation steht diesen beiden Aspekten entgegen, da sich durch interaktives Lernen die Wissensbasen im Zeitablauf angleichen. Daher ist die technologische Diversität der beiden Partner ein wichtiger Treiber für Innovationen und Kooperationen.

Um diese Zusammenhänge näher zu beleuchten, wird in Kapital 2 das Kooperationsverhalten von Firmen auf Basis von Längsschnittdaten der in Deutschland angemeldeten Biotechnologie-Patente der letzten 30 Jahre untersucht. Eine Kooperation ist immer dann zu beobachten, wenn mindestens zwei Akteure ein Patent gemeinsam angemeldet haben. Die Wahrscheinlichkeit einer Verbindung zwischen zwei potenziellen Partnern wird durch verschiedene Verhältnisvariablen erklärt. Als bestimmende Faktoren werden einerseits die kognitive Nähe gemessen als Überlappung der Wissensbasen, als das Verhältnis des potenziell neu zu akquirierenden Wissens vom Partner und der Wissenstransfer in den vorherigen Kooperationen herangezogen. Basierend auf der Zuteilung von Patenten zu technologischen Klassen werden die Wissensbasen der Akteure approximiert. Dies erlaubt die Bestimmung der Ähnlichkeit der Akteure in technologischer Hinsicht. Andererseits wird die soziale Nähe als die Anzahl an gemeinsam angemeldeten Patenten in den Vorperioden berücksichtigt. Weitere Aspekte, für die kontrolliert wird, da sie die Wahrscheinlichkeit der Kooperation ebenfalls maßgeblich beeinflussen, sind die innovativen Fähigkeiten, die Kooperationserfahrungen sowie die Position im gesamten Kollaborationsnetzwerk der Akteure. Mit Hilfe einer logistischen Panelregression wurde der Einfluss der primären Variablen und Kontrollvariablen auf die Wahrscheinlichkeit des (Fort-)bestehens der Verbindung geschätzt. Die Anwendung einer Panelschätzung erlaubt die systematische Verzerrung durch unbeobachtete Heterogenität zwischen kooperierenden und nicht kooperierenden Paaren zu reduzieren.

Zentrale Ergebnisse dieses Kapitels sind, dass die untersuchten Firmen eher einen Partnerwechsel bevorzugen und dass die Ähnlichkeit der Wissensbasen, der Beliebtheit der Partner und die Kompetenzen sowie die Erfahrung mit Kooperationen in der Vergangenheit die aktuellen Kooperationen begründen. Ein Wissenstransfer in Vorperioden und damit eine Angleichung der Wissensbasen schien in unserem Fall keinen signifikanten Einfluss auf die Wiederholung einer Kooperation zu haben. Die beobachtete Instabilität der Verbindungen steht im Gegensatz zu den Ergebnissen aus Studien zur Langlebigkeit strategischer Allianzen. Eine Erklärung dafür ist, dass F&E-Kooperationen eine Teilmenge strategischer Allianzen darstellen, für welche die Bedeutung der Neuheit des technologischen Wissens ab einem gewissen Zeitpunkt die der sozialen Nähe überwiegt. In Bezug auf die Ähnlichkeit lässt sich festhalten, dass sich ähnlich kompetente und prominente Partner eher finden als unähnliche Partner. Im Einklang mit anderen Studien zur Langlebigkeit von Kooperationen zeigt sich auch, dass ein kumulativer Vorteil die Chancen auf eine Kooperation signifikant erhöht.

Während in Kapitel 2 bilaterale Kooperationen als Subelement des Innovatorennetzwerks erklärt wurden, beschäftigt sich Kapital 3 mit der Erklärung der Entwicklung des F&E-Netzwerkes auf der Mesoebene. Speziell liegt der Fokus dieses Kapitels auf der Analyse der Effekte eines ausgewählten Politikinstruments, welches die Förderung regionaler Innovationssysteme zum Ziel hatte. Es wird untersucht, welchen Einfluss der „Spitzencluster-Wettbewerb", eine der größten nationalen, innovationspolitischen Maßnahmen, auf die Forschungsnetzwerke der Zuwendungsempfänger hatte. Der Beitrag dieser Studie zum Status quo der Forschung ist vielfältig. Die Evaluation solcher Politikprogramme, welche dem systemischen Charakter von Innovationen Rechnungs tragen, steckt noch in den Kinderschuhen. Bisher wurde der Einfluss einer Förderung auf die unterstützten Netzwerke eher qualitativ erfasst. In den letzten Jahren hat sich die soziale Netzwerkanalyse (SNA) als nützliches Werkzeug erwiesen, die Verbindungen zwischen den Akteuren und damit die Wissenstransferkanäle in einem Innovationssystem zu visualisieren und damit als Ganzes zu operationalisieren. So lassen sich nun auch potenzielle Effekte von Verbundförderung auf Systemebene analysieren.

Auf Basis einer originären, standardisierten Erhebung mit den Zuwendungsempfängern der „SCW"-Förderung wurden die Daten für die SNA generiert. Die Befragten waren gebeten, ihre zehn strategisch wichtigsten F&E-Kooperationspartner zu nennen und anzugeben, ob diese Verbindungen bereits vor der Förderung bestanden. Auf dieser Grundlage ließen sich für alle vier beobachteten regionalen Innovationssysteme (oder Cluster) die Forschungsnetzwerke darstellen und die jeweilige Struktur und der entsprechende Politikeinfluss vergleichen. Darüber hinaus war es möglich, die Verbindungen anhand der geografischen Reichweite, der strategischen der Bedeutung und der Art des Kooperationspartners (Forschungseinrichtung oder Unternehmen) zu qualifizieren. Interpretationen aus der quantitativen Analyse wurden mit Ergebnissen aus Akteursinterviews komplementiert.

Ein bedeutendes Ergebnis dieses Kapitels ist, dass der Wettbewerb sehr effektiv darin war einerseits neue Kooperationen zwischen den Akteuren anzustoßen, andererseits bestehende Verbindungen zu intensivieren. Die Verbindungen, welche durch das Programm beeinflusst wurden, waren überwiegend zwischen lokalen Akteueren in den Clustern. Neben der Zahl der Verbindungen in dem Netzwerk stieg aber auch die Zentralisierung, das heißt, die Verbindungen konzentrieren sich auf wenige prominente Akteure, die auch vorher schon stark in das Netzwerk eingebettet waren. Vor allem kleine und mittelständige Unternehmen nutzen die Möglichkeit, sich durch den Wettbewerb mit großen, bedeutenden Unternehmen in der Region zu vernetzen.

Der verstärkte Fokus dieser regionalen Innovationspolitik auf der Förderung vorwiegend regionaler Verbindungen begründet sich auf der Annahme, dass regionale Nähe zwischen den Kooperationspartnern den Wissensaustausch zwischen Akteuren und damit den Erfolg der kooperativen Innovationstätigkeiten erhöht. Diese Annahme ist in der Forschung jedoch kontrovers diskutiert. Während der Zusammenhang zwischen Kolokation von Akteuren und der Wahrscheinlichkeit dieser Akteure zu kooperieren ausgiebig untersucht wurde, wurde der Einfluss regionaler Nähe auf die Performance der Verbindungen zwischen diesen Akteuren bisher nur gering untersucht. Um die Qualität dieser Verbindungen zu eruieren und die Förderung regionaler Kooperationen zu begründen, bedarf es einer tiefergehenden Analyse dieses Zusammenhangs. Aus diesem Grund befasst sich Kapitel 4 mit der Frage nach den kontextualen Faktoren, die die Relation zwischen geografischer Nähe und dem Output von Forschungsprojekten determinieren.

Auch in diesem Kapitel verwenden wir den originären Datensatz, der auf den standardisierten Befragungen mit den Zuwendungsempfängern der Spitzencluster-Förderung basiert, welche zwischen in den Jahren zwischen2010 und 2013 erhoben wurden. Wir verwenden verschiedene Proxies für die regionale Nähe zwischen Projektpartnern und erklären damit drei Erfolgsvariablen.

Konzeptionell erfassen wir regionale Nähe in zwei Dimensionen: erstens wird die subjektive Bedeutung von regionaler Nähe für den Projekterfolg erfasst. Die Befragten konnten auf einer Likert-Skala direkt angeben, wie relevant die regionale Nähe zu ihren Kooperationspartnern war. Demgegenüber berücksichtigen wir die de facto regionale Nähe, in dem wir zwei quantitative Maßzahlen berechnen: die durchschnittliche geografische Entfernung der Kooperationspartner und die Entfernung zum Zentrum der Kooperationsaktivitäten. Mit letzterem kontrollieren wir für potenzielle Kern-Peripherie-Strukturen in den Kooperationsprojekten. In einer dreistufigen Analyse werden die Erfolgsfaktoren Projekterfolg (die Definition ist den Befragten überlassen), Projektzufriedenheit und anschließendes Projektergebnis anhand der regionalen Nähe und anderer Kontrollvariablen erklärt, um die Interdependenzen zwischen den Erfolgsvariablen zu berücksichtigen. Die Variable Projektzufriedenheit umfasst verschiedene Aspekte der Kooperation wie Know-How-Transfer und Koordination. Die Variable Projektergebnis schließt den Transfer von Projektergebnissen in andere Projekte und die Einführung von Innovationen ein. In einem ersten Schritt wird untersucht, unter welchen Bedingungen die Befragten die regionale Nähe als bedeutend für den Projekterfolg erachten. In einem zweiten Schritt wird die de facto regionale Nähe auf die verschiedenen Aspekte der Projektzufriedenheit als Zwischenprojekterfolg regressiert. Anschließend wird im dritten Schritt der Zusammenhang zwischen Projektzufriedenheit und Cross-Fertilisationseffekten und Innovationen als Resultat aus den Forschungsprojekten untersucht. Dabei wird angenommen, dass Projektzufriedenheit während der Projektlaufzeit den Projekterfolg am Ende der Projektlaufzeit bedingt.

Als Fazit des Kapitel 4 lässt sich festhalten, dass geografische Nähe der Kooperationspartner keine universelle Voraussetzung für den Erfolg des Forschungsprojektes darstellt. Tatsächlich liefern die Einschätzungen der einzelnen Befragten zur Bedeutung der regionalen Nähe ein sehr heterogenes Bild. Die Ergebnisse implizieren, dass die Art des involvierten und auszutauschenden Wissens darüber entscheidet, wie wichtig eine geringe Distanz der Kooperationspartner ist. Vor allen im Kontext von explorativer Forschung, wenn radikale Neuerungen entwickelt werden oder mit neuen Technologien experimentiert wird, scheint regionale Nähe besonders wichtig. Jedoch findet sich dieser Effekt nicht für Grundlagenforschung, was aber den Ergebnissen bisheriger Studien entspricht. Auch ist die Bedeutung regionaler Nähe für den Projekterfolg abhängig von der Art der kooperierenden Akteure. Für Unternehmen sinkt die Zufriedenheit mit den Projekten signifikant, je weiter entfernt sie von ihren Kooperationspartnern sitzen. Im Hinblick auf Projektendergebnisse zeigt sich darüber hinaus, dass Projektzufriedenheit und ebenso geografische Nähe die Cross-Fertilization von anderen Projekten unterstützen.

Während Kapitel 4 nicht explizit auf den Einfluss von staatlicher Förderung auf Verbindungen und deren anschließenden Output eingeht, sondern eine der grundlegenden Annahmen moderner regionaler Innovationspolitik prüft, liegt der Fokus von Kapitel 5 auf einer direkten Untersuchung des Einflusses von öffentlicher Förderung auf den Output von Forschungsprojekten. Kapitel 5 befasst sich im Detail mit dem Wissenstransfer von öffentlich geförderten Projekten im Vergleich zu nicht geförderten Projekten. Der Schwerpunkt der Analyse liegt einerseits auf der kognitiven Nähe der Wissensflüsse zwischen Wissensproduzenten (Erfindern) und den Wissensanwendern. In Hinblick auf die Innovationssystemsforschung sind die Wissensproduktion einerseits und die Wissensdiffusion andererseits wichtige Hebel für staatliche Einflussnahme. Eine zentrale Frage dieses Kapitels ist daher, inwieweit die finanzielle Unterstützung der Forschung durch die öffentliche Hand die Wissensproduktion und andererseits die Wissensdiffusion unterstützten kann. Es wird angenommen, dass öffentlich geförderte Projekte radikalere Neuerungen hervorbringen und im Ergebnis das produzierte Wissen eine breitere, diversere und interdisziplinärere Anwendung findet als bei nicht geförderten Projekten.

Um diese Forschungsfrage zu beantworten, werden Kooperationen auf Basis von Publikationsdaten aus der WebofScience-Datenbank untersucht. In die Analyse gehen alle Publikationen ein, die von mindestens einem deutschen Autor im Bereich der Medizintechnik zwischen 2007 und 2013 veröffentlicht wurden. Als Hinweis auf eine Förderung wurden die Informationen aus dem - zumeist obligatorischen- „Danksagung"-Abschnitt extrahiert und auf dieser Basis geförderte und nicht-geförderte Projekte miteinander verglichen. Als Forschungsoutput wurden die Zitierungen herangezogen, die ein Artikel nach seiner Veröffentlichung erhalten hat. Auf Basis eines Klassifikationssystems für Publikationen, welches Artikel verschiedenen Themengebieten zuordnet, wurde analysiert, wie interdisziplinär ein Artikel ist. Je mehr Disziplinen einen Artikel zitieren und je kognitiv entfernter die zitierenden Artikel sind, desto interdisziplinärer ist das Wissen, welches das Forschungsprojekt generiert hat. Ebenso wird auf Basis der Zitierungen untersucht, wie neu das generierte Wissen ist. Als Proxy für Neuheit wird die kognitive Nähe der zitierten Disziplin und der zitierenden Disziplin herangezogen. Kognitive Nähe wird anhand vorangegangener Kreuz-Zitierungen gemessen, das heißt, je öfter zwei Disziplinen sich zitieren, desto ähnlicher ist das Wissen, welches generiert wird. Um die Verzerrungen aus einem möglichen Selektionseffekt bei der Auswahl für eine öffentliche Förderung zu reduzieren, wird die Propensity Score Matching Methode angewandt. So wird dem Pool an geförderten Projekten eine geeignete Kontrollgruppe bestehend aus nicht geförderten Projekten zugeordnet und der Einfluss der Politikvariable kann bestimmt werden. Die Schätzung ist wiederrum zweistufig aufgebaut. In einem ersten Schritt wird für jedes Projekt die Wahrscheinlichkeit geschätzt, eine Förderung zu erhalten. Im nächsten Schritt wird dann der Zusammenhang zwischen öffentlicher Förderung und Interdisziplinarität der Anwendung des generierten Wissens untersucht.

Die empirische Analyse zeigt, dass die Ergebnisse aus öffentlich geförderten Projekten von einer größeren Varietät und Diversität an Disziplinen zitiert werden. Öffentliche Unterstützung kann somit effektiv den Wissenstransfer in kognitiv entferntere Bereiche fördern und unterstützt die Produktion von radikalen Neuerungen. Forschungsprojekte, die radikale Neuerungen anstreben, werden auf Grund des großen Risikos und der unsicheren Erfolgsprognosen selten ohne externen finanziellen Anreiz eingegangen.

Zusammenfassend lässt sich auf Basis der empirischen Analysen konstatieren, dass die Nähe zwischen Akteuren eine bedeutende Rolle für die Entwicklung der Verbindungen im Innovationssystem spielt. Auch hat die Politik einen maßgeblichen Einfluss auf diese Verbindungen: zum einen kann sie Anreize setzen, bestimmte Systemversagenstatbestände zu überwinden und lokale Akteure zu Kooperationen motivieren und hierdurch die Grundlage für einen effektiven Wissenstransfer zu schaffen. Andererseits kann sie veranlassen, das produzierte Wissen nicht nur in verwandte Bereiche zu verteilen, sondern verschiedene, diverse Disziplinen zu verbinden und so die Produktion radikaler Neuerungen zu unterstützen. Darüber hinaus sollten primär diverse Verbindungen initiiert werden, da redundantes Wissen die Wahrscheinlichkeit für Innovationen reduziert. Auch ist die Förderung ausschließlich regionaler Verbindungen skeptisch zu sehen, da technologische Aspekte eine bedeutendere Rolle für das Hervorbringen von Innovation spielen beziehungsweise regionale Nähe nur kontextbedingt eine wichtige Grundlage für den Erfolg von innovativen Projekten darstellt.

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Chapter 1

1. Introduction

1.1 Motivation and problem description

The quest for the explanation and the identification of determinants of economic development and welfare has always been the main challenge for economists. Identifying the levers for economic growth, which creates jobs in the long-term, is equally important to policy makers. In general, theoretical approaches to model economic growth assume that growth in economic output can be achieved in two ways: through the accumulation of traditional input factors (mainly capital and labor) or by the increase in efficiency of the usage of these input factors (Freeman and Soete 1997, Rosenberg 2004, Easterly and Levine 2001). In classical growth theories, varying national rates of economic growth were perceived mainly as the result of differences in capital accumulation and increase in labor input (Fagerberg et al. 2009). However, subsequent empirical analyses have yielded that these models failed to come close to reality. For instance, Abramowitz (1956) ,in his very influential study on the productivity growth of the US economy until the mid of the 20th century, found that an increase in the production input (labor and capital) accounted for only a minor part of the growing productivity. The largest part of the productivity growth was left unexplained (Rosenberg 2004, Fagerberg et al. 2009, Freeman and Soete 1997). He concluded that this 'residual' measures "our ignorance about the causes of economic growth" and points to where economists hereafter should focus the attention on (Abramowitz 1956, p.11). This 'residual' was later referred to as "total factor productivity", namely the efficiency of the use of the input factors (Solow 1957, Easterly and Levine 2001). Since the findings of Abramowitz were echoed in subsequent studies and diverging settings (for an overview see Fagerberg et al.2009), it has evolved as stylized fact that factor accumulation alone does not explain the full story. In turn, these changes in total factor productivity were attributed mainly to technical progress (Solow 1956, Easterly and Levine 2001). Solow was the first to explain long term economic growth by technological progress rather than pure factor accumulation, even though he introduced it as exogenous term into his model (Solow 1956, Fagerberg et al. 2009). Indeed, he found that a major part of the economic growth of the US economy was explained by technological advance, even though the processes of how technologies advance and how technical change emerges were treated as 'black box' (Rosenberg 1982, Teece 1992). The 1980th have seen a shift in the consideration of technical change as explanatory force of economic growth. As a response to the rather restricted and unsatisfactory explanations by neoclassical approaches, the new growth theory, pioneered by Paul Romer, incorporated technological change as endogenous in their growth models (Romer 1990, Fagerberg et al. 2009). Contrary to neo-classics, where technology was deemed as a public good that is accessible to everyone, technological change – understood as 'improvement in the instructions for mixing together raw materials' - was seen as the result of intentional actions by agents responding to market incentives and thus by no means a public good because it is at least partially excludable. (Romer 1990, p.2). In sum, technologies were not seen as given and coming from outside the model, but rather a consequence of endogenous adaption processes.

These developments have substantiated the relatively young research field on the economics of innovation, whose ideal founding father Joseph Schumpeter saw innovations as the main engine of economic change (Lundvall 2007). Providing explanations on what drives technological change as well as the enquiry of the nexus between innovation, market structure and economic development are the central aims of this research field (Dosi and Nelson 1994). Schumpeter defines innovation as the generation of new knowledge or the new combination of already existing knowledge (Schumpeter 1947). In his early work, he regarded the young and dynamic entrepreneur as originator of innovations who by introducing it to the market, induces a process of creative destruction in which new markets evolve and others vanish (Schumpeter 1934). In his later work, Schumpeter changed his perspective and argued that the R&D laboratories in large companies are the major source of innovation (Schumpeter, 1942). Evolutionary economists, starting with the seminal book by Nelson and Winter (1982), seized Schumpeter's ideas on the relation between firm size, market concentration and innovation. Nelson and Winter (1982) scrutinized the influence of industry specific effects on the sources of technical change. They find that the technological regime that is prevalent in the respective industry determines whether innovative activity is driven by entrepreneurs or large firms. Technological regimes thereby are understood as the technological environment that conditions the intensity of innovation, the concentration of innovative activity and the thread by new entrants (Nelson and Winter 1984, Winter 1984, Breschi et al. 2002). Accordingly, the variance in sectoral patterns of innovative activity can be explained by certain characteristics of the technological regimes: technological opportunities, appropriability of innovations, cumulativeness and the properties of the knowledge base (Malerba and Orsenigo 1997). Subsequent empirical analyses for several countries have supported the idea of the existence of divergent technological regimes (Malerba and Orsenigo 1997, Breschi et al. 2002). In turn, the technological capabilities of the firms are decisive for their survival on the market. Analogously to the Darwinian evolutionary theory, firms' fitness is contingent on their innovativeness (e.g. an increase in factor productivity leads to a reduction in unit costs). Competition is the selection mechanism that regulates the survival of the fittest (Dosi and Nelson 1994).

Given these findings on the importance of innovations for firm productivity and economic development, it appears to be crucial to open up the 'black box' of innovation and to elucidate the processes that originate innovation. It is without controversy, that intentional search efforts and knowledge accumulation increase the probability for innovation (Freeman and Soete 1997). Innovations are thus a function of investment in research and development (R&D). However, as already pointed out with the concept of technological regimes, the incentives of agents to invest in R&D and innovation are dependent on the characteristics of the knowledge involved and the nature of the innovation itself. In summarizing stylized facts of prior research on industrial innovation, Teece (1996) identifies certain major, mutually non-exclusive properties of technological innovation.

Uncertainty. Even though efforts to accumulate knowledge might increase the chances and potential to bring forth innovation, the search process inherent in innovative activities exhibits a significant random component (Dosi and Nelson 1994). This renders the outcomes and returns to innovation hardly predictable and therefore highly uncertain (Rosenberg 2004). The uncertainty and unpredictability of returns to innovation are caused by manifold reasons. For instance, not every search effort will automatically entail a scientific discovery or invention and new ideas are not automatically transformed into marketable products. Moreover, there is a high variation in the speed of success of new innovations, in case of the existence of knowledge spillovers the appropriability of returns is not warranted. However, given the rapid pace of technological progress, the largest source of uncertainty for innovative rents these days is the thread by becoming obsolete through the introduction of an already better and newer product or technology (Rosenberg 2004).

Path dependency. Mainly, technological advance takes place along certain paths in which the boundaries are defined by previous related innovative successes. In other words, novel technologies are developed within the realms of so called technological paradigms and along technological paths or trajectories. Radical innovations represent a radical shift from one technological paradigm to another (Teece 2008, Dosi 1982). A reason for this path dependent process, in which new technological knowledge builds upon prior technological knowledge, can be found in the ability to exploit and asses the value of novel knowledge. This ability is itself a function of prior related knowledge that agents (in the original theory of Cohen and Levinthal 1990 the agents were firms) accumulated in the past. Therefore agents/ firms search processes are path dependent.

Cumulative nature. The path dependency of technological progress is a result of its cumulative nature. Technological progress builds upon prior technological knowledge and develops along certain trajectories (Dosi 1982). Consequently, technological search is rather incremental (Dosi and Nelson 2013, Malerba and Orsenigo 1997, Breschi et al. 2002). Breschi et al. (2003) observed the cumulativeness of technological knowledge in an empirical study on the technological diversification strategies of firms from 18 different countries. In fact, they find that knowledge accumulation processes are incremental and path-dependent as firms diversify into related technologies but at the same time persistently innovate in the same technology.

Tacitness. Newly generated technological knowledge is characterized by an inherent degree of taciteness. This means, it resides in the heads of the inventor and is hard or even impossible to express in words or render it explicit (Polanyi 1962). While the degree of taciteness to some point reduces the risk of imitation, the transfer of tacit knowledge requires certain efforts. Hence, it can only be transferred by face-to-face-communication or mobile inventors (Breschi and Lissoni 2001, Audretsch and Feldman 1996).

Inappropriability. Closley related to the degree of tacitness of the knowledge is the issue of innapropriability. It concerns the ability to appropriate the returns to innovation by the inventor and to protect it from imitation (Dosi and Nelson 2013). A high degree of taciteness implies higher costs for imitation and thus it is easier to keep the returns to innovation. Depending on the economic character of the knowledge, the leakage of knowledge to agents other than the originator of knowledge, or in other words the existence of knowledge spillovers, combined with the uncertainty of rewards results in the danger of an underinvestment in R&D (Dosi and Nelson 2013, Cassiman and Veugelers 2002). Theoretically, there is a significant relationship between the degree of knowledge spillovers and the investment in R&D (Veugelers 1998, D'Aspremont and Jacquemin 1988), however evidence does not point to a monotonic relation between the difficulty of appropriability and the innovation intensity (Dosi and Nelson 2013).

These peculiarities of innovation have significant implications for the characteristics and organization of the search processes and the innovation intensity. The theory about distinct technological regimes is one example on how these properties determine the industrial structure of innovation. Another important inference that derives from these properties relates to the allocation of technological capabilities across economic agents. Firms react to markets and differ in the environment that they operate in and the problems they face and therefore differ in their search processes. Nelson and Winter (1982) concluded, that the source of variance in the fitness of the firms is to be found in their specific search processes (Dosi and Nelson 1994). Given the path dependent and cumulative nature of the search for novel technological knowledge (Dosi 1982) and the diverse environments, economic agents are heterogeneous in technological capabilities, knowledge and routines (Nelson and Winter 1982, Malerba 2002). This perception is incompatible with neoclassical economic theory and challenges the main assumption about homogenous and fully rational actors. Moreover, the heterogeneity in proprietary knowledge has consequences for the organization of R&D.

This heterogeneity in firm capabilities, its impact on technological innovation and survival in competition was addressed by many scholars from various schools of thought. Nelson and Winter (1982) originally considered a firms technological capabilities as routines and the variation in firms routines was perceived as the basis for technological variety and market dynamics (Dosi and Nelson 1994). Another stream of literature, settled at the border of management studies, draws on the research on the knowledge based view of the firm (Grant and Baden-

Fuller 1995) which bases on the resource based view proposed by Penrose (1959). Firms are considered as 'bundles of competencies' (Hamel 1991) and their idiosyncratic knowledge base is deemed as the result of firm specific accumulation processes in response to market conditions constituting their main competitive advantage. Even though, building up a proprietary knowledge resource, that is unique to the firm and difficult to imitate, is critical for firm survival in the knowledge driven economy (Lundvall and Johnson 1994), it limits the potential for generating and accessing novel knowledge. Thus, its exploitation is limited within firm boundaries and leads mostly to incremental improvements (Ahuja 2000, March 1991, Yang et al. 2010). Likewise, the economic theory on the development of absorptive capacity (Cohen and Levinthal 1990) points to path dependent processes of the accumulation of firm specific knowledge stocks. Cohen and Levinthal (1990) argue, that the ability of a firm to absorb and integrate knowledge is highly dependent on its stock of prior related knowledge. The identification of technological opportunities is thus guided by the amount of absorptive capacities. Thus, theoretically the potential for improvements and progress as a result of firms search processes, exploiting only their internal knowledge sources, can only be incremental (March 1991, Breschi et al. 2003). In order to achieve radical changes, firms thus need to gain access to complementary, external knowledge sources.

Moreover, the environment in which firms have to operate in has drastically changed in the last decades. Technologies have grown in complexity and innovation cycles have shortened. Thus, the economic landscape is characterized by high uncertainty and a rapid pace of technological change which turned investment in R&D, especially in the high-tech sectors, tremendously costly (Hagedoorn 2002, Rosenberg 2004). Thus, the access to external knowledge is inevitable to survive in the intensified competition. In this regard, Lundvall and Johnson (1994) have stressed that the ability to efficiently learn, rather than the possession of knowledge, has become the strategically most important resource in the learning economy.

One effective means for heterogeneously equipped agents to broaden the own knowledge base is the collaboration in R&D. Especially in high tech industries where knowledge is a crucial input factor and competition has developed as learning race, joint research has experienced a continuous growth since the late 1980s (Hagedoorn 2002, Mowery et al. 1996, Powell 1998). Similarly, this development has spurred the academic debate on the determinants of the formation of R&D collaboration and the success of joint research. Coming back to the properties of innovation, the motifs for collaboration in R&D can certainly be subsumed by three aspects: the agents heterogeneity in technological capabilities (*path-dependency* and *cumulativeness*), the increased uncertainty and the existence of knowledge spillovers (*taciteness* and *appropriability*) (Teece 1996). With regards to the agents' heterogeneity and uncertainty, incentives for strategic cooperation in R&D were investigated in the management literature based on the knowledge based perspective. It was emphasized that the access to and the acquisition of complementary knowledge counts among the major motifs of collaboration, whereas risk and costs sharing seem to be also important, but to a lesser extent (Grant and Baden-Fuller 2004). Especially for small firms with restricted resources, collaborations provide an alternative opportunity to compete with large firms (Teece 1992).

In the field of economics, scholars have focused on the appropriability of the generated technological knowledge and explained the investment in collaborative R&D with the existence of R&D-spillovers (Belderbos et al. 2004, Veugelers 1998, D'Aspremont and Jacquemin 1988, Cassiman and Veugelers 2002, Cohen and Levinthal 1990). A common finding in these models is that when the level of spillovers exceeds a certain critical threshold, investments in cooperative R&D increase. Although, evidence somewhat hints to a differential effect between outgoing spillovers and incoming spillovers (Belderbos et al. 2004). In the model of Cohen and Levinthal (1990), the degree of external knowledge flows provides an incentive for the firms to invest in internal R&D to build up absorptive capacity and to be able to absorb the external knowledge. Empirical studies support the hypotheses of a positive relationship between R&D collaboration and productivity and innovation (Uzzi und Spiro 2005, Singh and Fleming 2010, Bercovitz and Feldman 2011).

In the same vein, the more the research on the sources of innovation has advanced over time, the linear model of the innovation process from scientific discovery, to innovation, diffusion and imitation has been redeemed by a more interactive model, that incorporated feedback loops between the stages and producers and users of the innovation (Kline and Rosenberg 1984, Dosi and Nelson 2013). Allen (1983) identified and explained joint inventive activity and defined it as the institution of 'collective invention'. Van Hippel (1988) points to the fact that the sources of innovation vary and innovation might equally originate from users, manufactures, suppliers and others. Also, the strict conceptual separation between the scientific base and commercial application as a one-way street has been rescinded. Technological advances have equally propelled scientific advances as the other way round (Dosi and Nelson 2013). The chain-linked model (Kline and Rosenberg 1984), the concept of collective invention (Allen 1983) as well as the supplier-user interaction (van Hippel 1988) were precursors of what is known as the systemic perspective on innovation.

The growing awareness of the role of interaction in the innovation process constitutes the subsequent genesis of the research trajectory on innovation systems. A central proposition of this relatively recent research stream is that the innovative performance of a nation, region, sector or technology is contingent on the quality of the system of actors, their interdependencies and interconnections (cooperations and interactions), the institutional frame in which it is embedded as well as their competences (Carlsson et al. 2002). The efficiency of the interactive knowledge generation and diffusion determine significantly the capacity of the whole innovation system (Edquist 2005).

From the very outset, a more holistic perspective on innovation was introduced by Freeman (1987), considering the main actors and all the interactions, interdependencies and feedback loops in one comprehensive framework. While Freeman at this time introduced the prototype concept of the so called National System of Innovation to explain the national innovation intensity of Japan, subsequent scholars have delineated innovation systems at the national (Lundvall 1992, Nelson 1993), regional (Cooke et al. 1997, Braczyk et al. 1998), the sectoral (Breschi and Malerba 1997, Malerba and Orsenigo 1997) or the technological level (Carlsson et al. 2002) depending on the unit of analysis and the weights that are assigned to diverse factors at the disaggregate level. Irrespective of the version of the concept, the generic feature of the innovation systems is that it basically serves to describe the interactive generation and diffusion of new technological knowledge and its subsequent application (Carlsson et al. 2002). Edquist (2005) lists in more detail the most important activities conducted within the system, among others, creating new knowledge by conducting R&D, building up competences by education and commercialize the newly generated knowledge in marketable products, which he categorizes as the three kinds of interactive learning processes. Thus, interactive learning and networking between diverse actors lie at the heart of the concept of innovation systems.

The main elements of a system are *components*, the *relationships* between the components and *attributes* of the components and linkages (Carlsson et al. 2002). With respect to innovation systems, the main components are the actors that contribute to innovation such as firms, universities, research institutes but also the sources for financing the innovative activities such as venture capitalist or public agencies. Closely related to the activities proposed by Edquist (2005), Cantner & Graf (2003) further differentiate the actors into core poles according to their position in the knowledge production or knowledge exploitation process. The firms are subsumed as market pole, who aim to introduce the innovations into the market (learning through innovation). Public research institutes that generate basic knowledge constitute the scientific pole (learning through R&D and competence building) and private research institutes that basically engage in applied research are condensed as a technological-industrial pool (learning through R&D).

Furthermore, the institutions (such as the norms, habits, routines, practices and laws) as the regulating framework, in which innovative activity takes place are also main components characterizing a specific innovation system (Edquist 2005). Relationships in the system can be understood as the market and non-market linkages between the actors. These include also unintentional knowledge flows, spillovers, as well as intentional knowledge exchange within the scope of R&D cooperation (Carlsson et al. 2002). In turn, the attributes of the components and linkages can be understood as the characteristics of the systems such as the capabilities and competences of the actors to generate and diffuse technological knowledge. The dynamic evolution of the system is impelled by two major sources. First, the interactions between the components keep the system dynamic in that changes in characteristics of one component (capabilities) translate into changes of the overall configuration of the system (Carlsson et al. 2002). Second, drawing on the theoretical assumptions of evolutionary economics, the heterogeneity of actors and diversity in capabilities between them are crucial foundations for the dynamics of the system (Lundvall 2007).

In a nutshell, the innovation systems approach provides a sophisticated and profound basis for the analysis of the determinants of innovations as represents a compound framework accounting for the complex and intertwined coevolutionary processes between the innovative capabilities of agents, the division of innovative labor and the (formal and informal) linkages between these heterogeneous agents, that are the foundations for interactive learning and networking (Lundvall 2007). Although it covers a broad range of mechanisms that affect innovative capacity, it lacks a clear theoretical foundation of the processes on the micro-level that shape the configuration of the system. While it is assumed, that heterogeneity in the attributes of actors drives the dynamics of the system, it does not provide indepth explanations on where the heterogeneity originates from and whether there exists a certain optimal level of heterogeneity among actors. Moreover, the theoretical fragmentariness and the broad coverage of aspects as well as the difficulties of delineating appropriate borders of the system (geographical, political, technological) render the operationalization of the concept for empirical analyses an almost herculean task. Without a proper and comparable operationalization, an adequate performance assessment of the innovation systems is hardly impossible. Additionally, if performance of the systems cannot be measured, how can potential malfunctioning be identified. Furthermore, without a deeper insight into how exactly each element contributes to the performance of the system, one cannot deduce which screw has to be tightened so that the performance can be improved. Moreover, given that the emphasis in this concept is on networking and interactions between the actors, how do these networks evolve over time? Are there decreasing returns to connectivity on the meso-level? Research on overembeddedness (Uzzi 1997, Hagedoorn & Frankort 2008) as well as knowledge lock-ins (Bathelt et al. 2004) suggests the existence of an optimal degree of connectivity at the system level.

Since its synthesis, the systemic perspective on explaining the occurence of innovation has notably shaped the research and technology policy. Particularly, the support of networking and preferably the concept of clusters as a special type of regional innovation systems, have attracted the attention of policy makers. In Germany, the introduction of the BioRegio contest in the early 1990s marked the beginning of a new era of R&D funding programs, the so called systemic instruments (Smits & Kuhlmann 2004). The German innovation policy experienced a paradigmatic shift away from traditional R&D funding measures towards contests between regions with a special focus on collaborative R&D projects. Follow-up policy instrument have been developed in the recent years to strengthen the system as a whole and to stimulate the interaction between the actors of the system (Czarnitzki & Fier 2003). These novel systemic instruments of the innovation policy have put more emphasis on the advancement of networks and joint research projects in order to accelerate the transformation from inventions to marketable products.

Besides the popularity of the cluster concept in the policy sphere, the systemic perspective offered advanced understanding and rationales for policy interventions as compared to neoclassical theory. According to economic welfare theory, political interference is justified when the market coordination mechanisms are not able to result in optimal outcomes. Additionally, evolutionary economists pinpoint to the existence of system failures. Related to this view, the malfunctioning or ineffectiveness of innovation systems provides a reason for political action. Particularly, the presence of network failures in the sense of a deficiency of an optimal degree of linkages among actors in the innovation system formulates a rationale for cluster policies (Carlsson und Jacobson 1997, Andersson et al. 2004). Cantner et al. (2011), also focusing on regional innovation systems, identify three further deficiencies in connectivity among the actors that might prevent the innovation system to operate optimally and that provide a basis for political intervention: intermediation, reciprocity and compatibility. In the first case, intermediaries in the system, such as technology transfer offices or cluster managers, fail to connect the actors, which in turn are detained from the search for potential partners by the high transaction costs. Second, the lack of expected reciprocity or the lack of trust prevents the actors to link up with each other. Whilst the theoretical argumentation points to the existence of certain aspects of malfunctioning, the success of political intervention to remedy the deficiencies is hardly empirically provable. Coming back to the methodological challenge of measuring the performance of innovation systems, the difficulty of identifying potential malfunctioning of the system poses equally limits to the appropriate evaluation the impacts of systemic instruments of innovation policy. Due to the long term character of the effects of political support to R&D and the infancy of evaluation concepts, quantitative impact studies on policies that foster the linkages between actors in regional innovation systems or clusters, are relatively rare (Martin et al. 2011, Giuliani and Pietrobelli 2011, Fornahl et al. 2011. Moreover, the few existing analyses provide ambiguous results.

In light of these open issues, the concept of innovations systems provides manifold room for enrichment by further research. Therefore, the aim of this PhD thesis is to contribute to the in depth understanding of the dynamics at the micro-level of the innovation systems and to enlight the discussion on the possibilities for effective policy interventions. Our particular attention is on the networking between actors, as this element constitutes the 'glue' of the system (Carlsson et al. 2002) and represents the main mechanisms for knowledge diffusion and is therefore a crucial driver of the innovative capability of the system. In doing so, we aim to contribute to the rare empirical evidence on the dynamic coevolution of heterogeneous capabilities of innovative actors, interactive learning and networking. Specifically, we focus on cooperative agreements, namely R&D-cooperations, as their establishment provides "the key mechanism of network configuration" (Freeman 1991). Moreover, the choice of R&D collaboration as observational units is favorable with respect to political interventions, as the support of joint R&D is the core tool in systemic instruments of innovation policies. Plus, effects of prior systemic policy programs can most likely already be observed with regards to the structure of R&D collaboration. Thus, we aim to enlight the debate of the dynamics of the innovation systems by providing fresh empirical evidence on the interplay between the evolution of R&D cooperations, the heterogeneity in technological capabilities and the political influence herein.

Our contribution is twofold. On the one hand we aim to observe the formation and the stability of the linkages in an innovation system in combination with alternating technological capabilties. Adding on this, we also want to analyse the effects of policy support on the formation of these linkages. On the other hand, we are interested in the parameters that spur the performance of these R&D linkages. We quest for the sources of knowledge diffusion and innovation as performance measures of the R&D cooperations under study. Also here, we want to evaluate the effect of public funding of collaborative R&D on the knowledge diffusion from knowledge producers to knowledge users.

In sum, we aim to explain two pivotal phenomena related to the research on innovation systems, whose reasons of emergence are yet not fully understood: first, the occurrence of relationships in the innovation systems and their dynamic evolution in the course of changing technological capabilities. While the knowledge linkages build the infrastructure for knowledge flows, the second phenomenon concerns the performance of these linkages in terms of successful knowledge diffusion and innovation. As main explanatory factors, we consider the heterogeneity of agents and the role of policy intervention.

To characterize the heterogeneity of firms, we complement the concept of innovation systems by the theory of the supportive role of similarity on the formation of innovative linkages. The heterogeneity of actors in their routines, knowledge and capabilities is a main motif to exchange with sources of external knowledge, meaning that heterogeneity serves as a main rational for the search of collaboration partners (so the why we connect) (Grant and Baden-Fuller 2004). Furthermore, the degree of heterogeneity determines also with whom actors connect. Several streams of social science have found that the degree of similarity (so homogeneity) fosters linking up. In sociology the concept was termed as 'homophily', in innovation research Boschma (2005) coined it 'proximity' and pointed to the effect of partners' proximity in several dimension to the effectiveness of knowledge exchange and innovative capability. In R&D-alliances that explicitly aim at the generation of novel ideas and innovations, cognitive proximity as the basis for potential knowledge flows as well as social proximity as the control mechanism for knowledge flows might play a predominant role over other forms of proximity. For this reason, proximity between actors is a central concept that provides the theoretical basis for our subsequent empirical analysis. Additionally, we are particularly interested in the dynamic evolution of R&D-collaborations in order to derive ideas about the evolution of the systems towards volatile or rigid networks.

1.2 Structure of the thesis

Despite the prominence of the innovation systems approach in policy and academia, a deeper understanding of the processes that are at work at the micro level, particularly the interplay between the establishment of linkages, the knowledge exchange between the heterogeneous actors and political influence is hitherto missing. In addition, the approach exhibits some methodological challenges and conceptual ambiguities. First, this holistic approach to explain the emergence of innovations faces the challenge of an adequate operationalisation. When the argument of systems failure serves as a justification for policy intervention, a meaningful, quantitative evaluation of the capacity of the innovation system is necessary. This is associated with the intricacy of a valid valuation of the effects resulting from these novel systemic policy instruments. Second, previous conceptual reflections and their empirical validation have been rather static. Due to feedback loops and interdependencies, the systems configuration is continuously changing and differs dependent on the time of observation (Carlsson et al. 2002). A static study only captures a snapshot of the system at one certain point in time. Studies that examine the changes of the elements of the system or the system as a whole over time are few and far between. Thus, this thesis aims at analyzing the relationship between actor heterogeneity, R&D cooperation and the influence of innovation policy on the emergence of such linkages respectively the diffusion of results from these innovative activities. While several strands of literature offer a multitude of theoretical explanations for these relationships, a comprehensive dynamical empirical analysis that captures the coevolutionary processes is hitherto missing.

For this reason, the focus of this PhD thesis lies on a detailed empirical study of the emergence and the dynamic evolution of the interrelations between the innovative actors, the assessment of the quality of these linkages with respect to knowledge transfer and the output and opportunities for interference from the policy side. We mainly build our analyses on the innovation system approach and enhance this already rich framework by theoretical explanations from evolutionary economics, strategic management literature and economic geography.

To illuminate these interrelations holistically, this thesis is partitioned into two main parts. The focus of the first part, which comprises chapter 2 and 3, lies on the empirical investigation of crucial determinants that explain the establishment and the continuation of linkages between innovative actors. Specifically, we analyse the dynamic coevolution of bilateral, innovative cooperations and the heterogeneity respectively proximity of actors (Chapter 2) and the effects of public support on these linkages (Chapter 3).

While it can be assumed that actors anticipate which cooperations are the most rewarding in terms of the generations of innovations and enter these cooperations, the establishment of a joint research project is by no means an indication for subsequent success. To derive adequate policy implications, a qualitative statement about the performance of the induced collaborative linkages is required. Previous empirical research has shown that the determinants for the establishment of a cooperative link do not automatically condition its success (Boschma and Broekel 2012). On this account, the second main part of the thesis addresses the question of success factors of R&D collaborations. Thereby, the analysis concentrates on one condition that is still perceived by policy makers as decisive for the success of joint R&D and is a fundamental attribute of the concept of regional innovation systems: the regional proximity between the cooperation partners (Chapter 4). Withal, the positive association between regional proximity between actors and innovation is still not clearly evidenced and highly debatable, given the existence of other types of a-spatial proximities (Boschma and ter Wal 2011, Crescenzi 2014). Thus, we analyze whether cooperations with locally close partners outperform those with actors that have to span larger geographic distances.

A further aspect of successful research projects is the knowledge diffusion and the associated exchanges of research results. In Chapter 5, we analyze the effect of public support to research on the diffusion of research outcomes. Likewise, we also focus on the analysis of proximity between actors: the cognitive proximity between the knowledge producers and the knowledge users. In particular, we explore the relation between public funding and the spread of the knowledge into cognitive distal disciplines. Put it differently, we analyse whether public financial support can increase the generation of novel, interdisciplinary and highly relevant ideas and induce scientific advance.

To address the research questions from different angels, we employ a combination of various methodological approaches and datasets covering different technological fields. We gather information from secondary data sources such as patents and publications and complement them with information from primary data, namely from a survey and face to face interviews with beneficiaries of a specific national innovation programme. Chapter 2, 3 and 4 are the result of collaborative research projects of multiple authors, which substantially contributed to the progress and preparation of the chapters. A detailed overview over the contribution of the co-authors to each chapter can be found in the appendix. Furthermore, each of the chapters was presented at national and international conferences. A detailed list of conference presentation can also be found in the appendix. Moreover, chapter 2, 3 and 4 are either already published or in the process of publishing. A detailed report about the status of each of the chapters in the process of publishing can be found in the appendix.

1.2.1 Chapter 2

The dynamics of the relations in an innovation system are driven by strategic cooperation choices of actors on the micro level. These strategic choices are in turn driven by the heterogeneous technological capabilities of the actors (ter Wal and Boschma 2011). Building on the knowledge-based view of the firm (Grant and Baden-Fuller 1995) and conceptualizing heterogeneity as the proximity of the actors (Boschma 2005), the essence of Chapter 2 consists of the examination of the interplay of cooperation to introduce innovations and their longevity against the background of changing technological capabilities. We try to depict the feedback mechanisms between relationships in the innovation system and the attributes of the systems, namely the capabilities of the actors.

The similarity of cooperation partner has crystalized as a dominant determinant of innovative cooperations (Boschma 2005). It has been found, that actors, which resemble each other in several dimensions, have a higher propensity to jointly engage in research as compared to less similar actors. In this context, five dimension of proximity have been specified that affect the innovation propensity of cooperations. Mainly, technological and social proximity of actors have been found to be decisive for the development of innovation. Even though there is ample evidence on the constituent force of proximity in various dimensions for innovative cooperations, the long-term effects, probably also due to the limited availability of relational panel data, have hardly been subject to study so far. Also, findings on the interrelations between these several proximity dimensions, whether there exists a complementary or substitutive relationship, remain inconclusive. So far, social proximity has been identified as binding element of long term cooperation owing to the establishment of trust and thus social control over unintended knowledge spillovers (Gulati 1995, Gulati 1999). However, in the specific context of R&D cooperation, the novelty and complementarity of the knowledge of both partners is decisive. Continous cooperation opposes novelty since the knowledge bases of the partners converge through intersactive learning over time. Technological diversity of both partner warrants non-redundancy and potential novelty and is therefore an important driver of innovation.

Furthermore, the relation between certain proximity dimensions and the ongoing collaboration is by no means unidirectional (ter Wal and Boschma 2011). In fact, individual characteristic, such as technological capabilities, and thus the proximity to others coevolve over time with continuous collaboration (ter Wal and Boschma 2011, Balland et al. 2014). These dynamics have hardly been analyzed empirically (Balland et al. 2014). Most of the studies analyzing the relation between proximity and cooperation have been rather static. But the coevolution of factors driving collaboration choice and the evolution of ties can only be explored by the application of a dynamic approach. To emblaze these correlations further, chapter 2 contains a dynamic analysis of the cooperative behavior of firms on the basis of longitudinal data of all patents that were filed in the last 30 years in the German biotech sector. Cooperation is observable, when two actors jointly applied for a common patent. The probability of a potential linkage between two actors is explained by several relational variables.

As main predictors we determine on the one hand the cognitive proximity (as a proxy for the heterogeneity in technological capabilities) as measured by the overlap of the knowledge bases, the ratio of the potential knowledge gain as a measure of reciprocity and the knowledge exchange in prior collaboration. We approximate the knowledge bases of the actors by the assignment of patents to technological classes. This procedure allows to compare the vectors of technology stocks and to calculate the similarity in technological capabilities between the actors. On the other hand, we incorporate social proximity as the prior common collaboration experience, measured by the number of prior shared patents. Further aspects, that equally influence the collaboration probability and have to be controlled for are the innovative capabilities, the experience in collaborations in general as well as the positon of the actor in the overall collaboration network. By dint of logistic panel regression we estimate the effect of the primary variables and the control variables on the likelihood for continous cooperation. The application of panel estimations allows for a reduction of the systematic bias that is introduced through the unobserved heterogeneity between cooperating and non-cooperating pairs in the sample.

Key results of this chapter are that firms tend to prefer a switching of partners than to stick with the same partner, which is in line with the findings of Cantner and Graf (2006), who also find a partner switching behavior when analyzing the regional innovation system of Jena. Furthermore, similarity of the knowledge bases, the popularity of the partner, the competences and the past cooperative experience of the partner drive the cooperation choice. Knowledge transfer and thus the assimilation of the knowledge bases seemed to have no effect on the continuation of the cooperation. The observed instability of linkages seems to contradict the results of studies that emphasize the strength of so called strong ties and longevity of strategic alliances. One explanation could be that R&D cooperations represent a specific subset of strategic alliances, for which the relevance of novelty of technological knowledge outweighs the benefits of social proximity at some point. With respect to similarity, it can be concluded that similar competent and popular partners are more prone to connect than less akin partners. In accordance with other studies on the longevity of cooperations, we find that a cumulative advantage (Dahlander & McFarland 2013) increases the chances to link up significantly.

1.2.2 Chapter 3

While the explanation of bilaterial cooperations as a sub-element of the innovator network is at the core of chapter 2, we incorporate in chapter 3 the second crucial factor for the formation of innovative linkages: policy support. We focus on the mesolevel analysis of the development of whole R&D networks in regional bound clusters. We are particularly interested in the investigation of the effects of a specific policy instruments which aimed at the stimulation of linkages in regional innovation systems.

We explore the influence of the "Leading Edge Cluster Competition" (LECC), currently one of the largest German innovation policies, on the research collaboration networks of the beneficiaries in the selected cluster regions. The contribution of our study to the status quo research is manifold. When the study has been set up, the evaluation of such systemic types of policy programs was still in its infancy. Hitherto, the impact of funding on the selected networks was assessed only qualitatively. In the last few years, social network analysis has proven as a useful tool to visualize and inspect the linkages between innovative actors and thus the knowledge transfer channels in innovation systems. That way, potential effects of funding to collaborative projects can be surveyed at the system level. There have been only few attempts to apply SNA in the context of cluster policy evaluation (Giuliani and Pietrobelli 2011).

The data input for the SNA was generated from an original, standardized inquiry with the beneficiaries of the LECC-funding. The respondents were asked to mention their ten strategically most important R&D-partners and to indicate whether these connections were already existent before the participation in the competition. Based on this information, we display the R&D-networks for all of the four observed regional innovation systems (or clusters) and compare the respective structures and the policy influence therein. Moreover, it was possible to assess the linkages between the actors with respect to the geographic reach, the strategic importance and the kind of collaboration partner (research institute or company). Interpretations from the quantitative analysis were corroborated by results from face-to-face interviews with the beneficiaries.

A major lesson learned from the study in this chapter is that the competition was very effective in initiating novel cooperations between actors as well as intensifying existing cooperations. At the same time, the linkages that were affected by the policy in either way were predominantly between local actors in the selected clusters. Not only the number of linkages increased, but also the network centrality has increased owing to the policy intervention. I.e. we observed a tendency of the linkages to be concentrated on few prominent actors, which exhibited already a high degree of embeddedness before. Especially small and medium sized enterprises exploited the opportunity offered by the competition to connect to large, major companies in the region.

1.2.3 Chapter 4

The growing attention of innovation policy on the support of linkages between regional actors is grounded on the belief that regional proximity between cooperation partners increases the knowledge exchange between partners and thus the success of the joint innovation activities. This assumption is subject to controversial discussion among scholars (Crescenzi 2014). Whilst the nexus between colocation and the propensity to link up has been extensively studied, the interrelation between regional proximity and the performance of these linkages has been investigated to a very limited extent. To elicit the quality of these linkages and to verify the rationale for fostering regional linkages an in-depth analysis is necessary. For this reason, the research issue of the contextual factors that determine the relationship between geographical proximity and the output of research projects forms the core of chapter 4.

For this study we also exploit the original dataset gathered from the survey with the recipients of the LECC-funding that was conducted between 2010 and 2013. We avail several proxies to capture the regional proximity between the partners of the funded projects and explain three indicators of project success. Conceptually, we measure regional proximity in two dimensions: first we grasp the subjective relevance of geographical proximity for project success. The respondents were asked to directly indicate on a Likert-Scale whether they value regional proximity to their collaboration partners as an important condition for project success. Second, we account for the de facto regional proximity between the collaboration partners by calculating two alternative indexes: the average geographic distance between the partners and the distance to the centre of the cooperative activity. The latter captures the position of the respondent in potential core-periphery structures of the cooperation projects. In following a three-stage estimation procedure, we explore the variance in three success factors of the collaborative research projects: Project success as defined subjectively by the respondents, project satisfaction and subsequent project outputs. The differences in these success indicators are explained by regional proximity of the actors and other confounding factors. We estimated three interrelated models to account for potential interdependencies between the three success variables.

Project satisfaction encompasses various aspects of cooperation such as know-how-transfer or project coordination. The variable project output includes the cross-fertilization of other projects and the introduction of innovations as a result of the joint R&D project. In a first step, we analyse under which circumstances regional proximity was deemed relevant for the project success by the respondents. In a second step we regress the de facto geographical proximity on several facets of project satisfaction. Finally we analyse in a third step the association between project satisfaction and project success as indicated by cross-fertilization effects and the generation of innovations. Thereby, it is assumed that project satisfaction during the project period conditions the project success at the end of the project duration.

As a main conclusion of chapter 4 it can be noted that geographical proximity is not a universal condition for the success of the research project. In effect, judgments of the single respondents about the relevance of geographical proximity provided a very heterogeneous picture. These findings imply that the type of knowledge involved and to be exchanged determines the importance of a low distance between the cooperation partners. Regional proximity seems to be particularly crucial in the context of explorative research, when radical novelty is developed or in experiments with new technologies. Though, this effect cannot be found for basic research in general. This finding is however consistent with prior research. Likewise, the significance of regional proximity for project success is contingent on the type of cooperating actor. The satisfaction with the cooperation decreases for firms, the larger the distance is to their cooperation partners. With respect to final project results, we find, as expected, that project satisfaction as well as geographical proximity promote cross-fertilization effects of other projects within the same organization.

1.2.4 Chapter 5

While in chapter 4 we do not explicitly address the influence of government funding on the interrelations of the innovative actors and the associated final output but rather test a main underlying assumption of modern innovation policy, the focus of chapter 5 lies on a direct examination of the effect of public support on the output of research projects.

Prior studies have observed an increasing contribution of science to technologoical advance (Dosi and Nelson 2013, Mansfield 1998). In the same vein, Lundvall (2007) deemed science-based research processes, 'the mode of STI learning', as a crucial source of knowledge production in the innovation system. Therefore, we shift our perspective in this chapter towards the examination of what Cantner and Graf (2003) called the scientific pole of actors in an innovation system. We explicitly investigated the role of publicly funded research on the production and diffusion of newly generated knowledge. More specifically, we analyze, how the knowledge diffuses from the science poles and fertilizes subsequent work and partially also technological-industrial pole when they publish their inventions (Cantner & Graf 2003). Moreover, we are particularly interested, whether knowledge from publicly funded research might flow into more cognitively distant domains. This allows implications on whether public interventions might increase the connectivity of actors with diverse knowledge bases in the innovation system and thus increase the chances of the production of radical innovations.

In detail, chapter 5 deals with the knowledge diffusion from publicly funded projects as compared to non-funded projects. The analysis of the cognitive distance that is spanned by knowledge flows between knowledge producers (here inventors or scientists) and knowledge applicants (any type of actor) lies at the heart of the analyses in this chapter. With respect to the research on innovation systems, knowledge production and knowledge diffusion constitute main levers for political intervention. A central research question is thus, to which extent can financial support by the public domain stimulate knowledge production and knowledge diffusion. Basically, we hypothesize that publicly funded projects have higher chances to generate radical novelty and that the produced knowledge fertilizes following research to a broader, more diverse and more interdisciplinary degree. As a context for our analyses, we chose a typical science based area, the field of Medical Devices, in which the publicly funded research is a critical element in the sectoral innovation system and indispensable for the production of novel devices (Freeman & Soete 1997).

To answer this research question, we operationalize cooperation as co-authorships on scientific publications gathered from the WebofScience-Database. We include all publications that were co-authored by minimum one German author, published in the field of Medical Devices between 2007 and 2013. As evidence for funding we extracted the information from the -largely compulsory- acknowledgement sections in scientific journal articles. On this basis, we differentiated between projects that received additional public funds and projects that did not receive additional funds. This procedure brings about the main advantage, that the output of the research projects, as codified by scientific publication, can be directly attributed to public funding. No messy matching of two distinct dataset is necessary. To measure research output we consider citations that the articles under study received after publication by other subsequent articles. On the basis of a classification system for publications, which assignes journals to topical categories, we identified the degree of interdisciplinarity of an article. Topical categories are perceived to represent knowledge components. Cross-citation between divers knowledge components can be interpreted as knowledge flows. The more heterogeneous these knowledge components are, the more radical and novel is the link (knowledge flow) between them.

The more articles from diverse disciplines cite an article and the larger the cognitive distance between cited and citing article, the more interdisciplinary is the knowledge that was generated in the research project. Likewise, we analyze the degree of novelty of this generated knowledge on the basis of forward citations to articles. The cognitive distance of between the cited article and the citing articles serves as a proxy for the novelty of the published idea in the cited article. Thereby, cognitive distance is measured on the basis of co-citations between disciplines in the past, i.e. the likelihood of a potential citation between two categories. In other words, the more articles from two categories cite each other, the more related the knowledge is that is produced. To correct for a potential bias that is introduced by a non-random selection into the treatment (receiving additional public funds), we employ propensity score matching methods. In doing so, the group of observations who received public funding is matched to an adequate non-funded control group which is similar in all characteristics besides the receipt of the public funding. The basic assumption is that after controlling for potential confounding factors, the difference in the means between both groups can be attributed to the treatment, namely the public support. The estimation procedure is designed in two steps. In a first step the propensity for each project in the sample to receive supplementary public funds is estimated contingent on the certain pre-treatment characteristics (such as author experience, team diversity, etc). Based on these propensity scores the groups are matched and we analyze the relation between public funding and novelty of the idea, interdisciplinarity of the application and impact of the publication in a second step.

Basically, we found that collaborative research which focuses on basic topics and is conducted at interdisciplinary organizations is favored by funding agencies. Second, we indeed find evidence that the results of funded projects display a higher propensity for interdisciplinary application than those of non-funded projects. Also, publicly funded projects are prone to develop ideas which combine novel and disparate streams of knowledge as compared to non-funded projects. Consequently, the allocation of supplementary public research funds might serve as a risk premium and compensate for the higher costs and risks involved and therefore induce interdisciplinary collaboration. Regarding our research question about the additional payoff of public funds in terms of scientific impact, the results appear to be less conclusive. We find partial support for our hypothesis that publicly funded projects will achieve a larger impact contribution. Our results suggest that the receipt of public funds indeed opens the door to prestigious journals and increases the likelihood of being cited. Contrariwise, additional project funding and the source of the supplementary funds are irrelevant for the origination of breakthrough ideas. Rather, breakthrough ideas develop in environments where international researchers including at least one expert researcher collaborate and combine multiple knowledge inputs.

In sum, we find evidence that public support can indeed increase the connectivity of heterogeneous actors and combine diverse pieces of knowledge which in turn can increase the innovative capability of the whole system. Further research on this topic, especially concerning the consequences on the system level, is needed.

Chapter 2

2. The coevolution of innovative ties, proximity and competences - Towards a dynamic approach of innovation cooperation

2.1 Introduction

The growing complexity and shortening of cycles inherent in the innovation process have changed the industrial and technological environment in which firms operate. The associated increase in uncertainty and costs accompanying R&D projects has shaped a landscape that favors collaboration (Hagedoorn 2002). Especially in high tech industries where knowledge creation and accumulation is a crucial input factor and competition has developed as learning race, joint research has experienced a continuous growth since the 1980s (Mowery et al. 1996, Powell 1998).

A basic feature of joint research is the exchange and sharing of knowledge among the cooperation partners. Actors choose research cooperation in expectation of the highest potential knowledge gain. In this context, the importance of similarity between cooperation partners for knowledge transfer and successful collaboration has been stressed by several scholars. Similarity determines with whom we connect because it creates trust, facilitates knowledge flows and increases the mutual attractiveness of potential collaboration partners (McPherson et al. 2001, Boschma 2005). Similarity or proximity in three dimensions, namely cognitive, social and in regards to competences, seems to play a cardinal role for knowledge exchange in collaborations aiming at the generation of innovation.

These three dimensions are not simply given exogenously and static but they develop hand-in-hand with the duration of collaboration. Trust and experience as well as common understanding will increase over time on the one hand and the knowledge differences get decreased on the other. These dynamics are supposed to determine whether always the same partners continuously cooperate or whether there is partner switching to be observed over time. Increasing trust, experience and common understanding should contribute to the continuation of the partnership because they increase the efficiency of knowledge exchange and sharing. Contrariwise, a decrease in knowledge differences between partners, which means that cognitive proximity between them declines, indicates exploited opportunities to exchange and share knowledge and hence should lead to partner switching.

The relation between certain proximity dimensions and the ongoing collaboration is by no means unidirectional (ter Wal and Boschma 2011). In fact, individual characteristic, such as technological capabilities, and thus the proximity to others coevolve over time with continuous collaboration (ter Wal and Boschma 2011, Balland et al. 2014). These dynamics have hardly been analyzed empirically (Balland et al. 2014). Most of the studies analyzing the relation between proximity and cooperation have been rather static. But the coevolution of factors driving collaboration choice and the evolution of ties can only be explored by the application of a dynamic approach.

In this chapter we want to contribute to the field of dynamic approaches and analyze the interplay between cognitive proximity in terms of knowledge similarity, knowledge exchange and collaboration. We focus our analysis on ties of innovator networks defined as an ensemble of direct and indirect connections where the direct ones are collaborations in research aiming at producing innovations (Cantner and Graf 2006). We track the individual actors and their collaborations over time and pursue the following core research question: *In how far do knowledge dynamics between two cooperating actors determine the continuation of their innovative ties?* Hence, we mainly address the dynamics of the cognitive proximity between partners and take the other two dimensions, trust and competences, rather into the controls.

Our descriptive analysis suggests that firms are in general rather prone to switch their cooperation partner than to repeat the collaboration with a certain partner. In line with this, we find no significant effect of prior knowledge transfer and common cooperation experience between partners on (repeated) cooperation. The empirical analysis shows further that overlap between the firms' knowledge bases, an uneven distribution of the reciprocal potential for knowledge exchange, general collaboration experience of the partners and similarity in popularity of the collaboration partners are favorable for cooperation. Moreover, we find that firms prefer to cooperate with partners that are different in organizational nature and age.

This chapter is organized as follows: In section **2.2** we provide a general overview over basic concepts and main arguments describing the relation between similarity in knowledge, experience and their effect on tie formation. Building on this, we characterize how these relations dynamically coevolve with ongoing collaboration and present our hypotheses. Section **2.3** puts forward our methodological approach including data and variable descriptions. In section **2.4**, the final results are presented and discussed. Section **2.5** concludes and offers opportunities for further research avenues.

2.2 Knowledge dynamics and the evolution of innovation linkages

2.2.1 The role of cognitive proximity, social proximity and similarity in competences in innovative tie formation

The increased orientation towards collaboration especially in R&D has led to an upsurge of studies analyzing the advantages and incentives for alliance formation that were pushing forward this trend (e.g. Ahuja 2000, Hamel 1991, Hagedoorn 2002, Powell 1998, Gilsing et al. 2008, Khanna et al. 1998, Gulati 1999, Mowery et al. 1996). Essentially most alliances are motivated by cost arguments in terms of the access to external resources that are too costly to be acquired internally (Kogut et al. 1992). In innovation-oriented alliances the access to technology and knowledge related resources of a partner, whether in form of a certain technical infrastructure or more importantly in form of technological capabilities and complementary skills, constitutes the main motive for joint research, besides the sharing of risks and R&D costs (Hagedoorn 2002). Especially in high tech industries, firms are solely not able to generate all relevant resources internally in order to survive in the face of the high pace of technological change (Powell and Grodal 2006). According to the knowledge based view of the firm (drawing on the resource based view originally proposed by Penrose (1959)) a firm's knowledge base, understood as a unique and difficult to imitate resource, constitutes a key competitive advantage (Grant and Baden-Fuller 1995). In this regard, firms can be seen as "bundles of competencies" which they accumulated throughout their lifespan (Hamel 1991). Since firms face different problem solutions and environments, knowledge gathered by firms is an idiosyncratic property and quite heterogeneous among firms (Cantner und Graf 2011). Firms, even in the same industry or market, differ in what they know and are able to accomplish with their competences. As much as this proprietary knowledge resource provides a basis for opportunities, its exploitation is limited within firm boundaries and leads mostly to incremental and not necessarily optimal improvements (Ahuja 2000, March 1991, Yang et al. 2010). To broaden the knowledge base and to explore new possibilities for recombination and radical innovations, firms are reliant on external sources of knowledge (March 1991, Yang et al. 2010). As Freeman (1991) already argued, successful innovators extend their search for the solution of complex problems to external sources in their environment. Consequently, the generation of knowledge and innovation result progressively from a collective learning process among various actors which interact formally or in an informal way (Asheim and Gertler 2006).

In innovation oriented alliances, rational actors choose their potential interaction partners according to the highest expected outcome in terms of successful knowledge exchange and potential innovations. The efficacy of knowledge exchange between two or more actors is steered by the degree of heterogeneity between them. The proximity approach, proposed originally by Boschma (2005), emphasizes that the similarity – conceptually the inverse of heterogeneity - or proximity in various dimensions affects the ease of knowledge transfer between actors. Depending on the type of alliance under observation, different dimensions might be prominent. In R&D-alliances that explicitly aim at the generation of novel ideas and innovations, cognitive proximity as the basis for potential knowledge flows as well as social proximity as the control mechanism for knowledge flows might play a predominant role over other forms of proximity.

Cognitive proximity can be understood as the similarity of knowledge bases, which can determine the degree of knowledge exchange between actors in two opposing ways. Collective learning is characterized by two central elements which are in a trade-off relation to each other: namely mutual understanding and learning potential. Mutual understanding addresses the degree by which different actors understand each other and this increases along the cognitive proximity scale. Hence potential partners need to exhibit some degree of overlap in their knowledge bases – cognitive proximity - to warrant a mutual understanding.[1]

Learning potentials concern the amount of how much mutually can be learned and decrease with cognitive proximity. The heterogeneity of firms in the knowledge space is a source of learning effects as higher dissimilarity offers to higher learning potentials and more knowledge can be exchanged (Nooteboom 2005).

Combining the two dimensions of cognitive proximity as a condition for mutual understanding and as a source of knowledge exchange, suggests the existence of a "medium degree" of proximity at which a most beneficial exchange of knowledge is effectuated (Nooteboom 1999, Boschma 2005, Gilsing et al. 2008). A deviation from this level will either lead to higher potentials for exchanging knowledge combined with a lower common understanding or to a higher common understanding combined with lower potentials for novelty. Consequently, if an actor strategically and rationally searches for a potential research partner, he should, at least from a theoretical point of view, connect with partners to which his knowledge stock exhibits a certain degree of overlap as well as a certain degree of complementarity to obtain the potential for creating novelty.

The second condition for effective collaboration to take place addresses the controllability of the knowledge exchange/sharing relation. Here the strength of social ties between collaborators, also called social proximity, comes into play. Social proximity accounts for familiarity and trust between cooperation partners which in turn ease the transfer of tacit knowledge and re-

[1] Closely related is the concept of the ability to absorb external knowledge (absorptive capacity); it is to a large extent a function of the relatedness of the knowledge bases of collaboration partners (Cohen and Levinthal 1990, Cantner and Meder 2007, Boschma 2005). The lack of absorptive capacities results rather in a sharing of knowledge than in exchanging it, as the partners are not able to integrate the external knowledge into their own knowledge stock.

duce the occurrence of opportunistic behavior. Trust affects the efficiency of knowledge transfer in a way that familiar partners have already internalized norms of communication and undesired behavior such as free riding can be better controlled (Granovetter 2005). In consequence, the cooperation with trusted partners warrants higher reciprocity for yielded efforts. Often proposed mechanisms for social proximity to develop are mobile inventors which often maintain social relations to their former workplace, the positive experience gained in previous collaboration, knowing each other already before cooperation as well as the indirect acquaintance through a common partner (ter Wal and Boschma 2009). Consequently, a strategic and rational actor should prefer to link to already acquainted others. Besides cognitive proximity and social proximity, Boschma (2005) also suggests geographic proximity, organizational proximity as well as institutional proximity between partners to support learning and innovation. For the success of R&D-collaborations and the generation of innovations, we assume that social proximity and cognitive proximity outweigh other proximity dimensions since the creation of new ideas and the generation of innovation is a costly and uncertain process which is primarily determined by the knowledge involved (Mowery et al. 1998). In focusing on the examination of learning dynamics in R&D collaborations, we concentrate our argumentation on these two relevant dimensions of proximity. The likelihood of a new collaboration increases with social and to a certain degree with cognitive proximity of the potential partners.

Recent empirical findings underpin these arguments. Despite the differences in the measurement of the proximity dimensions, the positive effect of social proximity on collaboration probability has developed as stylized fact throughout the majority of studies of bilateral collaboration and the factors that explain its establishment and the exchange of knowledge (Ahuja 2000, Paier and Scherngell 2008, Mowery et al. 1998, Cantner and Meder 2007, Singh 2005, Powell 1998, Gulati and Gargiuolo 1999, Gulati 1995, Gulati 1999, Broekel and Boschma 2012, Criscuolo et al. 2010).

The results concerning cognitive proximity exhibit larger heterogeneity mainly due to the difficulty of finding appropriate proxies and the divergence of applied measures. Paier and Scherngell (2008), Cantner and Meder (2007) as well as Singh (2005) find a pure positive effect of knowledge overlap on tie formation, whereas Mowery et al. (1998), Criscuolo et al. (2010) and Wuyts et al. (2005) provide evidence for the inverted u-relationship between cognitive proximity and the proclivity to cooperate respectively to share knowledge as originally proposed by Nooteboom (1999). Gilsing et al (2008) and Wuyts et al. (2005) have additionally examined how proximity affects the innovative performance of R&D projects and their findings are in line with the aforementioned as the relation between cognitive proximity and innovative outcome follows an inverted u-shaped curve. Contrariwise Broekel und Boschma (2012) observe the so called proximity paradox in the analysis of link formation and link performance in the aviation industry: Although proximity seems to guide the formation of new R&D alliances, especially cognitive proximity hinders the innovative performance of the observed links.

Scholars have identified further factors that induce actors' collaboration opportunities that go beyond the link specific proximity. These are on the one hand economic factors as the accumulated capabilities and resources and on the other hand the general embeddedness of a firm in its relevant environment (industry, region, etc.). Both shape the perceived attractiveness of actors as a potential collaboration partner in a positive way as they serve as signal of competence to other actors in the network (Ahuja 2000, Stuart 2000). In general, firms with a higher resource endowment, e.g. innovative capabilities/ technical capital (past innovation activity, technology stock), can exploit more opportunities to form links as they are perceived more competent and are able to offer more knowledge and relevant information to their potential partners (Ahuja 2000). In turn, the number of connections that the firm already possesses - its embeddedness - favors new collaborations. In network studies a continuously recurring phenomenon is that popular actors (in terms of their number of linkages or their centrality) tend to become more popular (often referred to as preferential attachment (Barabasi and Albert 1999))[2]. This can be attributed to two effects: on the one hand highly connected actors have a broader access to information about potential partners (Gilsing et al. 2008). So the more connections an actor has, the more information he automatically also has about the partners of his partners and the more visible are potential partners to him. On the other hand, the central firm/ actor is also perceived more attractive by potential partners because the information about the central actor diffuses more widely and fast among a high number of potential partners. Moreover, a high number of connections signals to potential partners a high level of competencies concerning experience in managing and organizing alliances, a higher stock of technical capabilities and access to a broad and diverse knowledge pool (Ahuja 2000, Gulati 1999). Guliani (2007) for instance finds that the most central actors in the knowledge network possess the most comprehensive knowledge base. The causal relation of this link is however not clear.

However, the capabilities of firms/actors to establish continuously new links are not infinite. The returns to the creation of new links are decreasing with the total number of linkages as the managing costs of all linkages increase while the information benefits decrease (Hagedoorn and Frankort 2008, Ahuja 2000). Moreover, overembeddedness poses the risk of a lock-in and of forfeiting access to novel and non-redundant information and thus of reducing innovative potential (Uzzi 1997, Gilsing et al. 2008). Accordingly, Wuyts et al. (2005) corroborate this curvilinear relationship also for the composition of linkages. They find that the diversity of the collaboration portfolio positively influences innovativeness up to a certain optimal threshold. In regard of the aforementioned, with growing popularity and opportunities actors have to rationalize on their collaboration choices and might become increasingly selective in their partner choice (Ahuja 2000).

In the context of mutual agreements on collaboration and the search for the optimal linkages out of a pool of multiple potential partners, reciprocity becomes most important. I.e. firms or actors want their efforts and resources invested in the collaboration to be returned. This creates trust among the potential partners and makes collaboration more likely and sustainable (Cantner et al. 2011). Moreover, the balance of invested efforts of partners and reciprocated learning decides about the well-functioning and longevity of the alliance. An unbalance of resources or unilateral learning might result in asymmetric power of bargaining and dependency (Hamel 1991, Khanna et al. 1998). Firms/Actors find their attractiveness in terms of resources and efforts reciprocated in collaborations with others that are similarly endowed. In sociological studies on the relations of individuals the attractiveness of similarity has been termed as homophily (Rogers and Bhowmik 1970, McPherson et al. 2001). In the context of R&D collaborations, homophily might be driven by the search for reciprocity: actors that are similar in experience and competence exhibit higher reciprocal potential and thus have mutual incentives for associating with each other (Cantner and Meder 2007).

2.2.2 The dynamics of tie formation

Albeit much work has been done on the identification of factors that lead to the formation of innovative alliances, still little is known about the factors that determine the longevity of these alliances (Dahlander and McFarland 2013). Due to the difficulty of finding comprehensive longitudinal data on collaboration, most of the previous studies on innovation networks have relied on static analyses. Also conceptual frameworks like Boschma's proximity approach are basically static in nature (Balland et al. 2015). In addition, the relation between firm competence, proximity and collaboration is characterized by strong interconnectedness. The embeddedness of firms also feeds back into the proximity to other actors and in turn influences the

[2] In its origins preferential attachment describes the aspect that new entrants in the network preferably connect to central actors (Barabasi and Albert 1999).

attractiveness as potential partner and future collaboration opportunities (Balland et al. 2015). With regard to bilateral collaborations, the proximity dimensions between the partners change throughout the collaboration and this has consequences for the continuation of this collaboration. In view of the underexplored coevolution of these factors but as well the already existing evidence on the paradoxical effects of proximity and embeddedness, it is still unclear whether collaboration alliances are finite and develop towards a certain date of expiry and related to that, whether continuation or termination of an alliance can be used as an indication for the success of an R&D alliance. These coevolutionary processes can only be captured by dynamic approaches.

Advances towards this direction have been recently made mainly in the literature on the research of networks (Balland et al. 2012, Broekel 2012, ter Wal 2014). These scholars have developed frameworks to empirically analyze the parallel development of proximity, structural embeddedness and the overall linkage distribution. One main contribution of this work was the inclusion of endogenous network forces (the feedback effects of the structural position in the network) as an explanation for the probability of link formation besides relational effects (proximity) (Gilsing et al. 2008). First findings congruently show that the relevance of different proximity dimensions for the network configuration changes over time. Ter Wal (2014) elaborates the role of geographic proximity and triadic closure[3] (which is close to social proximity (Boschma and Frenken 2010)) in the network dynamics of the German biotech industry. He finds that the effect of geographic proximity disappears over time while social aspects increase in importance over time. In opposite, the analysis of a creative industry like the video game industry yielded that the effects of geographical and social proximity were constantly pronounced throughout all stages of the industry, while cognitive aspects were only relevant in later stages (Balland et al. 2012). Furthermore, also the interrelations between the certain proximity dimension themselves have been subject to studies. Cognitive, social, intuitional and geographical proximity have been found to coevolve over time, while the association between cognitive and institutional proximity does not decease over time (Broekel 2012). On the regional level, examining the network of innovators in Jena over two periods, Cantner and Graf (2006) find that the configuration of technological proximity among the actors changes over time in combination with instability of collaboration. From that they conclude that the very process of knowledge exchange depletes the cooperation potential between two partners which eventually renders cooperation obsolete.

However, the various mechanisms that cause a change of proximities as well as the association with actions on the micro level are still not sufficiently considered (Balland et al. 2012). In regard of this gap in the literature we take a dynamic perspective to make a step towards describing the coevolution of collaboration decisions, proximity and competences. Hence, we go beyond the mere explanation of the formation of innovative ties by analyzing the endurance of these linkages over time and relate this to the change in the underlying cognitive and social proximity as well as the competences of actors.

Two opposing effects have emanated from the ongoing debate about the effects social aspects and cognitive aspects on the continuation respectively discontinuation of collaborative ties. First, familiarity breeds trust and eases communication among partners (Gulati 1995). Therefore, building up link specific social capital and hence social proximity contributes to the continuation and therefore stability of linkages (Gulati 1995, Gulati and Gargiuolo 1999, Cantner et al. 2010). Secondly, an increase of cognitive proximity between collaborating partners on the one hand increases the mutual understanding, but on the other hand depletes the novelty potential and reduces the incentives to continue the collaboration (Wuyts et al. 2005). In terms of the development of innovation potentials over time, we expect the positive returns of increased

[3] The concept of triadic closure describes the phenomenon that actors that are indirectly linked by a third actor in period t-1 have a higher likelihood to establish a direct link in period t (ter Wal 2014).

social proximity and mutual understanding between partners to be outweighed by the negative returns of too similar knowledge bases. The argument against long-term relations derives from the necessity of diversity of knowledge for successful innovation (Nooteboom 1998, Gilsing et al. 2008). In sum, repeated ties increase the ease and speed of information to diffuse while infrequent ties serve as a source of novel and non-redundant knowledge (Granovetter 2005).

(a) Cognitive proximity

Adding to what has already been done, we unravel the multifaceted concept of cognitive proximity into *overlap*, *reciprocal potential* and *knowledge transfer* and track their dynamics within the evolution of collaboration.

Basically, the decision of forming or maintaining a link is continuously evaluated according to the involved benefits in terms of potential knowledge gains and innovative potential (Hamel 1991, Wuyts et al. 2005). The knowledge endowments of partners can be considered as pool for potential knowledge flows. For these potential knowledge flows to be effectuated, two conditions have to be met: first, a certain minimum similarity of knowledge bases, the *overlap*, is necessary to provide a basis for mutual understanding. The ability to absorb external knowledge is to a large extent a function of the relatedness of the knowledge bases of collaboration partners (Cohen and Levinthal 1990, Cantner and Meder 2007, Boschma 2005). The exchange of knowledge requires as a second condition potential knowledge that can be acquired because it is novel for the partner and not similar to the knowledge he already possesses. This implies that the dissimilarity of knowledge bases is also fruitful for potential knowledge flows. Only if the expected knowledge gains are positive, a collaboration will be established or continued.

In a dynamic perspective, partners move along this proposed cognitive proximity scale in increasing their overlap when collaborations evolve. After collaboration has been settled, partners that are able to learn will experience an assimilation of knowledge bases which results in an increase in *overlap* but as well in a decrease of novelty potential (Balland et al. 2015, Nooteboom 1998, Wuyts et al. 2005). The positive effects of overlap on mutual understanding will be compensated at a certain point of time by the negative effects on novelty creation (Boschma et al. 2015). These dynamic reverse effects have been found in empirical studies on the persistence of collaborations between researchers (Dahlander and McFarland 2013) or on the performance of ongoing cooperations between organizations (Beaudrey and Schiffauerova 2011, Wuyts et al. 2005). Too much intellectual similarity in terms of overlap in prior cited literature in publications hampers the maintenance of collaborative ties between researchers at the Stanford University (Dahlander and McFarland 2013). A lack of diversity decreases innovative performance in repeated collaborations as patent rates and the quality of patents diminish in long term collaborations (Beaudrey and Schiffauerova 2011) as well as the introduction of technical novelty become less likely the less variation an actor has in his collaboration portfolio (Wuyts et al. 2005). Therefore we assume that strategic actors that seek to maximize the benefits for innovation out of the collaboration will consequently terminate it after this optimal level of overlap will be exceeded.

Hypothesis 1a: *The relation between cognitive overlap of two actors and the likelihood of their continued collaboration follows an inverse u-curve.*

Considering the sheer overlap of knowledge alone does not necessarily imply the full exploitation of learning potentials, since the remaining novel and complementary knowledge in the partner's knowledge base is neglected (Mowery et al. 1998). This becomes especially relevant in a dynamic examination of collaborations. The novelty potential does not necessarily decrease with overlap over time, when the knowledge bases of partners increase disproportionally to the overlap. Remaining novelty potentials serve as a main incentive to maintain collaboration. Furthermore, collaborations as mutual agreements only establish or continue if both partners have respective incentives. In general these incentives encompass a certain level of reciprocity: actors want their invested efforts and competences to be reciprocated. Regarding potential knowledge flows, actors search for collaborations in which they expect the amount of new knowledge that is 'offered' to the partner to be reciprocated (Cantner et al. 2011). A collaborative opportunity is evaluated more attractive the higher this *reciprocal potential* is (Cantner and Meder 2007). In other words, the likelihood for collaboration increases with the equality of knowledge gains for both partners (the increase in reciprocal potential). We assume that the search for reciprocity in knowledge gains also is relevant for the continuation of collaboration.

Hypothesis 1b: *The reciprocal potential between two actors is positively associated with the likelihood of their continued collaboration.*

Apart from the overlap and reciprocal potentials, the very process of learning between the partners also has consequences for the continuation respectively termination of collaboration (Hamel 1991, Khanna et al. 1998). We define learning as the outcome of successful knowledge transfer, i.e. the successful integration of external knowledge into the own knowledge stock. This includes that the newly integrated knowledge can be as well applied outside the cooperative activity (Khanna et al. 1998). When learning potentials are exploited and knowledge has been transferred, the collaboration becomes obsolete to the partner that benefits from learning (Hamel 1991). Additionally, learning also influences the power distribution among the partners. An asymmetry in learning might lead to an imbalance in bargaining power and dependency structures. Competitive collaborations can be understood as learning race in which the 'first learner' gains a higher bargaining power and the lagging partner becomes less attractive (Hamel 1991, Khanna et al. 1998). As a consequence, learning might cause the finalization of collaboration by shifting the power balance as well as by decreasing the innovative potential. In this regard the longevity of an alliance can be rather interpreted as (learning) failure than as a success (Hamel 1991). We propose that the degree of learning determines the continuation of collaboration. In line with the cognitive and power arguments, we assume that effective knowledge exchange will decrease the incentives to maintain the collaboration. If, on the contrary, knowledge is only shared but not transferred, actors retain sufficient diversity in knowledge in order to benefit from the continuation of the collaboration. Ergo, we expect that accomplished knowledge exchange will lead to the termination of collaboration while mere knowledge sharing will result in continued collaboration.

Hypothesis 1c*: Knowledge transfer between two actors is negatively associated with the likelihood of their continued collaboration.*

(b) Social proximity

Beyond cognitive aspects, in the case of the collaborations among researchers at the Stanford University a shared history likewise increased the probability of continuing the collaboration (Dahlander and McFarland 2013). So the established link specific social capital seems to reinforce collaboration (Gulati 1995). A reason for this lies in the effect that social proximity has on the comfort of communication. Social proximity is associated with trust, the establishment of mutually agreed social norms and the control over undesired, non-cooperative behavior such as opportunism (Walker at al. 2003, Granovetter 2005, Boschma 2005). Given that social proximity establishes through experience gained in prior successful cooperation, its supportive effects on knowledge exchange increasingly unfold with the repetition of the cooperation. In this sense, increasing trust could explain the persistency in cooperation observed for alliances of firms (e.g. Gulati 1995, Mowery et al. 1998). However, the relevance of social aspects might be contingent on the context of the collaboration. Cantner et al. (2010) for instance find that social capital as measured by the frequency of the contact only plays a role for innovative outcome in cooperations with research institutes. In a dynamic context, we expect that in innovation cooperation the past common experience as indication for social proximity will ceteris paribus enforce future collaboration.

Hypothesis 2: *The likelihood of continued collaboration between two actors increases with their prior common experience.*

(c) Competence

Furthermore, other factors that coevolve with collaboration and are subject to temporal changes are the actor's capabilities and overall experiences as well as the embeddedness in the overall network. Innovative capabilities and experience in managing collaborative agreements have been found to increase an actor's attractiveness as collaboration partners (Gulati 1999, Ahuja 2000, Stuart 2000). With increasing number of innovative collaboration, the experience in running an alliance, managing skills as well as the innovative capabilities accumulate. This in turn attracts further potential partners. Under the assumption that the condition of reciprocity needs to be fulfilled for a collaboration to be maintained, we expect that the likelihood for continued cooperation is positively associated with the combined innovative and collaborative experience of both partners.

Hypothesis 3a: *The higher the general inventive/ innovative experience of both partners the higher the likelihood for their continued collaboration.*

Hypothesis 3b: *The higher the general collaboration experience of both partners the higher the likelihood for their continued collaboration*.

The embeddedness of an actor in terms of the number of collaborative ties he already established also determines the number of opportunities for further collaborations. A certain path dependency in the evolution of networks is explained by the phenomenon that the 'rich get richer' over time, which means that central actors tend to become more central over time (Barabasi and Albert 1999). This mechanism is known as preferential attachment or cumulative advantage (Barabasi and Albert 1999, Dahlander and McFarland 2013). This process might be explained by the broad access to information that central actors have about potential partners as well as their high visibility for other potential partners (Ahuja 2000). However, the reciprocity criterion applies here as well. In order to maximize the benefits of the collaboration, central actors are more likely to find their invested efforts to be reciprocated by actors that exhibit the same degree of popularity. Moreover, the bargaining power of central firms is higher (Gilsing et al. 2008). To maintain collaboration, the power needs to be equally distributed among the partners to avoid unilateral dependence (Hamel 1991). Therefore, partners are more likely to connect and to maintain this connection when they possess a similar amount of collaborative ties (Dahlander and McFarland 2013).

Hypothesis 3c: *The higher the similarity in popularity of two actors the higher the likelihood for their continued collaboration.*

2.3 Methodology

In our theoretical considerations, we identified three main factors that might explain the repetition of innovative linkages in our longitudinal study: cognitive and social proximity between the cooperation partners as well as the similarity in competences both partners bring into the collaboration. In the following, we will present the database we used, the variables we created and the methodology we applied.

2.3.1 Data

For constructing potential and realized linkages we use relational information found in patent applications. Successful collaboration leaves a trail in public patent data since patented inventions can be considered as the output of a preceding intensive cooperative research process (Singh 2005). In this context, cooperative patents comprise by definition inventive success. Although patent data come with certain limitations (see Griliches 1990, ter Wal 2009), they provide a rich and comprehensive data base on inventive activities. While working with patents one has to carefully define the scope of analysis in order to avoid the bias introduced by unobserved heterogeneity in patenting behavior (across industries, nations etc). To reduce this bias from inter-country and inter-industry differences, we narrow our analysis to patents that were filed by German applicants in the field of Biotechnology between 1978 and 2010. The Biotech industry is characterized by a high propensity to patent as well as a high frequency of joint research (Griliches 1990, ter Wal 2009, Powell and Grodal 2006). We gathered the data from the OECD-Regpat database[4] which covers patent applications to the EPO and the USPTO (Maraut et al. 2008). To match the collaborative actors to their respective other patents, we used the OECD HAN[5] that provides harmonized applicant names.

The use of patent data in our analysis requires some qualifications. First, for our analysis the pool of potential collaborators is given by all applicants that applied at least once for a patent in our focal time window from 1978 to 2010. Due to entries, this pool is not fix over time but rather grows from year to year so that we have to deal with an unbalanced panel. Secondly, a link between actors occurs when actors appear together as applicants on one patent document (co-application). The probability of false positives in detecting collaborations is assumed to be very small, since a co-application comes with a cost of reducing the claim of the patent for the applicant. Thirdly, it is debatable if continuous cooperation can be observed in patent data. If two applicants are persistently co-patenting we assume that they still conduct joint research. In this sense, we can identify long lasting relationships but we may underestimate the number of ongoing partnerships that do not result in patents. Fourth, patents have been established as a measure of technological capabilities (Mowery et al. 1996). The qualification of patent data as a proxy for firms' knowledge stock derives from the disaggregate information it provides. The international patent classification (IPC) offers a standardized and very fine technological classification system that allows for assigning the protected invention to a certain technology field as well as for characterizing the firms' research activities by constructing firm specific technology portfolios (Griliches 1990, Jaffe 1986). Jaffe (1986) was one of the first to use patent data as a proxy for firm's technological competences. He constructed the knowledge portfolios as a vector of patent classes in which firms patented and computed the distances between technology vectors of firms to obtain a measure of proximity among them. Subsequent studies followed Jaffe's approach in using patent classes to display a firm's technology portfolio, technological distances among firms or potential knowledge spillover pools in the firm's environment (Cantner and Meder 2007, Cantner and Graf 2006, Boschma and Frenken 2010, Benner and Walfogel 2008). We also make use of this rich information in constructing the knowledge portfolios of the actors and tracing their changes over time. The approximation of knowledge portfolios by means of patent information is hardly exercisable at the level of the individual inventor. Therefore, we focus our analysis on the organizational level.

2.3.2 Sample

The basic characteristics of the sample are shown in table 2.1. The sample consists of 197 firms that applied for patents with partners in the focal time period. In order to analyze the

[4] Version: Regpat January 2012 edition.

[5] Version: HAN January 2013 edition.

dynamics of cooperation choice, we consider only the choice of firms that cooperated already at least once in two years prior to the focal time period. This reduces our sample to 91 firms. After they entered the sample for the first time, each of the 91 firms was paired with the pool of its potential cooperation partners and its collaborative behavior was observed over the following years. All patenting actors that were active in the focal year or entered in years before compose the pool of their potential cooperation partners (Cantner and Meder 2007). For all possible combinations we assign a one for each realized cooperation and a zero otherwise. Double pairs are excluded. The size of the pool of potential partners is non-decreasing from year to year. It amounts to 2,369 potential partners in maximum.

The collaborations we look at include per definition at least one firm. This implies that the observations are not symmetric, i.e. we focus on firms, but we allow the potential partner in the pool to be of any type (firm, university, etc.). Taking together all possible pairs that occurred in the 32 years of analysis, our sample consists of 321,683 possibilities to form dyads, of which 293 in the end got realized.

Table 2.1 provides an overview over some selected sample characteristics. When we divide actors according to their overall collaboration activity over the whole period or their all-time partner portfolio (Wuyts et al. 2005), we observe 106 firms, that only collaborate once (so called *one shot*), 27 that collaborate at least twice but with different partners (so called *hop-on-hop-of*), 24 that persistently collaborate with the same partner (*persistent*) and 40 that pursue a mixed strategy (*mix-type*). For the purpose of our analysis, we focus on the firms that collaborate at least twice (excluding the one shot collaborators). Concerning the continuity of linkages we find that 60 of the 293 linkages are persistently observed while 138 are non-recurring. Thereof, the majority of linkages is repeated once and the maximum number of times that a link was subsequently observed equals 6.

2.3.3 Variables

We aim to explain the reappearance of linkages that were established between 1983 and 2010. Let us assume, we observe that a certain firm cooperated with a partner in 1997 and this link reoccurs in 1998. This is what we call repeated cooperation. From 1999 on, this link does not reoccur anymore. What our analysis aims at is to explain why the variable for cooperation (or dependent variable) becomes zero after 1998. In order to explain this, we use variables that are constructed via the cooperation partners accumulated characteristics in the years before. Moreover, all explanatory variables are lagged by one year. Under the assumption that collaboration is the outcome of a mutual agreement, we establish the explanatory variables by putting the characteristics of both actors into relation. The process of partner selection is thus modeled as matching process between the firm's attributes and the attributes of the respective partner. In our analysis, the attractiveness of the collaboration opportunity (better fit) is evaluated on the basis of the reciprocity in social, technological and experience aspects. Table 2.2 contains a comprehensive description of the variables used.

Dependent Variable

The dependent variable *Coop* represents the cooperation among two actors in the current year and is of binary nature, taking the value one if there is cooperation between one pair of partners and zero, if there is none. Since we are interested in explaining continuous collaboration respectively the dissolution of cooperation, non-recurring links, that were existent in periods before (or technically speaking the dependent variable changed from 1 to zero), are detected by the variable experience (see below).

Table 2.1 Sample characteristics

I. Actors	**Number**
a) Size of the pool of potential partners	**2,369**
b) Cooperative firms	**197**
One-shot	106
Repeaters	91
Hop-on-Hop-off	27
Mix-type	40
Persistent	24
c) Partner Diversity	
Collaboration partners of focal firms	
Min	1
Max	17
Median	2
II. Links	
a) Possible links	**321,683**
Realized links	293
Repeated links	60
Non-recurring link	138
b) Continuity of links	
Distribution of linkages across times of repetition (without dupli-cates)	
0	138
1	41
2	11
3	3
4	3
5	1
6	1

Independent Variables

(a) Cognitive proximity

Overlap: A widely accepted procedure to operationalize the construct of cognitive proximity is to consider some kind of activity classification of the actors. Concerning innovative activities, the patent documentation in form of the International Patent Classification (IPC) offers a useful and extensively used classification of technological activities. In empirical studies it is claimed that based on this categorization technological proximity can be measured as a sub aspect of cognitive proximity (Gilsing et al. 2008). In accordance with prior studies, we also rely on this classification assigned to patent documents and use technological proximity as a proxy for the multifaceted concept of cognitive proximity.

For the test of hypothesis 1a we include a simple measure that has been used in a couple of studies before. In order to observe whether a minimum level of mutual understanding of both partners is guaranteed, we calculate the areas of knowledge of both partners that overlap. In technical terms, this measure is simply the count of the IPC-classes that the (potential) partners share. To correct for the fact that a potential overlap is more likely for firms with larger portfolios, we divide overlap by the sum of the IPC classes in the portfolios of both partners and therefore use the relative overlap as one measure of cognitive proximity (*RelOverlap*). We also include this measure as a quadratic term to capture the trade-off between minimum levels of knowledge overlap as a warrant for mutual understanding and maximum levels of overlap as a hurdle to innovation due to the redundancy of knowledge (*RelOverlap^2*).

Reciprocal Potential: Following Cantner and Meder (2007), we operationalize the potential (knowledge) benefits from a potential collaboration as the relation of the new knowledge that both partners bring into the collaboration to test hypothesis 1b. However, we extend their approach by differentiating the single classes that are new to the partner rather than solely considering the raw number of patents. We count the number of non-overlapping IPC classes for each actor and take the ratio of the minimum of new knowledge classes and the maximum of new knowledge classes. This measure is named *ReciPot*. It is a continuous variable which ranges between 0 and 1, taking a 1, when the amount of new knowledge that the partners offer is equal (perfect reciprocity). The measure for potential benefit approaches zero, the more unequal the amount of non-overlapping knowledge amount of partners is or in other words the less reciprocal the gain is between the partners.

Knowledge transfer: In order to test hypothesis 1c we need to measure the knowledge transfer between collaborators. Citations of previous documents (patents and publications) on the patent became a favored instrument of scientific authors to detect knowledge spillovers (e.g. Griliches 1990, Jaffe et al. 1993, Hall et al. 2001, Nomaler and Verspagen 2008, Nelson 2009, Schmoch 1993, Mowery et al. 1996, Singh 2005). An often raised criticism is that patent citations may not imply real knowledge flows since a considerable amount of citations is added rather by the patent examiner than by the inventor/ applicant himself.

Table 2.2 Description of variables

Used for:	Variable name	Description	Obs	Mean	Std. Dev.	Min	Max
DV	*Coop*	Binary variable, indicating whether the respective pair cooperated or not in a certain year.	321,683	0.00	0.03	0	1
H 1a	*RelOverlap*	Continuous variable, indicating the overlap relative to the overall knowledge. Measured as the ratio of common IPC-classes to the sum of all IPC classes both partners cover.	319,323	0.05	0.07	0	0.5
	RelOverlap^2	The squared values of overlap.	319,323	0.01	0.02	0	0.25
H 1b	*ReciPot*	Continuous variable between zero and one, measuring the ratio between the minimum and the maximum of non-overlapping knowledge classes of both partners. The higher the value, the more equal is the number of potential new classes.	319,256	0.23	0.27	0	1
H 1c	*TransKnowledge*	Binary variable, indicating whether there has been a knowledge exchange in the previous period.	321,683	0.00	0.03	0	1
H 2	*CoopExp*	Count variable to measure social proximity. It is indicating, how often the partners cooperated before the cooperation in question.	321,683	0.00	0.07	0	7
H 3a	*DyadSinglePAT5*	Logarithm of the sum of the number of single-patents of both partners in previous 5 years	311,728	4.40	2.73	0	10.77
H 3b	*DyadCoopPAT5*	Logarithm of the sum of the number of co-patents of both partners in previous 5 years	311,728	3.42	1.66	0	8.94
H 3c	*DCentrality*	Absolute difference in degree centrality of both actors.	321,683	1.45	0.99	0	11
Controls	*DPatAge*	Difference in age (year of first patenting activity) of both partners.	321,683	7.80	6.36	0	30
	DStatus	Binary variable, indicating whether the partners are of the same type. Variable takes one when both are different, zero when both are firms.	321,683	0.55	0.50	0	1
Interactions:	*TransKnowledge* CoopExp*	Interaction between knowledge *kt_before* and *experience*.	321,683	0.00	0.06	0	7
	TransKnowledge RelOverlap*	Interaction between *kt_before* and *overlap*.	319,323	0.00	0.00	0	0.35

We take a different avenue and measure knowledge transfer between partners: We define the vector of technological classes that a firm has patented in as its cumulated knowledge stock and compare pre- and post-collaboration knowledge stocks. We define knowledge transfer as the occurrence of a new[6] patent class in the firm's patent portfolio after the collaboration has taken place (the co-patent was filed). To attribute the portfolio changes to the cooperation, the newly added class must have been part of the pre-collaboration knowledge base of the partner. On the basis of this measure we are able to differentiate pure knowledge sharing, as the pure access to knowledge, from knowledge exchange, the integration of new knowledge into own knowledge base. We assume that if a class is applied afterwards on single patents, the knowledge has successfully been integrated and is now applicable without any further collaboration. Based on this procedure, the binary variable *TransKnowledge* indicates whether knowledge has been exchanged in prior collaborations or not. This variable takes the value one if either partner has gained new knowledge and zero otherwise. This means, that it captures both: symmetric and asymmetric learning.

Our three measures of cognitive proximity, namely *RelOverlap*, *ReciPot* and *TransKnowledge*, do not develop independently from each other. Their change over time rather goes hand in hand. Therefore, we exemplify the dynamics in these three variables in figure 2.1.Two actors, I and II, hold specific knowledge portfolios before the cooperation (pre-collaboration). Actor I's portfolio comprises ABCDEF; actor II's, ABGH. The knowledge overlap in t-1 is given by AB and amounts to 0.2, relative to the overall knowledge. The reciprocal potential equals 0.5, because actor II possessess two knowledge units that actor I can gain as opposed to four knowledge units that actor II might be able to acquire from actor I. In other words, actor I can gain at most only half of the amount of knowledge that actor II, the partner, stands to gain. Formulated differently, actor II can earn twice of new knowledge that is being offered to actor I. In this example, the potential gains are unequal. Assume that collaboration then leads to symmetric learning in that C and G are exchanged. Actor I's post-collaboration portfolio is thereby enlarged to ABCDEFG; actor II's to ABCGH. As a result, the overlap has increased to ABCEG and amounts now to 0.3 in relation to the overall knowledge possessed by the two firms. In turn, the ratio between the potential knowledge gains has decreased to 0.3, because actor II now only offers one new knowledge unit to actor I, whereas actor I now offers three knowledge units to actor II. The potential for knowledge flows has thus decreased and become more uneven. The attractiveness of this fictive alliance and the likelihood that it will continue have therefore declined. This example illustrates the case of knowledge having been efficiently exchanged. When actors collaborate but are unable to integrate new knowledge into their stock, then knowledge has only been shared and the collaboration is more likely to continue than if they are able to integrate the new knowledge. In this sense, a continuation of collaboration can be interpreted as a failure to learn (Hamel, 1991).

(b) Social proximity

Common Experience: In order to test whether the probability for the (re-)creation of a link increases with the social proximity between the partners (hypothesis 2), we include the common *CoopExp,* that is measuring how often the pair has been cooperating prior to the cooperation in question, as a proxy for social proximity. The number of prior research projects with the partner is a commonly used measure for the strength of the tie and assumed to capture the trust and ease of communication between the partners (Cantner and Meder 2007).

[6] *New* in this context means, that the patent class may not occur in the pre-cooperation portfolio before the application of the co-patent.

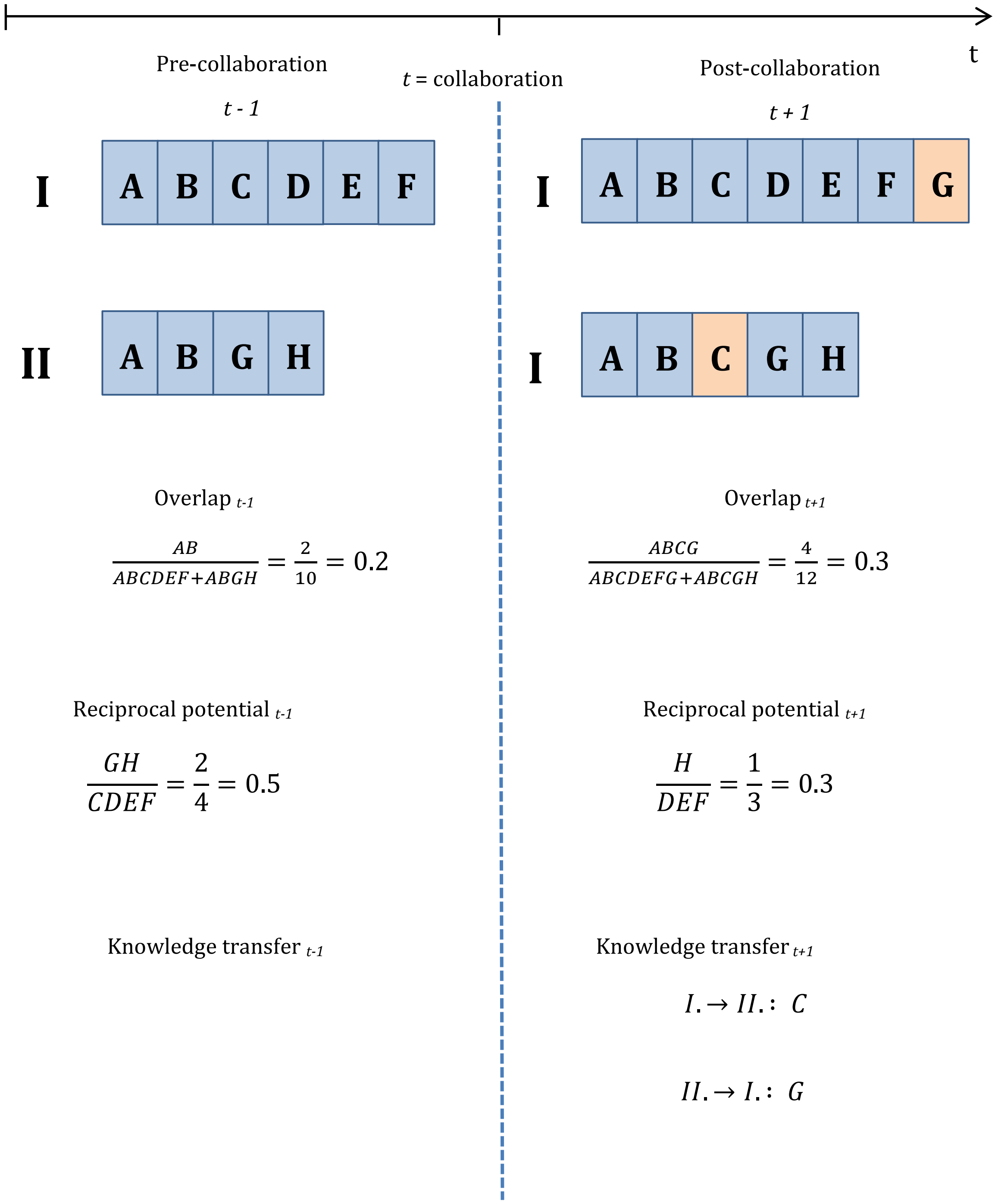


Figure 2.1 The dynamics in cognitive proximity and collaboration (example)

(c) Competences

Innovative Capabilities: Patents are an approved proxy for innovative activities, since the number of patents an actor holds is highly correlated with his R&D activities (Mowery et al. 1996). To elaborate on the relation between the accumulated technological capital and the continuation of linkages (hypothesis 3a), we therefore consider the sum of the single patents (no co-patents) that both partners owned in the five years prior to the collaboration as a proxy for their accumulated innovative capabilities (*DyadSinglePAT5*). To delimit the domain of the variable we take the logarithm of these values. We limit the time of observations to the preceding five year period to account for the depreciation of innovative capabilities and assume the knowledge to be almost obsolescent after this period (Hall 2007, Czarnitzki et al. 2006).

General collaboration experience: Analogously, to capture the attractiveness of the collaboration opportunity in terms of management ease, we take the sum of the shared patents (co-patents) that both actors held in the five years prior to the collaboration as a proxy for their accumulated collaboration experience (*DyadCoopPAT5*). Since we want to detect the general collaboration experience, this measure adds up all collaborations except the collaboration in question. The greater the collaborative experience is the higher is the likelihood for further collaborations. Here we also assume average capability depreciation after five years and apply the logarithmic transformation to delimit the range of the variable.

Popularity: Guliani (2007) argues, due to reciprocal incentives, it is more likely that popular (as measured by their number of other linkages), central actors connect to similarly embedded actors. The potential for knowledge spillovers might be higher when partners are equally popular and possess a similar pool of potential knowledge sources (links). To test this relation (hypothesis 3c) we use the absolute difference of the degree centrality (the number of links) between two partners in the year before the collaboration and name this variable *DCentrality* (Dahlander and McFarland 2013). Theoretically, this measure is closely related to the general collaboration experience. However we capture here the reciprocity in popularity in collaboration activity rather than the pure amount of previous collaboration activity.

Control variables: Apart from technological, social and competence aspects, we also want to control for additional effects stemming from organizational and age similarity. Both might increase the likelihood for collaboration due to ease of communication when they are exposed to the same institutional factors and environments (organizational similarity) or when they had the same time to operate in these environments and to accumulate experience and resources (age similarity). Organizational dissimilarity – *DStatus* – is a binary variable taking the value one when both actors are of different organizational nature and zero when they are of the same organizational type (interfirm collaboration). *DPatAge* is the absolute difference in the age of the actors (measured as the length of appearance since their first occurrence on a patent). Our age variable is also assumed to capture the effect of firm size, since the age and the size of the firm are usually highly correlated.

2.3.4 Estimation strategy

The choice of a pair of two partners to cooperate is modeled as the probability to observe the realization of a link ($coop_{i,j,t}$ taking the value of one) dependent on the explanatory variables as introduced in section 2.3.3. The decision to collaborate with a respective partner is a binary one. Therefore we estimate the following logistic model (see Kennedy 2009):

$$log\left[\frac{P(Coop_{i,j,t}=1)}{1-P(Coop_{i,j,t}=1)}\right]$$
$$= \beta_0 + \beta_1 RelOverlap_{i,j,t-1} + \beta_2 RelOverlap\hat{}2_{i,j,t-1} + \beta_3 ReciPot_{i,j,t-1}$$
$$+ \beta_4 TransKnowledge_{i,j,t-n} + \beta_5 CoopExp_{i,j,t-n} + \beta_6 DyadSinglePAT5_{i,j,t-1}$$
$$+ \beta_7 DyadCoopPAT5_{i,j,t-1} + \beta_8 DCentrality_{i,j,t-1}$$
$$+ \beta_9 TransKnowledge_{i,j,t-n} * CoopExp_{i,j,t-n} + \beta_{10} TransKnowledge_{i,j,t-n}$$
$$* RelOverlap_{i,j,t-1} + \beta_{11} DPatAge_{i,j,t} + \beta_{12} DStatus_{i,j,t} + \varepsilon_{i,j,t}$$

We include all realized and potential i, j combinations over the time period from 1983 to 2010. To avoid potential biases from restricting our sample to collaborative actors only, we include all possible combinations between the focal firms and all actors that at least patented once. However, including combinations with all potential actors in the sample (also those that never collaborated) introduces a source of bias due to unobserved heterogeneity. That means dyads in the control group, that never get realized, might differ systematically in unobserved factors from dyads that got realized at least once. These differences in unobserved characteristics might account for systematic differences in the general propensity to collaborate between cooperating and non-cooperating actors. Moreover, each single dyad might have established or non-established due to other specific factors that we do not observe and can therefore not include into our model (Gulati and Gargiulo 1999, Heckman 1981). To account for pair-specific heterogeneity, we apply a random effects panel model by including a random intercept for each pair. Doing that, we assume that the unobserved differences in the dyads are the results of a random process. However, this method also comes with the strong assumption that the unobserved factors are not correlated with any of the explanatory variables. This assumption is hard to test empirically. Contrariwise the fixed effects estimator would remove these time-invariant factors, but results in a dramatic shrinkage of sample size. This comes at a cost, namely that the number of observations would drop from more than 300,000 to 501. Moreover, random effects estimation allows us to include further time-invariant variables like *DStatus* into the model. In view of these considerations, we prefer the random effects over the fixed effects model.

Another issue that arises when analyzing network data is the dependence of observations. The observations are not completely independent because individual actors might be part of multiple dyads. Consequently, the estimates are consistent but the standard errors might be underestimated (Kennedy 2009). Since we cannot make any distributional assumption, we obtain robust standard errors by means of bootstrapping methods for panel data. Therefore we calculate the standard errors from the empirical distribution that is drawn by resampling the original dataset in 1000 iterations. Another form of bootstrapping that is commonly used in analyzing dyadic data is gathering the empirical distribution by a repeated random permutation of the complete adjacency matrix or the so called MRQAP. Whilst this method has proven to be appropriate for linear models with continuous dependent variable, it is still unclear how this method performs when analyzing binary models (Broekel et al. 2014, Dekker et al. 2007). Moreover this method has hardly been tested in panel settings.

2.4 Results

2.4.1 Descriptives

Diversity in Partner Portfolio

To get a first overview over the diversity of the firms' partner portfolios, we consider the number of different partners firms cooperated with over the whole period from 1978 to 2010. Table 2.1 in section 2.3.2 provides some summary statistics about the number of partners (Part I., row c) and the continuity of links (Part II. Links, row a and b). The whole distribution of actors over the number of different partners can be found in figure 2.2 in the appendix. Most firms cooperate on average (the median equals 2) with two different partners, whereas only a few cooperate with a larger variety of actors. The maximum the number of different partners in one portfolio amounts 17. In other words, one firm cooperated with 17 different actors over the whole time. For the firms in our sample this implies that repeated collaboration with only one partner is not a dominant behavior.

Longevity of links

Concerning the longevity of links, we find that of 293 realized links, 138 were realized just once (non-recurring), whereas 60 links were repeated at least once (the sum of repetitive links amounts to 155). Without double counting of the repeated links, the number of realized combinations equals 198 of which the majority (138 or 70%) was non-recurring. Among the sustainable links the major share was repeated only once (41) and the maximum number of link repetition equals to 6. In contrast to the prior findings by Gulati (1995) as well as Gulati and Gargiulo (1999) who find stability in link formation, our first findings suggest, that firms are rather prone to change partners regularly than to repeat collaboration with the same partner. Our findings complement the results by Wuyts et al. (2005) but also with Cantner and Graf (2006) in that the search for diversity of knowledge sources leads firms to rather switch their R&D-partners.

2.4.2 Estimation results

For a first overview, table 2.4 in the Appendix contains the bilateral correlations between the variables included into the estimations. With regards to correlations between the explanatory variables, we don't seem to have a severe problem of collinearity. With respect to the correlation between the explanatory variables and the dependent variable (*Coop*), we find that *RelOverlap*, *TransKnowledge*, *CoopExp*, *DyadSingle-PAT5*, *DyadCoopPAT5* and *DStatus* are slightly positively correlated with cooperation whereas *ReciPOT*, *DCentrality* and *DPatAge* show a negative sign. To gain a more detailed understanding of the forces that determine the partner choice, we ran a random effects logistic regression on our panel data.

Table 2.3 shows the outcome of our estimations of for seven model variations. The results for the base model only comprising the two control variables *DStatus* and *DPatAge* are given in the last column. We find that *DStatus* is highly significant and positively linked to the probability to cooperate (*Coop*), which indicates that firms prefer to cooperate with partners that are of a different organizational form.

Concerning the dynamics in cognitive proximity, we analyze the three dimensions overlap (*RelOverlap*), reciprocal potential (and knowledge transfer. First, we find that the squared term of the relative overlap (*RelOverlapl^2*) between the knowledge bases of the two partners is positively and highly significant related to the probability to collaborate. However, we do not find support for the existence of a moderate level of overlap and consequently for our hypothesis 1a. When controlling for combined effects of experience and overlap (column “Interactions”) as well as in the full model (“Full”), we only find a pure positive correlation between overlap and the likelihood of collaboration. Thus, the degree of mutual understanding seems to increase the likelihood for the reformation of linkages. Second, the impression concerning the search for diversity from figure 2.2 is confirmed by our estimation results. We find that firms are more likely to reconnect to actors that differ from them in the amount of potentially new knowledge. The negative relation between reciprocal potential (*ReciPot*) and the likelihood for collaboration indicates that reciprocity in knowledge gains is not a necessary precondition for continuity of collaborations. Our result is opposite to the assumed relation in hypothesis 1b. Third and concerning hypothesis 1c, we do not find a significantly positive relation between collaboration and previous knowledge transfer (*TransKnowledge*). Our results seem to contradict our hypotheses on the relevance of knowledge diversity in the evolution of cooperation. Concerning cognitive proximity, the need for mutual understanding seems to play a predominant role over the reciprocity in potential knowledge gains.

Regarding social proximity where we suggest with hypothesis 2 that the propensity of collaboration increases with prior common experience, we empirically find no connection between the chances for cooperation and prior common experience (*CoopExp*). Also the transformation of the variable into a binary one, taking values of one when they minimum cooperated once prior to the actual collaboration, does not yield different results.

Even though common experience does not play a significant role in partner choice, the combined overall cooperation experience (*DyadCoopPAT5*) is positively and significantly associated with the recreation of linkages. This means that collaboration choices are preferred when at least one actor exhibits a large amount of accumulated capabilities in managing cooperation. This finding conforms to the results of Gulati (1999) who observes the same supportive effect of general collaboration experience of an actor on his chances of forming linkages. The importance of the cumulative advantages is also reflected in the negative relation between collaboration propensity and the difference in popularity (*DCentrality*). In contrast to knowledge benefits, firms are rather guided by reciprocal incentives when it comes to accumulated cooperation capabilities and experience. Our results indicate that they prefer to link up with actors that offer an equal amount of accumulated resources. Dahlander and McFarland (2013) find the same negative association for the difference in what they call *cumulative advantage* and the persistency in collaborations between researchers at the Stanford University. This effect however disappears when controlling for all other variables in the full model. Contrariwise, the common cumulative innovative potential as measured in the total single patents both actors (*DyadSinglePAT5*) hold seems to be rather irrelevant when it comes to partner choice. Therefore, we find support for our hypotheses 3b and 3c, but not for hypothesis 3a.

Consequently, our findings provide evidence for the reinforcing impact of similarity in knowledge and accumulated capabilities on attractiveness of collaboration options and link maintenance. Nevertheless, firms also seek for some degree of heterogeneity with regards to the controls *DStatus* and *DPatAge* as the probability for (repeated) collaboration increases when the partner is not a firm or the partner is significantly different in patenting experience. However, these findings can be partially attributed to the specificities of research in Biotech. One reason is that industry-university relationships are a prevalent phenomenon in German Biotech. Since the innovation process is rather linear with discoveries being introduced by public research institutes, the industry-university collaboration is an important technology transfer mechanism and thus makes it more likely. Furthermore, the influence of the difference in patenting age might reflect another widespread form of collaboration agreement in Biotech: the joint research between young, small companies as the creative engine and large pharmaceutical companies functioning as a source of financial resources (Powell et al. 1996, McKelvey 1997, ter Wal 2014).

Table 2.3 Estimation results of the random effects logistic regression

Method	**Random-effects logistic regression**									
Dep. Var.	Coop									
	H 1a	**H 1b**	**H 1c**	**H 2**	**H 2 with CoopExpBin**	**H 3 a-c**	**Interactions**	**Interactions with CoopExpBin**	**Controls**	**Full**
RelOverlap	5.5655						**27.0777*****	**0.0076*****		**28.2185*****
	(1.58)						(7.79)	(5.11)		(4.37)
RelOverlap^2	**49.7110*****									-13.0516
	(5.59)									(-1.07)
ReciPot		**-2.2486*****								**-2.6359*****
		(-3.88)								(-3.03)
TransKnowledge			0.9032				1.6796	**1.5995***		2.0168
			(1.19)				(1.53)	(1.67)		(1.49)
CoopExp				0.0077	0.8366		-0.1455	-0.3620		0.0705
				(0.03)	(1.24)		(-0.33)	(-1.42)		(0.10)
DyadSinglePAT5						-0.0431				**0.1954*****
						(-1.00)				(2.67)
DyadCoopPAT5						**0.6109*****				**0.6792*****
						(9.53)				(4.38)
DCentrality						**-1.1718****				-0.7779
						(-1.97)				(-1.49)
TransKnowledge CoopExp*							-0.9984	omitted		-1.2623
							(-1.51)			(-1.62)
TransKnowledge RelOverlap*							-4.3422	-3.2172		-0.7173
							(-0.70)	(-0.55)		(-0.12)
DStatus	**1.2470*****	**1.1283*****	**0.9980*****	**1.0228*****	**1.0167*****	**1.1042*****	**1.4245*****	**1.0985*****	**1.0215*****	**1.5400*****
	(4.18)	(4.39)	(4.40)	(4.29)	(4.55)	(4.42)	(4.06)	(4.40)	(4.15)	(3.82)
DPatAge	**0.0743*****	-0.0003	-0.0041	-0.0039	-0.0057	**-0.0393****	**0.1149*****	-0.0053	-0.0039	**0.0454****
	(-3.43)	(-0.01)	(-0.23)	(-0.23)	(-0.34)	(-2.19)	(4.69)	(-0.30)	(-0.23)	(2.19)
constant	**-20.9707*****	**-17.1154*****	**-14.1513*****	**-14.3361*****	**-15.5535*****	**-14.8631*****	**-24.0424*****	**-14.3735*****	**-14.3457*****	**-20.8766*****
	(-15.62)	(-13.09)	(-8.44)	(-8.17)	(-12.14)	(-7.66)	(-8.81)	(-7.93)	(-9.34)	(-4.83)
No. of Obs.	319,323	319,256	321,683	321,683	321,683	311,728	319,323	319,323	321,683	309,344
No. of Groups	142,417	142,384	142,984	142,984	142,984	139,318	142,417	142,417	142,984	138,721
LR chi2	-1610.31	1019.03	479.56	613.07	-1798.19	542.03	-1604.7	-1782.08	-1808.19	-1445.35
Prob > chi2	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000
Wald chi2(3)		33.08	19.68	19.89	21.69					
Wald chi2(5)						178.66				
Wald chi2(7)							146.14			
Wald chi2(6)								53.85		
Wald chi2(2)									17.62	
Wald chi2(4)	164.27									
Wald chi2(12)										163.19
/lnsig2u	3.4286	3.2234	2.7003	2.7382	2.9423	2.7401	3.6029	2.7222	2.7404	2.9432
sigma_u	5.5528	5.0114	3.8579	3.9318	4.3543	3.9355	6.05834	3.9006	3.9362	4.3562
rho	0.9036	0.8842	0.8190	0.8245	0.8521	0.8248	0.9177	0.8222	0.8249	0.8523

Robust z statistics in parentheses

*significant at 10%, **significant at 5%, ***significant at 1%

In sum, our findings generally suggest that both similarity as well as diversity of actors provide incentives for the formation of alliances. Similarity plays a specific role in partner choice with regards to general collaboration experience (*DyadCoopPAT5*) and the accumulation of resources (*DCentrality*). Actors seek to connect to actors that are able to reciprocate their general collaboration expertise as well to provide a certain basis for mutual understanding. The reciprocity in knowledge gains and the amount of innovative capabilities seem to play a comparatively subordinate role. In turn, with regards to organizational similarity and patenting age, actors are inclined to choose diverse partners.

2.5 Conclusion and further research avenues

The aim of this study was to elaborate on the coevolution of several attributes of cognitive proximity, social proximity, and similarity in competencies as collaboration between two actors progresses. We have contributed to the debate on whether networks are rather stable (i.e., with actors always cooperating with the same partners) or volatile (i.e., with actors changing partners regularly). Our findings suggest that firms are prone more to switching their cooperation partner than to repeating the collaboration with a given partner. We found no significant effect of knowledge transfer and prior common experience on repeated link formation. Instead, we found that firms prefer to cooperate with a partner whose knowledge bases and accumulated collaboration experience are rather similar to their own and whose organizational nature and patenting age are rather dissimilar to their own. We did not find evidence to support the hypothesis that potential for innovation and collaboration decreases as the overlap of the knowledge bases increases (Gilsing et al., 2008; Nooteboom, 1998; Wuyts et al., 2005).

Our methodology has limitations and drawbacks that one must consider when interpreting the final results. First, the degree to which the number of linkages observable in our data matches that in the real world heavily depends on the patenting practices among actors (e.g., cross-patenting or cases in which a central institution may administrate the patenting process and is therefore the only applicant). Including only those collaborations that are defined by coapplication might underestimate the number of actual linkages. Yet if we were also to take account of the connections realized through shared inventors, we might overestimate the number of linkages (Ter Wal & Boschma, 2009). In addition, we expect the number of disregarded cases to be rather small because inventor mobility is rare in Europe (Ter Wal &Boschma, 2009). Crescenzi, Gagliardi, and Percoco (2013) estimated that barely 5% of inventors change their employer. A closely related drawback to our methodology is the underrepresentation of informal ties, for we considered only formal collaboration agreements. Prior studies have emphasized the importance that informal ties have for innovative outcomes (e.g., Powell & Grodal, 2006), but it has been found that formal ties, especially in the life sciences, are generally preceded by informal ties (Powell et al., 1996). On this basis we argue that preceding informal ties are manifest in formal ties and are therefore captured in the study of the latter.

Second, by focusing on the research of the dynamics in bilateral R&D collaboration, we set aside the study of the effects of the micromechanism on the overall network structure. We thereby also opted to forgo explicit consideration of the feedback effects that an actor's position in the overall network has on partner choices at the microlevel. We tried to control for this limitation by incorporating information on whether an actor was highly connected (central) or rather peripheral and by adapting the standard errors accordingly. However, recent research on networks has made advances regarding the explicit modeling of endogenous structural mechanisms such as triadic closure and preferential attachment (Broekel et al., 2014). Our analysis could be extended by elaborating the overall network evolution as a result of partner choice at the microlevel, a selection that is itself determined by similarity and diversity aspects. Stochastic actor-oriented models, for instance, allow for examination of the relationship between the individual partner choice and overall network dynamics (Balland et al., 2013). In this context, however, it is debatable to what extent firms can directly influence and are aware of the network beyond their ego network (direct connections) (Gilsing et al., 2008).

The third concern about studies that focus on analyzing a certain pattern in a specific industry is the generalizability of their results. Application of our results is limited, for example, by the appearance of patterns that might be caused by industry specificities. However, some of the factors that our analysis identifies (e.g., positive effects of overlap, the reciprocal cumulative advantage and reciprocal general collaboration experience) have also been observed in other environments and at other levels of observations (Cantner & Meder, 2007; Dahlander & McFarland, 2013; Gulati, 1999).

In view of our results and the type of analysis suggested with this study, we have taken a further step in the effort to disentangle the coevolution of the proximity of collaboration partners and the formation and repetition of cooperative ties. In doing so, we have already taken into consideration factors that go beyond dyadic relationships, factors such as network characteristics. Extending this dimension in future research will help improve the understanding of the dynamics of cooperation networks at the core of clusters and of local and regional innovation systems.

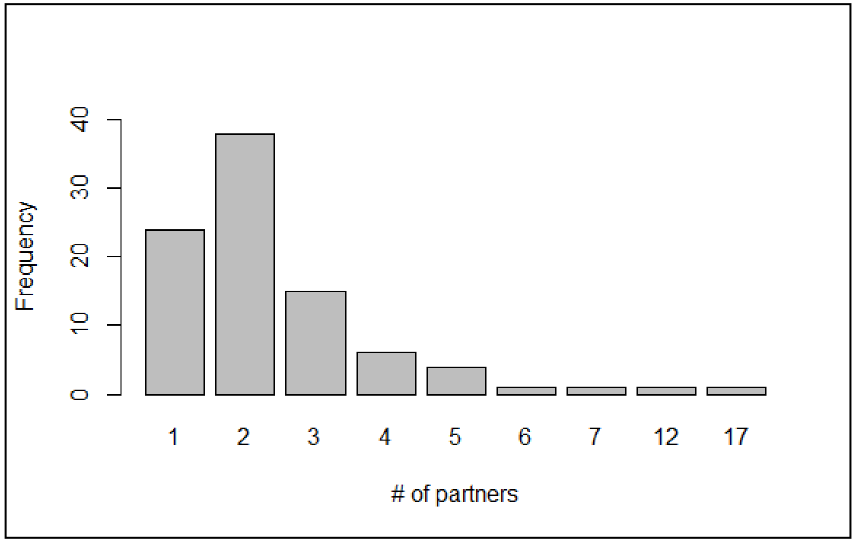
2.6 Appendix

Table 2.4 Correlation between explanatory variable and dependent variables

	Coop	*RelOverlap*	*RelOverlap^2*	*ReciPot*	*Trans Knowledge*	*CoopExp*	*DCentrality*	*Dyad SinglePAT5*	*Dyad CoopPAT5*	*DStatus*	*DPatAge*
Coop	1										
RelOverlap	0.0471*	1									
RelOverlap^2	0.0673*	0.9098*	1								
ReciPot	-0.0079*	0.2081*	0.1861*	1							
TransKnowledge	0.2332*	0.0250*	0.0219*	-0.0019	1						
CoopExp	0.2479*	0.0265*	0.0253*	-0.0058*	0.6577*	1					
DCentrality	-0.0182*	-0.0381*	-0.0255*	0.0252*	0.0059*	-0.0004	1				
DyadSinglePAT5	0.0105*	-0.1366*	-0.1083*	-0.4396*	0.0241*	0.0172*	0.0222*	1			
DyadCoopPAT5	0.0215*	-0.1455*	-0.1079*	-0.3693*	0.0351*	0.0298*	0.0770*	0.6526*	1		
DStatus	0.0123*	-0.0120*	-0.0001	-0.0652*	0.0071*	0.0058*	0.0005	-0.1169*	-0.0053*	1	
DPatAge	-0.0021	-0.2131*	-0.1684*	-0.1866*	-0.0029	-0.0046*	0.0937*	0.1638*	0.2781*	-0.0054	1

*significant at 1%

Figure 2.2 Diversity of partner portfolio



Chapter 3

3. Policy induced innovation networks: the case of the German "Leading-Edge Cluster Competition"

3.1 Introduction

The introduction of the BioRegio contest in the early 1990s marked the beginning of a new era of R&D funding programs. The German innovation policy experienced a paradigmatic shift away from traditional R&D funding measures towards contests between regions with a special focus on collaborative R&D projects. Central to these new competitive approaches were the stimulation of interregional competition, promoting the establishment of regional clusters and the improvement of the functionality of the regional innovation system (Eickelpasch and Fritsch 2005, Staehler et al. 2007). In this context, the presumed economic and technological benefits of clustering serve as a main rationale for modern cluster policies. The main current national cluster funding program – the Leading-Edge Cluster Competition (Spitzencluster-Wettbewerb) – was launched in 2007 by the German ministry for education and research (BMBF). 15 clusters were selected in three waves (2008, 2010, 2012) and have been funded for a five-year period with up to 40 million Euro each. One of its main goals is the stimulation of regional networking as a lever for innovation and economic growth.

With the rising number of these programs, one major question arose: Does the public promotion of clusters provide an effective and/or efficient measure to achieve the defined goals? Currently, only a few studies try to provide an answer to this question by evaluating cluster policies. To fill this gap, the present chapter examines the impact of the Leading-Edge Cluster Competition (hereinafter referred to as LECC) on networking in the selected clusters. In analysing a unique dataset gathered from a survey of the beneficiaries, we are able to directly attribute the creation of linkages to policy influence. In particular, we contribute to the literature in two ways: first, we enrich the discussion on the effectiveness of policy endeavours and add to the rare empirical evidence on the impacts of cluster policies. Second, this study is one of the few which analyses the effects of a specific cluster policy on the linkages and the related network structure by means of social network analysis (SNA).

This chapter is organized as follows: In section **3.2** we provide the basic theoretical rationales for cluster policies and discuss the results of existing studies that focused on the evaluation of cluster policy impacts. Subsequently, we briefly introduce the concept and objectives of the LECC and describe the research methodology, focusing on the network aspect, in section **3.3**. We present our results in section **3.4** and conclude in section **3.5**.

3.2 The "Leading-Edge Cluster Competition", clustering and cluster policies

In 2007 the German ministry for education and research (BMBF) followed up previous successful devices by launching the LECC, an initiative that aims at strengthening Germany's innovation potential and economic success by means of promoting regional clusters. The support of

“Leading Edge Clusters” should result in the exploitation of regional innovation potentials and finally in innovation and economic growth. The program was open for all types of technologies and focused on the funding of clusters with the most promising strategies for future markets that have the potential to count among the “Leading Edge” in their respective industry (BMBF 2012).

Overall, 15 clusters were selected in three waves (2008, 2010, 2012), to be labeled as “Leading-Edge Clusters” and to be funded for a five-year period with up to 40 million Euro each. The selection was consigned to an independent jury of publicly renowned experts from industry and academia.

Moreover, an accompanying evaluation is conducted to monitor the achievement of the declared goals and to derive concrete recommendations for the advancement of the measurement. Therefore, timely evaluations, especially of innovative funding schemes, are a crucial learning mechanism for the adaptive policy maker (Metcalfe 1995).

One main claim of the program is the support of regional networks. The idea is that the creation of an innovative environment, including intensive R&D collaboration between research institutes and industry, should boost an eminent innovative performance that allows for reaching an international leading position.

The entering of regional networks as a focal point of the national research and innovation policy rooted in the increased perception of innovative activities exhibiting a strong regional component and that embeddedness in networks is crucial to firms’ innovativeness and competitiveness. Thus, theoretical concepts that account for the regional character of innovation, such as the cluster approach (Porter 1998) or the idea of the regional innovation system (Cooke and Morgan 1994, Braczyk et al. 1998), constitute the rationale for modern innovation policy.

Since the end of the 19th century, scholars theorize on the economic benefits that arise for firms locating in geographic agglomerations of related industries (Marshall, 1890, Porter, 1998). In addition, several empirical studies provide evidence on the positive effects of co-location on innovation (Audretsch and Feldman 1996, Baptista and Swann 1998, Beaudry and Breschi 2003, Aharonson et al. 2008, Lecocq et al. 2009).

The reasons for clustering are manifold. Theorists argue that firms in clusters exploit the advantages of low transaction costs as they are located close to specialized suppliers and clients and have access to a specialized labor pool or are exposed to competitive pressure which drives profitability (e.g. Porter 1998). Furthermore, the proximity to scientific institutions and firms within the same or related industries results in the existence of a common knowledge spillover pool. Nevertheless, spatial proximity per se is neither a necessary nor a sufficient condition for knowledge spillovers (Giuliani 2007, Breschi and Lissoni 2009). The exploitation of existing innovation potentials in certain regions and the efficiency of the regional innovation system depends heavily on the degree of networking among regional actors (Koschatzky 2000, Sternberg 2000, Fritsch and Eickelpasch 2005).

Innovations develop during a collective learning process of several actors in which common knowledge generation, accumulation and diffusion are crucial ingredients (Asheim and Gertler 2006). Especially in the early stages of technology development, when knowledge is specific and complex, continuous communication and face-to-face contacts are indispensable for the efficient transmission of knowledge (Feldman 1994, Breschi and Lissoni 2001). The ease and costs of linkages and knowledge exchange are in turn related to the geographical distance of the correspondent actors. Moreover, spatial proximity allows for the development of trustful relationships and decreases the social distance among related actors (Boschma 2005). Hence, a firm’s integration into the regional innovation network providing access to external knowledge sources is a crucial determinant of the firm’s learning process and resulting innovative capabilities (Koschatzky 2000).

Although these insights constitute the core rationale for regional cluster policies fostering joint R&D projects, potential gains from clustering do not suffice as a legitimization for political intervention. According to economic welfare theory, political interference is justified when the market coordination mechanisms are not able to result in efficient/optimal outcomes. Evolutionary economists complement these classical arguments by pinpointing to the existence of system failures. Related to this view, the malfunctioning or ineffectiveness of innovation systems provides a reason for political action. Particularly, the presence of network failures in the sense of a deficiency of an optimal degree of linkages among actors in the innovation system formulates a rationale for cluster policies (Carlsson und Jacobson 1997, Andersson et al. 2004). Hence, the declared aim of the current German cluster policy, the LECC and related programs is the generation of value added for the region and for the national economy by stimulating the creation of regional networks.

With the expiration of the early pioneer programs and the subsequent introduction of new expanded instruments, such as the LECC in Germany, questions regarding the effectiveness and/or efficiency of the public promotion of clusters came up. Evaluation studies of cluster policies were introduced with the purpose to analyse the surplus for the region and the economy that is attributable to the funding measure. Due to the long term character of these effects and the infancy of evaluation concepts, quantitative impact studies on cluster policies are relatively rare and there have been only few attempts to apply SNA in the context of cluster policy evaluation (see Giuliani and Pietrobelli 2011 for a review). Moreover, the few existing analyses provide ambiguous results.

Martin et al. (2011) evaluate the impact of cluster policy on certain firm variables (for instance production and employment) and find no robust effects compared to non-funded firms. In fact, the policy measure which was included in their examination, the French "Local Productive Systems" program, focused rather on the idea of the industrial districts and merely inter-firm collaboration than on the concept of the regional innovation system. Nishimura and Okamuro (2011) find that mere participation in the Japanese Industrial Cluster Project has no significant effect on the R&D productivity of firms. Only if cluster participants collaborate with national universities in the same cluster region positive effects were observed.

In a more general framework, Fornahl et al. (2011) evaluate how R&D subsidies, network embeddedness, and locational factors are related to the innovative performance of biotech firms in Germany. Their findings suggest that location in a cluster, even after controlling for embeddedness into knowledge networks, has a positive effect on patent performance. In contrast, R&D subsidies have no effect when given to single firms, and only a slight effect when R&D collaborations are supported. Counterfactual analyses of specific cluster funding programs in Germany show that the success of BioRegio and related programs is grounded above all on the mobilization of long-term cooperations that would not have existed without the program. In this process, primarily collaborations between firms and research institutions were initiated (Staehler et al. 2007). Similar results are obtained by Falck et al. (2010), who find that firms in targeted industries of a regional cluster initiative are more likely to become innovators despite a reduction of their R&D expenditures. Engel et al. (2012) compare the performances of winning regions to non-winning regions in the BioRegio and BioProfile contest in terms of patents and public R&D projects. They find strong short-term effects, but these effects seem to diminish in the long run.

Overall, it appears that only cluster policies that lead to increased and/or intensified collaboration have an impact on innovative and economic performance of funded actors. It remains unclear how policies change the structure of interaction in form of collaboration networks and how these changes influence knowledge flows and subsequent performance. Since we evaluate an on-going program, we focus on the former, i.e. on the policy effect on the structure and intensity of interaction as an intermediate outcome rather than on economic impacts. With the application of SNA, we are able to observe the underlying network structures in the selected clusters and the ramifications originated by political influence. This allows us to provide a hint whether first politically desired effects occurred.

3.3 Data and research methodology

Our empirical analysis is based on a survey of actors (benefiting firms and public research organizations) of four clusters (labelled A to D) that were chosen as "Leading-Edge Clusters" in the first wave of the competition at the end of 2008.[7] The survey was conducted in late summer of 2011, almost three years after the announcement of the winning cluster regions of the first wave, to capture first effects on the network structure. Additionally, in autumn 2011 face-to-face interviews were conducted with a small sample (6) of actors per cluster (24 in sum) in order to add to our understanding and complement the interpretation of the results from the survey.

We construct R&D networks on the basis of survey data by means of a free recall method with a fixed choice design (Guliani and Pietrobelli, 2011). Thereby, beneficiaries (firms and research institutes) were asked to list the names and address of their up to ten (strategically) most important R&D cooperation partners. The address information was used to assign actors to be located in the cluster region, in the rest of Germany, in the rest of Europe, or outside Europe. The cluster regions are defined as those regions which host the majority of the respective beneficiaries. All clusters span several NUTS 3 regions (Kreise) and some cross boundaries of NUTS 2 regions (Länder). Therefore, the cluster regions are individually defined as combinations of NUTS 3 regions.

Even though it is argued that the roster recall method is to be preferred (ter Wal and Boschma 2009, Giuliani and Pietrobelli 2011), we chose the free recall design for mainly two reasons. First, the generation of a fixed list of actors (roster) would have led to large differences in the size of the clusters (imposed by the empirical design), since the cluster managements define their boundaries in quite different ways (e.g. only funded actors, only formal members of the cluster association, all actors that somehow participate in cluster activities). Secondly, with a roster recall linkages to R&D partners who are not cluster actors could not be observed. However, such extra local (and extra cluster) linkages are of high relevance for cluster success (Bathelt et al. 2004). Our decision for the fixed choice approach in limiting the number of partners to the ten most important ones followed primarily two considerations. On the one hand the acquisition effort of sufficient data for the network analysis is still within the bounds of feasibility for the respondents. On the other hand, the focus on the most important R&D partners allows us to assume an equal weight of the mentioned linkages and prevents the overestimation of linkages with lower intensity.

The formation of R&D cooperations is based on the expected benefits of both partners arising from collaborative activities. These benefits can arise in different ways depending on the type of strategies partners pursue.

To grasp in more detail the nature of the observed network and to understand the underlying motivations that lead to the choice of the partner or the maintaining of a link, we collected information on attributes of these linkages, namely the reason for the strategic importance of the link. Motives to cooperate are manifold: collaboration partners might be chosen as a valuable source "of applied knowledge" or "of basic knowledge". In both cases, learning from the partners' competencies is a central rationale for collaboration. Cooperations might also be formed because partners supply their specific capabilities to a common task, i.e. "complementary com-

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[7] The response rate, especially of firms, in one cluster was too low for a meaningful analysis. For reasons of confidentiality, we have to refrain from characterizing the clusters in more detail. Even though the clusters differ with respect to technological specialization, age, and location, we cannot make use of this information in our analysis.

petences" are the source of strategic importance of a partnership. Partners might also be valuable because of their specific "research infrastructure" not present in firm's own facilities. To account for these different motives for partner choice, we asked the firms[8] to indicate, for each partnership, the motives that qualify it as strategically important.

Furthermore, to attribute the observed network dynamics to the influence of the policy, the actors were explicitly asked, whether the mentioned relations have existed before 2007 (date of the announcement of the LECC and if they were initiated or intensified by the cluster initiative). Hence, our analysis relies on the comparison of the network structure before and after the policy started. We have to acknowledge that this is only an artificial dynamism since we do not have the information about the most important R&D partners in 2007, but can only observe a subset of those that were active at that time, namely those that were still present at the time of the survey.

3.4 How policy influences cluster structures

3.4.1 Actor structures

Describing the actor structures in the four clusters, we distinguish four groups. First, *beneficiaries* are those organizations that receive subsidies from the LECC. Second, those beneficiaries who replied to our survey are the *respondents*. Third, *actors* are all the nodes in the network, i.e. all respondents and all organizations that were named by the respondents. Fourth, *cluster actors* refer to those actors that are members of the respective cluster association. This group encompasses all beneficiaries but also organizations that receive no direct funding.

A first view at the composition of the networks of strategically important R&D partners in the four clusters (table 3.1) reveals that the network size as measured by the number of nodes (actors) varies between 44 (cluster B) and 97 (cluster C). Some of this variation can be attributed to the different number of respondents, which ranges from 12 (clusters B and D) to 17 (clusters A and C).

Regarding the regional distribution of actors, it can be seen that the majority is located within the cluster or national boundaries. Only a small fraction of actors is located outside Germany, with some differences between the clusters. The consideration of the distribution of linkages exposes an almost similar picture. Most of the linkages are directed into the cluster region, followed by national linkages. Nevertheless, the clusters display remarkable differences concerning the focus on intraregional linkages and the embeddedness in international networks. It is noticeable that while cluster B seems to find a number of R&D partners internationally, cluster D is almost exclusively cooperating on a regional and national scale.

3.4.2 Network structure and effects of the "Leading-Edge Cluster Competition"

In table 3.2, structural indicators and their changes in the course of the LECC are presented; in figure 3.3 (appendix) network visualizations are displayed. To infer on the effect of the cluster policy, we compare the measures for the network based on all reported linkages with those for the network consisting only of those linkages that were present before 2007 (when the LECC was announced).

[8] We did not ask the research institutes since the motives to cooperate differ between the private and the public sphere.

Table 3.1 Composition of the clusters and their networks of strategically important R&D partners

Cluster	A	B	C	D
Beneficiaries: no. of organizations that received a questionnaire	24	19	33	35
Respondents: no. of organizations that provided information about their R&D partners	17	12	17	12
Response rate (2)/(1)	71%	63%	52%	34%
Actors: no. of nodes in the network	61	44	97	48
Cluster actors: no. of nodes that are members of the cluster association	24	20	41	25
Share of actors located in cluster region	36.1%	50.0%	45.4%	47.9%
... in Germany	50.8%	20.5%	37.1%	47.9%
... in Europe	8.2%	11.4%	7.2%	4.2%
... outside Europe	4.9%	18.2%	10.3%	0.0%
Number of linkages	101	43	126	58
... into cluster region	53.5%	48.8%	55.6%	55.2%
... to Germany	38.6%	20.9%	31.0%	41.4%
... to Europe	5.0%	11.6%	5.6%	3.4%
... to outside of Europe	3.0%	18.6%	7.9%	0.0%

One of the first important findings from the network analysis is that the policy has a significant positive impact on the intensity of networking[9]. On average, more than half (52.5 %) of the existing linkages were affected by the LECC in the sense of initiation or intensification, with a minimum of 42.9% in cluster C and a maximum of 65.3% in cluster A. The majority of these links (35.6 %) was initiated by the program, indicating a strong impact of the policy measure on networking. Accounting only for the linkages among respondents, network density (all active linkages divided by the number of possible linkages) increased in all four clusters (on average from 4.9% to 11.5%). In cluster C, the increase from 8.1% to 13.2% is the lowest in relative terms, indicating that the cluster was already well connected before participation. According to face-to-face interviews with some of the actors, this increase of linkages is mainly a consequence of the increased visibility of potential partners and synergy potential triggered by the LECC; i.e. the policy measure mitigates the problem of intermediation within the clusters (Cantner et al. 2011). Furthermore, new partners entered projects via reputational advice from already known partners. The newly established contacts were initiated with the expectation to cooperate in the long run and beyond the own core competences.

[9] Since we cannot observe the whole network in 2007, one could expect that some past linkages dissolved and the policy effect on the intensity is overestimated. However, being asked about the change in total number of cooperation partners, 80% of the beneficiaries reported an increase.

Besides this policy effect on the intensity of collaboration between actors, we also observe a structural change with respect to the concentration of partnerships on few central actors. Attributable to the public funding, the extent of the centralization (based on the indegree) (Freeman 1979) increases in three of the four clusters and on average from 4.4% to 8.8%. This suggests that the newly established ties are preferentially formed with actors who were already central before the clusters decided to participate in the LECC.

The clusters exhibit certain differences concerning their interior network structure. Cluster A and C form in each case a connected network since their network consists of only one component. That is to say that each actor is directly or indirectly connected to the network. The remaining clusters display a more fragile network topology. Moreover, clusters A and D seem to be more concentrated on few central actors, while cluster B displays a less hierarchical structure. The average number of connections also shows some differences between the clusters. In cluster B, the average respondent named 3.6 important cooperation partners (outdegree) while in cluster C more than twice this number (7.4) was reported. The mean indegree tells us how often the average actor is being named as a R&D partner. In cluster B this measure is below one (0.98), indicating that some actors are not named at all (of course, these can only be respondents). The maximum is observed in cluster A, in which actors are named 1.66 times on average.

In table 3.3, we report the share of policy initiated (intensified) linkages to cluster actors in all policy initiated (intensified) linkages. For the induced (intensified) linkages, these shares range between 67 and 90% (65 and 82%), indicating that new cooperations are mainly established among cluster members. However, these figures also show that the cluster policy also mobilizes partnerships beyond the cluster boundaries.

In summary we find that the LECC has proven successful in meeting the objective to foster the networking activities in the regions. The basis for an intensified and broader knowledge transfer is founded, which may lead to a higher innovative performance of the system in the future.

Table 3.2 Structural indicators for each network with and without policy impact

Cluster	A	B	C	D	Ø
Linkages initiated by cluster program	45.5%	41.9%	20.6%	34.5%	35.6%
Linkages intensified by cluster program	19.8%	11.6%	22.2%	13.8%	16.9%
Linkages initiated or intensified by cluster program	65.3%	53.5%	42.9%	48.3%	52.5%
Density (among respondents)	0.154	0.068	0.132	0.106	0.115
Density (among respondents before 2007)	0.063	0.023	0.081	0.030	0.049
Components (weak)	1	3	1	3	
Centralization (indegree)	0.141	0.024	0.081	0.104	0.088
Centralization (before 2007)	0.053	0.034	0.042	0.048	0.044
Mean outdegree (only respondents)	5.941	3.583	7.412	4.833	5.645
Mean indegree (whole network)	1.656	0.977	1.278	1.208	1.304

Table 3.3 Policy affected linkages to cluster actors (percentages)

	A	B	C	D
Share of policy initiated linkages to cluster actors	71.7	66.7	84.6	90.0
Share of policy intensified linkages to cluster actors	65.0	80.0	82.1	75.0

3.4.3 Geographic reach

A clear-cut direction of the policy influence becomes evident when analysing the geographical reach of the cooperation links. Although certain cluster specificities in the regional focus of the ties exist (see table 3.1 and the discussion in 3.4.1), the overall picture reveals a strong effect on regional and national linkages. Table 3.4 compares policy induced linkages with non-induced linkages for each cluster and in total. In all clusters we observe a significantly higher share of local linkages for the induced linkages compared to the non-induced links. In most cases this goes hand in hand with lower shares of linkages at higher geographical distance. Exceptions are worldwide linkages in cluster A and national linkages in cluster B. A comparison of the regional distribution of all linkages reveals that roughly 75 % of induced linkages are local, while only 44 % of non-induced linkages are local. The majority of the remaining induced linkages are national with few international linkages being triggered by policy. The shares for the non-induced linkages to the rest of Germany and to outside Europe are significantly higher, while the difference for linkages to European partners is large but not significant.

Table 3.4 Regional distribution of policy induced vs. non-induced linkages (percentages)

Cluster	A		B		C		D		Total		
Share of linkages induced by LECC	45.5		41.9		20.6		34.5		33.5		
	induced		induced		induced		induced		induced		
	yes	no	yes	no	yes	no	yes	no	yes	no	t-statistic
Geographic reach thereof											
... into cluster region	67.4	41.8	72.2	32.0	80.8	49.0	85.0	39.5	74.5	43.6	(-5.78)
... to Germany	23.9	50.9	22.2	20.0	15.4	35.0	15.0	55.3	20.0	40.8	(4.10)
... to Europe	4.3	5.5	5.6	16.0	3.8	6.0	0.0	5.3	3.6	6.9	(1.31)
... to outside Europe	4.3	1.8	0.0	32.0	0.0	10.0	0.0	0.0	1.8	8.7	(2.99)
Pearson's Chi-squared	8.4 (df = 3)		10.2 (df = 3)		9.1 (df = 3)		11.1 (df = 2)		29.1 (df = 3)		

Consequently, and corresponding to the declared aim of the policy, the LECC primarily stimulates local connections among actors and affects to a lower extent the creation of ties on a national and international level. Hence, in a first instance the LECC is effective in fostering intraregional networks.

3.4.4 Science-industry interaction

Another important goal of the LECC is to connect industry and science to increase the speed of transfer of scientific discoveries into marketable products (BMBF 2012). Figure 3.1 shows the shares of all linkages within and between industry and science in the first bar for each cluster while the respective shares in the second bar are restricted to the linkages induced by the LECC. In three of the four clusters, research cooperations between firms and public research dominate. The connections that were induced by the LECC show a relatively stronger focus on interactions between firms, which is actually quite surprising given the stated goal of the policy. Across all clusters, 25% of the non-induced linkages are between firms compared to 35% firm-firm linkages among the induced linkages. Accordingly, linkages among public research as well as linkages between firms and public research are less frequent among the induced linkages then among the non-induced partnerships.[10] Overall, the differences between clusters imply that the motives to cooperate with specific partners are to be found in the regional and technological environment rather than in some (presumed) requirements stated by the policy maker. At the same time, the policy seems to favour market oriented research collaborations between firms rather than science-industry interactions.

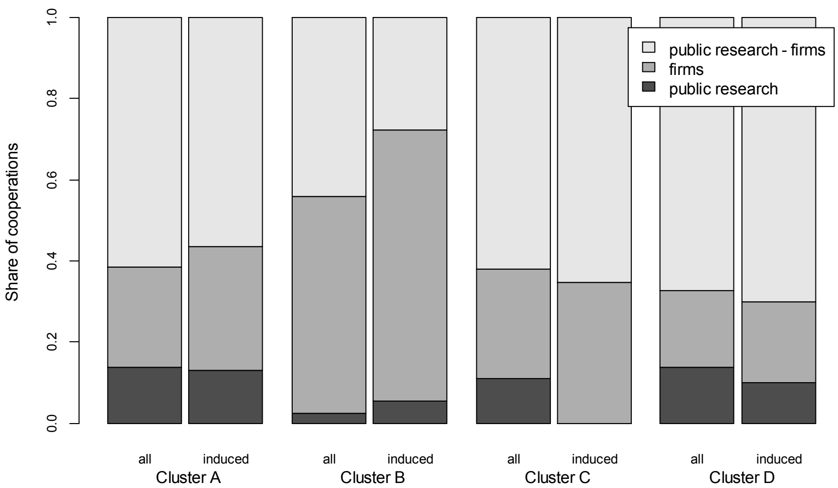

Figure 3.1 Interaction between science and industry

3.4.5 Relevance of linkages

To grasp the nature of the existing and newly established links, we asked the beneficiaries to substantiate the strategic importance of their links according to the four motives discussed in section 3.3. With respect to cluster specificities in the motives to cooperate, we observe some generalities but also some notable differences. The responses are summarized in figure 3.2 for each cluster distinguishing between all partnerships (dark grey) and only those that were initiated by the cluster policy (light grey). This allows us to identify differences between clusters in their motivation to cooperate and also gives us the opportunity to observe any systematic deviations of policy induced linkages from the overall picture.

[10] A Chi-squared test comparing the two distributions shows a significant difference at the 10%-level.

First of all, access to sources of applied knowledge is, with one exception, the most important reason for the strategic importance of R&D collaborations. This is followed by the technical infrastructure that is available with the R&D partners. The acquisition of basic knowledge is especially important in cluster A, while complementary capabilities are of high importance in cluster D.

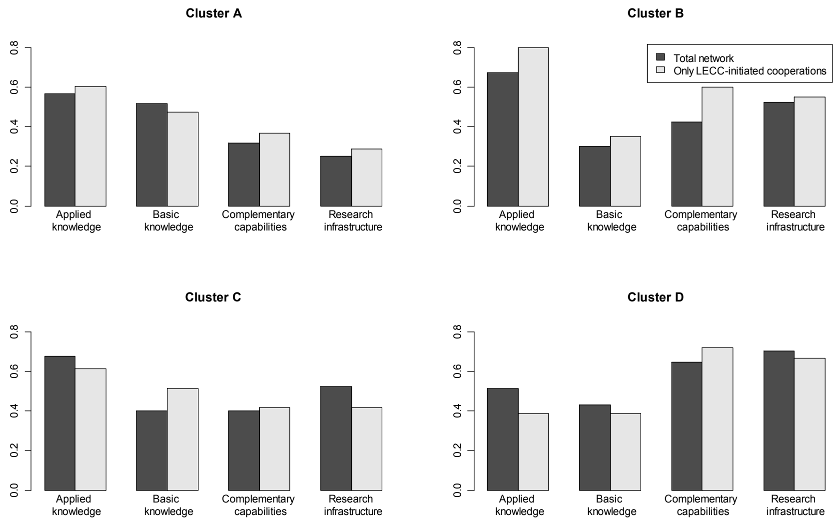

Figure 3.2 Reasons for strategic importance of R&D partners

In general, the policy induced linkages are not biased towards any of these motives. A statistically significant difference only arises for the use of research infrastructure, which shows to be of lower strategic importance for policy induced cooperations[11]. In cluster B, it seems that the LECC managed to bring together actors with complementary capabilities and strengthened the exchange of applied knowledge. In cluster C the acquisition of basic knowledge was reinforced. From an evaluation perspective, this result reflects the high flexibility of the policy measure since it is open for various types of partnerships.

3.5 Discussion and conclusion

Policies aiming at the promotion of clusters are frequently conducted but only seldom evaluated (Martin and Sunley 2003, Brenner and Schlump 2011). The aim of this study was to add to our understanding of the effects and mechanisms of cluster policies by analysing the impact of the German Leading-Edge Cluster Competition on the underlying network structure. Since the LECC is an on-going initiative, we could only report intermediate effects on networking within the funded clusters. By means of Social Network Analysis on the basis of a carefully constructed questionnaire it was possible to identify effects on the network of strategically important R&D partners within the clusters that are attributable to the policy instrument.

Our results show a significant effect on the network structure in terms of density, centralization and geographical reach. Measures on structural effects in terms of number (breadth),

[11] For 53.2% of the pre-existing partnerships and 38.2% of the policy-induced partnerships, the use of research infrastructure was mentioned as a strategic asset. A t-test shows that this difference is significant at the 5% level.

weight (intensity) and distribution of linkages (centralization) indicate policy influences already three years after starting the funding.

First, on average more than half of the existing linkages were either initiated or intensified by the LECC with the consequence of an increased density of the networks. Second, since the majority of these policy-affected linkages are within the cluster regions, the LECC shifted the focus of collaboration towards local networking. While such an effect is quite natural for a cluster oriented policy, it is not to be judged without some scepticism. Experiences of a Japanese cluster initiative show that local firms have a higher R&D productivity if they collaborate with partners outside the cluster (Nishimura and Okamuro 2011). Moreover, path-dependencies for firms and regions which can lead to spatial lock-in in the long run inhere in the mere search for internal collaborations (Sternberg 2000). These concerns have also been brought up in the discussion on local buzz and global pipelines (Bathelt et al. 2004) and have been related to the stage of the cluster within its life-cycle by Brenner and Schlump (2011). They suggest that a network renewal by means of increased cluster external linkages is especially important in more mature phases of cluster development. Since the four clusters analysed in this chapter differ considerably with respect to age or maturity of technology, the dimension "stage in a cluster life cycle" requires further scrutiny.

A third result is concerned with the distribution of linkages within the networks. In three out of four cases the network becomes more centralized, i.e. it exhibits a stronger orientation towards a few, central actors. Interviews with selected beneficiaries in the clusters suggest that this development is rated particularly important for the integration of SMEs within the cluster. For small firms, which in general struggle with difficulties to get in contact with large firms, the LECC offers opportunities to connect to these; the firm representatives value these contacts of crucial importance for their long term integration into the network and finally their innovative performance. However, more centralized networks are also more vulnerable, since their dependence on the functioning of single actors is higher as compared to other network structures. With respect to the rate of knowledge diffusion, Cowan and Jonard (2004) could show that small world structures are the superior form of organization. The results of Schilling and Phelps (2007) on the structure of industry networks add to the difficulties in evaluating this development towards increased centralization. They find negative effects of network centralization on future patenting in the short run but positive effects in the long run.

Fourth, with respect to the interaction between science and industry, we find that the majority of connections that were affected by policy link firms with universities or research institutes. However, the LECC does not increase the relative frequency of science-industry linkages but slightly favours linkages within industry. We interpret the differential policy impact among the clusters as a sign of flexibility of the policy measure as it leaves the choices of partnership to the beneficiaries.

With respect to our research design, we have to acknowledge some limitations. While we can observe cooperations that were established as a consequence of the LECC, we are unable to make statements about linkages that were present before the policy started and have become obsolete. We cannot exclude that newly formed partnerships substituted previous relationships, which would imply that we overestimate the impact of the LECC on the interaction intensity. However, this problem is somehow mitigated since additional sources of information indicate an overall increase in collaboration intensity.

Overall, while we can state that the LECC has met its objective to intensify collaboration among innovative actors, our intermediate evaluation does not allow us to infer, that this will lead to a better performance of the selected clusters in the future. At this stage, we are unable to provide evidence on correlations between the observed structural changes and the innovative performance of the cluster regions. Statements in this direction will require a subsequent long term analysis including comparisons to non-funded clusters.

3.6 Appendix

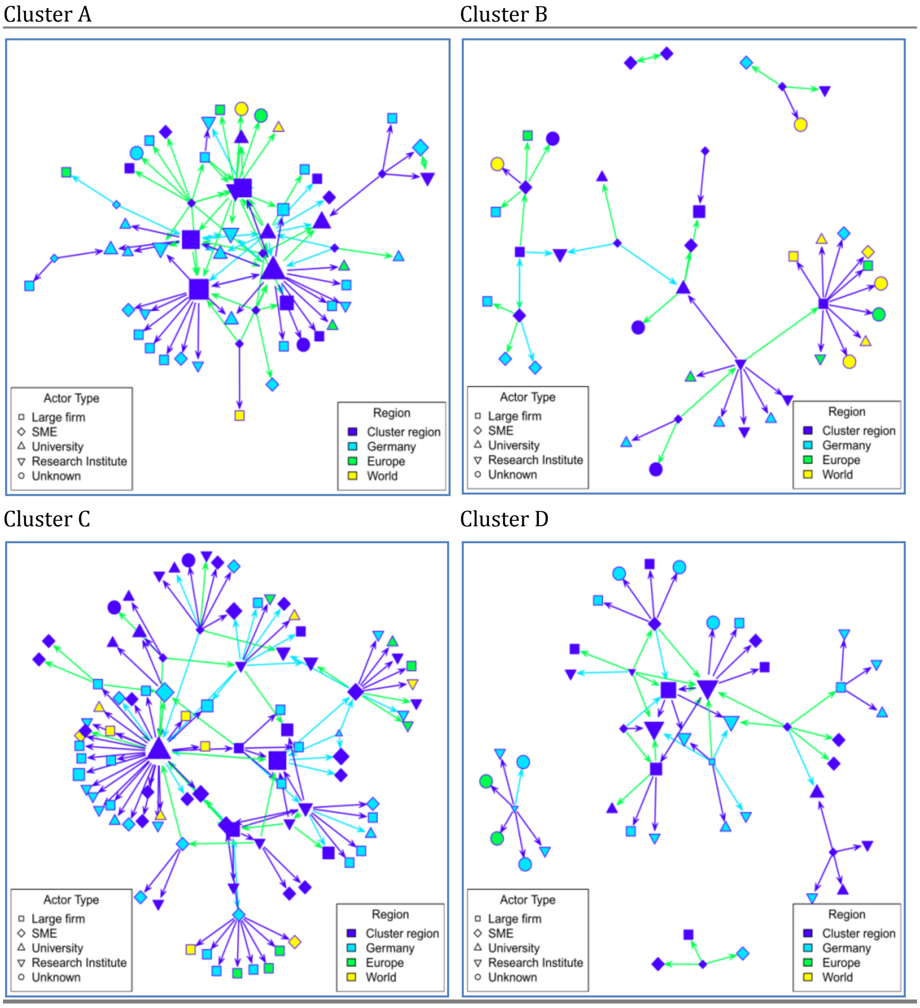

Figure 3.3 Networks of strategically important R&D partners in clusters A to D

Arrows indicate a partnership from the respondent to one of the most important R&D partners. Green arrows indicate that the partnership was initiated through participation in the LECC, light blue arrows indicate that the partnership was intensified through the policy, and dark blue arrows indicate partnerships that were not influenced by the policy. Node size is proportional to indegree, i.e. to the frequency of being named as a partner. The colours and the shapes of the nodes indicate the actor's geographic location and type according to the legend.

Chapter 4

4. The role of geographical proximity for project performance – Evidence from the German „Leading - Edge Cluster Competition”[12]

4.1 Introduction

The perception that innovative activities exhibit a strong regional component and insights into the supportive role of co-location and regional networking on innovation led to a shift in modern innovation policy towards the funding clusters or regional networks (Eickelpasch and Fritsch 2005, Koschatzky 2000). The concepts of Marshallian agglomeration externalities, the cluster approach, and the regional systems of innovation approach (Porter 1990, Cooke et al. 1997, Baptista and Swann 1998, Galliano, D., Magrini, MB., Triboulet, P. (2014)), which provide the theoretical basis for modern regionally oriented innovation policy, stress the beneficial role of geographical proximity and other types of proximity between private and public actors for knowledge production and exchange, innovation, and productivity. The main arguments in favor of co-location concern the ease of local actors to form collaborative linkages and their efficiency in terms of knowledge exchange. Moreover, this supportive effect of geographical proximity might be reinforced by the interplay with other types of proximities or non-spatial proximities (Boschma 2005, ter Wal and Boschma, 2009, Crescenzi 2014, Torre and Wallet 2014). While the ex-ante constituent effects of geographical proximity – along other proximity dimensions – on the formation of research alliances has been vastly examined (Hazir and Autant-Bernard 2011), little attention has been paid to the actual consequences of geographical co-location of alliance partners for subsequent performance (Crescenzi 2014). In addition, concrete conclusions and implications can hardly be drawn from the few studies on this topic as they reveal a quite ambiguous picture and give rise to the question about unobserved factors that mediate the relationship between geographical proximity and alliance performance.

Despite this rare evidence and our vague understanding of the role of geographical proximity for the performance of research alliances, cluster policies focus almost exclusively on fostering regional linkages without considering other contextual factors. Therefore the aims of this study are to analyze the role of geographical proximity within publicly funded clusters and thereby to raise the question whether R&D partners within cluster programs should be located more or less distant from each other. We approach this question by providing evidence on the relevance of geographical proximity for project performance. In addition, we elaborate on further contex-

[12] The authors gratefully acknowledge financial support from the Federal Ministry of Education and Research (BMBF) for the research project „Begleitende Evaluierung des Spitzencluster-Wettbewerbs“ which provided the data for this study. Susanne Hinzmann thankfully acknowledges the German Research Foundation (DFG) for providing a scholarship within the DFG-GRK 1411 “The Economics of Innovative Change”. Furthermore, we are very thankful to our colleagues from the Chair of Microeconomics and the research group DFG-GRK 1411 as well as the participants of the 7th Summer Conference in Regional Science in Marburg for their very helpful comments and suggestions.

tual factors that mediate this relationship. So, we go beyond explaining *why* linkages have become apparent and analyze *how* these linkages perform and *what* explains their variation.

To do so, we use an original and unique dataset from a survey with project managers of collaborative R&D projects that were funded within the German "Leading-Edge Cluster Competition" (LECC). The program aims at funding joint R&D-projects and support regional networking in selected cluster regions in Germany. Given that the clusters differ substantially in terms of geographic reach, we think this sample serves well for our purposes.

With the analysis of this rich data, we try to shed some light on the complex and multifaceted relationship between geographical proximity and the outcome of publicly funded R&D projects. Overall, we find that the relationship between geographical proximity and project success is by no means univocal but rather mediated by various technological, organizational and institutional aspects. Our findings suggest that the nature of knowledge determines the degree to which collaborators prefer or perceive it necessary to be co-located. The relevance of geographical proximity increases in contexts where knowledge is novel to the organization and the innovation endeavor is more radical while this effect is less pronounced for projects in basic research. In addition, we find significant actor specific differences concerning the role of geographical distance for project satisfaction. Firms' project satisfaction decreases significantly compared to that of research institutes with increasing distance to their collaboration partners. In line with existing studies (Gulati 1995, Gulati and Gargiuolo 1999, Mowery et al. 1998, Ahuja 2000, Singh 2005), that underpin the importance of social proximity for successful cooperation, we observe that common project experience is a strong predictor of project satisfaction. Contrariwise, we cannot observe a substitutive relationship between geographical proximity and social proximity. With regard to final project results, we find that both, geographical proximity and project satisfaction support the cross-fertilization effects between LECC projects and other projects.

The chapter is organized as follows: in Section **4.2**, we provide a general overview of the related literature and present major findings from prior studies on the relation between proximity and project performance. Building on that, we derive our research hypotheses in Section **4.3**. Section **4.4** will introduce our basic methodology. Subsequently, the hypotheses are tested in Section **4.5**. The final section concludes, discusses our results and highlights policy implications and potential avenues for further research.

4.2 Proximity and performance

The early 1990s have seen an upsurge of studies which fathomed the factors behind the phenomenon of regionally clustered innovative activities and their uneven distribution across space (Jaffe et al. 1993, Audretsch and Feldman 1996, Porter 1990, 1998). The discovery of the beneficial effects of co-location of economic actors has equally affected academia and policy makers in the development of new regional concepts and policy programs.

The economic benefits of co-location have already been described by Alfred Marshall in 1890 in his study on the externalities that arise from agglomeration of specialized firms in Italian industrial districts. According to him, the basic advantages that arise from the dense location of similar actors stem from the exploitation of regional synergy effects and opportunities for resource sharing. Co-located economic agents share access to specialized labor and supplier markets and benefit from the proximity to important customers and local markets. These ideas experienced a renaissance after Porter made the idea of agglomeration of companies and organisations from related industries popular and subsumed them under the concept of clusters (Porter 1998). In contrast to Marshall, Porter has emphasized the vital role of increased cooperation and competitive pressure in limited geographical space as explanatory factors for superior innovative and economic performance of spatially concentrated actors. However, the role of geographical proximity on networking, learning and innovation came to the fore in later concepts. One of main ones is the regional innovation systems approach, which focused more on explaining the regional production of knowledge and innovations rather than on pure economic benefits (Cooke et al. 1997, Braczyk et al. 1998). The idea behind regional innovation systems is that a region's innovation potential is strongly contingent on the interplay of several actors of knowledge production and usage, the linkages among them and the involved region-specific institutions. Another ongoing debate in a related stream of literature concerns the optimal regional industry structure and the exploitation of agglomeration externalities, that is specialization vs. diversification, in order to benefit from co-location (Frenken et al. 2007, van Oort et al. 2015, Galliano et al. 2014).

The main ingredient common to all these concepts which constitutes the importance of geographical proximity for innovative capabilities is the observation that local knowledge spillovers are spatially bounded (Jaffe et al. 1993, Mansfield and Lee 1996, Crescenzi 2014). Technological know-how is sticky since it has tacit components (Polanyi 1966, Cowan et al. 2000). Therefore its diffusion requires continuous face-to-face interactions especially in the early stages of an industry when newly generated knowledge is highly complex and specific and therefore hard to codify (Breschi and Lissoni 2001, Audretsch and Feldman 1996). In this regard, geographical proximity has been pointed out to be supportive for knowledge transfer by decreasing the costs of traveling, of obtaining face-to-face contacts and for partner search (Breschi and Lissoni 2001).

Building on that, more recent studies have challenged the view that solely being co-located to innovative actors is a sufficient precondition for the exploitation of the fruitful effects of local knowledge spillovers. They emphasize the crucial role of the embeddedness in regional networks to gain access to the prolific regional knowledge pool and to be connected to appropriate partners (Giuliani 2007). It is not only geographical proximity but also its interplay with other types of non-spatial proximities that drive the formation of these linkages and their efficiency in terms of knowledge exchange (Boschma 2005, ter Wal and Boschma 2009, Crescenzi 2014, Torre and Wallet 2014). More concretely, the probability to form research collaborations is positively affected by the regional proximity of actors certainly due to cost advantages but also through fostering the establishment of social proximity and cognitive proximity between potentially connected actors. Closely co-located actors are more prone to connect with each other as they have a higher awareness of each other and can more easily observe their respective capabilities and opportunities compared to those of more remote actors (Hazir and Autant-Bernard 2011). Over time repeated interpersonal contacts and efficient knowledge exchange are responsible for the emergence of two non-spatial proximities, cognitive proximity between partners on the one hand and social proximity (trust) among them on the other (Boschma 2005). The cognitive dimension manifests in a common knowledge base and appropriate absorptive capacities that are decisive to warrant common understanding and learning entailing efficient knowledge transfer and higher potentials to innovate (Cohen and Levinthal, 1990, Noteboom et al. 2007, Boschma 2005, Crescenzi 2014). And social proximity between the collaboration partners serves as a control mechanism to reduce the risk of undesired knowledge flows and the danger of opportunistic behavior (Breschi and Lissoni 2003, Boschma 2005, Cantner and Graf 2011). However, contrary to geographical proximity, the positive effects of these two main non-spatial proximities are not infinite: scholars have emphasized that the positive effects might revert once actors are too close. Especially too much cognitive proximity might also impede learning and innovation due to redundancy of knowledge (Nooteboom et al. 2007). The existence of an optimal level of proximity has been labeled as proximity paradox (Boschma and Broekel 2012, Cassi and Plunket 2014) or goldilocks effect (Fitjar et al. 2015).

Empirical studies on this issue have emphasized various types of proximity as *constituent* factors for the formation of research collaboration (Katz 1994, Cantner and Meder 2007, Cassi et al. 2014, Balland et al. 2013, Singh 2005, Cassi and Plunket 2012, Boschma and Broekel 2012). While focusing on geographical proximity, Hazir and Autant-Bernard (2011) refer to this as the *ex-ante* effect of proximity on the collaboration decision as actors expect higher returns from collaboration with proximate partners and therefore connect to them. Most work in this field studies either the collaboration propensity conditional on geographical proximity along with other proximity dimensions or explain how geographically distant partnerships are characterized.

For instance, Cantner and Meder (2007) analyse German co-applications for patents from all topical areas to investigate whether geographical and cognitive proximity increase the likelihood to collaborate. They find that both proximity dimensions increase the probability to appear on a co-patent.

D'Este and Iammarino (2010) investigate the frequency of university-firm relationships in the UK and the spanned geographic distance therein. They explain the frequency of collaborations by the distance between partners and regress geographic distance on several partner characteristics. They observe that geographical proximity fosters the frequency of interaction between industry and academia in applied research (engineering disciplines) but not in basic research. Another interesting finding is that partners' expertise might substitute for geographic distance. The benefits of expertise seem to outweigh the costs of collaboration over larger distances. However they find that this effect decays when the distance becomes too large.

Following this study, Garcia et al. (2013) ascertain whether similar patterns can be observed for industry-university linkages in Brazil. They also control for the quality of research output when explaining the geographic distance between research partners. In line with D'Este and Iammarino (2010) they find that partners are more prone to look outward for higher expertise, but again this relationship is rather curvilinear and only holds up to an intermediate level of distance.

While there is vast empirical evidence on the interplay between (geographical) proximities and the formation of cooperation, there is sparse evidence on the role of geographical proximity for project outcomes, i.e. the *ex-post* effects of proximity on collaboration. Geographical proximity is found to be positively correlated with firm performance in terms of economic and innovative outcomes (Oerlemans and Meeus 2005), with survival rates of SMEs (Staber 2001) or with continuation respectively successful finish of research projects (Lhuillery and Pfister 2009). No proximity effects are observed on cooperation satisfaction or the longevity of industry-research partnerships (Mora-Valentin et al. 2004). However, these studies do not account for other types of proximity, such as social or cognitive ones. The study by Boschma and Broekel (2012) is the only one that considers multiple types of proximities. They find a somewhat paradoxical effect of geographical proximity on performance of collaborations in the Dutch Aviation Industry: while co-location seems to be a crucial driver of link formation, it does not affect subsequent innovative performance. This is what they call the proximity paradox. Cassi and Plunket 2014 confirm this finding in that geographical proximity is crucial for link formation, but seems to be irrelevant for the outcomes of the collaborations as measured by forward citations to patents in the field of genomics. Fitjar et al. (2015) even find a reverse effect: geographical distant partners are more likely to be innovative and to introduce new products.

In sum, the ambiguous and sparse evidence on the role of geographical proximity for project success questions the necessity to primarily foster regional linkages in modern innovation policy. And in light of recent findings on the danger of regional technological lock-in and the vital role of extra-regional linkages in their prevention one may ask whether this policy perspective is too restricted and even outdated (Bathelt et al. 2004)? In order to give an answer it is necessary to analyze whether there are main confounding factors that condition the supportive role of geographical proximity on project performance. In this respect, the relevance of geographical proximity for the successful implementation of R&D projects seems to be still a relevant research issue (Hazir and Autant-Bernard 2011). Building on this, we investigate research relationships that have already been formed and analyze how project managers evaluate project performance contingent on their project partners' geographical proximity as well as further confounding, mediating or moderating factors. So, our focus is not on explaining why certain linkages have been formed, but rather on how these linkages perform.

4.3 Hypotheses

The performance of R&D projects can be measured in many ways. A successful project is mostly understood as one that meets predefined goals. In the research on innovation, innovative performance - the generation of an innovation as the output of a research project or R&D productivity - are the most obvious indicators for success (Brown and Svenson 1988). However, there is a lag between research conduct and the time until the innovative output becomes apparent in observable data (such as patents or products). The repetition or longevity of a research collaboration as well as mutual knowledge transfer can also be viewed as a project success (Hamel 1991, Lhuillery and Pfister 2009). Furthermore, the satisfaction of project managers with the project processes can be an early indicator for project success that is correlated to later innovative outputs (Mora-Valentin et al. 2004). We try to combine several output measures, namely self-reported project satisfaction and subsequent innovative output to analyze the role of geographical proximity for the success of a research cooperation.

Three interrelated research questions constitute the framework for our analysis: Do cooperating actors perceive geographical proximity necessary in order to be successful? Does geographical proximity yield higher satisfaction in cooperative projects? Does geographical proximity indirectly via project satisfaction and directly increase success chances in terms of final project results?

We suggest that technological and organizational specificities of collaborative research projects govern the necessity for geographical proximity and that geographical proximity along with other factors increases project satisfaction and in turn the final project results. Our main assumption is that geographical proximity eases coordination and knowledge transfer within collaborations and increases the probability of success via decreasing the costs of personal contacts, leading to better communication and knowledge exchange conditions, and the creation of trust (Boschma, 2005). However, the context of the research projects in terms of research orientation, exploration of new knowledge and the familiarity with research partners determines the need for continuous personal interaction and might render the argument for the advantages of geographical proximity obsolete.

Novelty and the relevance of geographical proximity

To be more specific, we assume that geographical proximity is especially relevant for project success, if the project focus is on exploring a radical novelty rather than a mere advancement of previous results. Therefore, when we consider novelty, we relate it to the exploration of new opportunities rather than the continuation or exploitation of prior generated knowledge (March 1991). Because knowledge in explorative research is highly complex and specific, it is hard to codify and to share without permanent personal communication and interaction. Since, as pointed out earlier, geographical proximity eases personal interaction and knowledge exchanges, we assume that more explorative and novel research projects are more reliant on close geographical linkages and that geographical proximity becomes more relevant for project success with a higher degree of novelty of the project. Since novelty can be measured along several dimensions and we operationalize the concept of novelty accordingly.

As first dimension, research endeavors can be characterized as novel when they are targeting radical novelties that significantly differ from prior research results. So for radicalness of the knowledge produced as the first dimension of novelty we suggest:

Hypothesis 1a: *The relevance of geographical proximity for project success increases with the radicalness of the novelty.*

A second dimension of novelty relates to the familiarity with the technology applied in the research project. Actors who are unfamiliar with the technology utilized in the project might require face-to-face interaction with their partners more frequently to increase learning. Therefore we assume that respondents who work with a technology that is new to them value geographical proximity to their partners higher. Hence, we propose:

Hypothesis 1b: *The relevance of geographical proximity for project success increases with the novelty of the applied technology within the project.*

A third dimension of novelty concerns whether projects establish new research lines or represent a continuation of activities from prior projects. Contrariwise to radicalness and familiarity with the applied technology, geographical proximity might be less relevant for projects that perpetuate activities from prior related projects since certain routines and processes or institutions are already established. Therefore we assume that:

Hypothesis 1c: *The relevance of geographical proximity for project success decreases with the number of prior related projects.*

The link between proximity and project satisfaction

Building on that, we explore how geographical proximity is associated with project performance. As a first step we consider project satisfaction as the intermediate outcome. Based on the above argument, we presume that geographically close partners tend to be more satisfied with their projects since communication and knowledge exchange is eased by geographical proximity.

Hypothesis 2a: *Project satisfaction increases with geographical proximity between partners.*

In the same vain, we expect that social proximity also directly effects cooperation satisfaction. We assume a positive relationship between social proximity and project satisfaction.

Hypothesis 2b: *Project satisfaction is positively associated with social proximity (acquaintance of partners).*

For the direct relation formulated in H2a and b we additionally consider other confounding factors and moderation effects. First, this relationship might be moderated by the perceived relevance of geographical proximity for project success. For respondents who deem co-location to their partners as irrelevant, the actual distance to their partners should not affect project satisfaction. Vice versa, we expect that actors, who evaluate geographical proximity to partners as essential while their project partners are remotely located, will be less satisfied with the project.

Hypothesis 2c: *The link between project satisfaction and geographical distance is moderated by the relevance of geographical proximity for project success.*

Another important factor driving project satisfaction is the acquaintance of partners through prior project experience, i.e. social proximity. Multiple studies have pushed forward arguments for a substitutive relationship between geographical proximity and social proximity. In our study we assume that collaboration with distant partners is easier when they have previously worked together and could establish communication routines and trust. When partners are socially proximate they already exhibit a certain level of trust and are not reliant on frequent interaction and observation of the partner's behavior. Therefore we assume that already known partners are unaffected by geographic distance in their satisfaction with the overall collaboration.

Hypothesis 2d: *The relation between geographical proximity and project satisfaction is moderated by social proximity between the partners.*

Project performance

Finally, and based on the arguments that already led to hypothesis 2a , we expect that projects between geographically proximate partners are more successful than between distant partners. However, we assume that in addition to a direct effect of proximity on success there is also an indirect effect via increased project satisfaction. It seems plausible to expect that more satisfied researchers display higher productivity and more outcomes. Also project satisfaction captures latent problems/ hurdles within the projects, which might hinder the success of the project. Therefore, we assume:

Hypothesis 3a: *Project outcome is positively correlated with geographical proximity.*

and

Hypothesis 3b: *Project outcome is positively correlated with project satisfaction.*

4.4 Methodology

4.4.1 Data

The "Leading-Edge Cluster Competition" was a national, technology open cluster funding program launched by the German Federal Ministry for Education and Research (BMBF) in 2007, which aimed at funding collaborative R&D projects in selected cluster regions.

Through the bottom up approach of the policy, there was no narrow definition of what can be actually understood as a cluster. The necessary conditions that had to be met by potential candidates comprise that the innovative clusters had to possess strong expertise in their focal technology field and at the same time exceed a certain critical mass of international operating forms and reputable research institutes in the focal technology field. Furthermore they should hold a strong international market position, have a dynamic research focus and exhibit potentials for increasing their profile and competiveness (Rothgang et al. 2014).

Following recommendations of an expert jury, the Federal Ministry appointed 15 Clusters in three waves (2008, 2010, 2012) to be labeled as "Leading-Edge Clusters" and to receive funds amounting up to 40 million euros per cluster over a 5 year period. The funds were distributed to organizations in the winning clusters to conduct R&D projects in collaboration with cluster partners[13] under a common leading cluster theme. Within the scope of the BMBF funded research project "Evaluation of the German LECC", surveys were conducted between 2010 and 2013 with beneficiaries of the ten selected clusters of the first two waves[14]. As part of these surveys, project managers were asked to evaluate processes and activities within the LECC-

[13] Cluster partners do not necessarily have to be located in the cluster region.

[14] Since the third wave was selected in 2012 and the distribution of funds for the single projects effectively started in 2013, it was too early to collect meaningful data by means of surveys with these beneficiaries.

funded projects. To analyze cooperative processes, we consider only those respondents who participated in a joint research project (i.e. we excluded information from individual projects). These joint research projects can be understood as collaborations which are divided into subprojects concerned with specific aspects relevant to the common themes. The respondents, either employees of a research institute, a university or a firm, were the managers of these subprojects. Therefore, our dataset includes multiple responses within the same joint projects. This allows us to calculate relative distance measures within one joint project as well as to observe deviations in satisfaction levels of respondents within the same project. We exploit this unique dataset and complement information on project activities and outcomes with information on respondent's geographical location. Even though the data was collected in consecutive interrogation rounds at different points in time, several items were not repeatedly reported and therefore our data is of cross-sectional nature.

4.4.2 Sample characteristics

In total, our sample comprises 475 consistent responses across all interrogation rounds by project managers of 101 joint projects. Table 4.1 provides an overview of the sample characteristics and the distribution of responses across clusters and actor types. The responses are almost equally distributed across actor types (last column). When annulling size differences and aggregate answers of large firms and SMEs, a dominance of firms prevails in the data set (two thirds of the respondents are enterprises). The number of responses per cluster is very uneven (last row), ranging from a minimum of 23 to a maximum of 98 cases. This can partly be explained by the fact that the second wave clusters comprise a larger number of beneficiaries.

Table 4.1 Distribution of answers across Clusters and actor type

	First round					Second round					
	BioRN	Cool Silicon	FOE	Aviation	Solar Valley	m4	MV	Micro-Tec	Software	Logistic	∑
Large firms	5	8	15	20	19	2	12	19	7	35	142
SME	16	10	3	8	7	17	24	35	11	31	162
RI	2	15	10	11	22	22	13	35	9	32	171
∑	23	33	28	39	48	41	49	89	27	98	

4.4.3 Variables

In order to analyze the interplay between geographical proximity, project satisfaction and project performance, we estimate three models with different dependent variables capturing three interrelated topics: the *relevance of geographical proximity for project success*, *project satisfaction* and *project results*. The description of the variables including selected summary statistics can be found in table 4.6 in the appendix.

Dependent Variables

Perceived relevance of geographical proximity for project success (self-reported). In the first model, we aim to explain under which circumstances project managers *perceive* geographical proximity between project partners to be relevant for the success of the research project (*perceived relevance of geographical proximity*). The managers were asked to evaluate on a scale from 1 to 5 (where 1 equals "I strongly disagree" and 5 "I strongly agree") whether geographical proximity is a central precondition for their project success. Since the managers report about their perception about the importance of geographical proximity, this is a subjective measure that is necessary to explain why some projects span over larger distances.

Project satisfaction. One possible way to define the success of research projects is by measuring the satisfaction with the project processes by the actors. We assume that projects with more satisfied project managers will also result in higher projects outputs (in terms of innovation and cross-fertilization). Thus, project satisfaction represents an intermediate result of the research endeavor. For this reason, we explain in the second model the self-reported satisfaction with aspects of the project implementation as indicated by the project managers . In detail, they were asked to indicate on a scale from 1 to 5 - lower values correspond to lower satisfaction and vice versa – how satisfied they are with the cooperation in general (*satisfaction with cooperation (public research)* for cooperations with public research institutes or universities*, satisfaction with cooperation (firms)* for cooperations with companies), know-how transfer into their own organization (*satisfaction with know-how transfer (public research), satisfaction with know-how transfer (firms)*), information transfer between the partners (s*atisfaction with information transfer (public research), satisfaction with information transfer (firms)*), and coordination with the partners (*satisfaction with coordination (public research), satisfaction with coordination (firms)*). Since some of the projects were still running while the survey was conducted, we assume that project satisfaction items already capture the prospective project success that manifests in concrete project outputs in later stages. One advantage of measuring project success in this way is that successful projects can be identified earlier as compared to projects that are evaluated by means of patents or other concrete outputs.

Project results. Besides project satisfaction, we are also interested in analyzing whether projects with more satisfied project managers automatically result in a higher innovative performance. To elaborate on the relation between project satisfaction and final project outputs, we proxy project success by indicators for cross-fertilization effects (*cross fertilization*) and innovative performance (*introduction of innovation (binary)*). Concerning cross fertilization, respondents were asked if project results can already be used as inputs for other projects in the organization's portfolio (from 1 – strong disagreement to 5 – strong agreement). Innovation output is captured as binary information (0=no, 1=yes) if novel and significantly improved products, services and processes have been launched by the respondent organization as a result of the project work.

We assume project satisfaction and project results to be strongly correlated. This could be simply due to the fact that both proxies might capture the same underlying factor and face the danger of being highly endogenous. The separate collection of information on project satisfaction and project output in different interrogation rounds – project satisfaction was asked in 2010/2011, the project results in 2013 – reduces this risk. The data collection process along with the project progress is shown in figure 4.1.

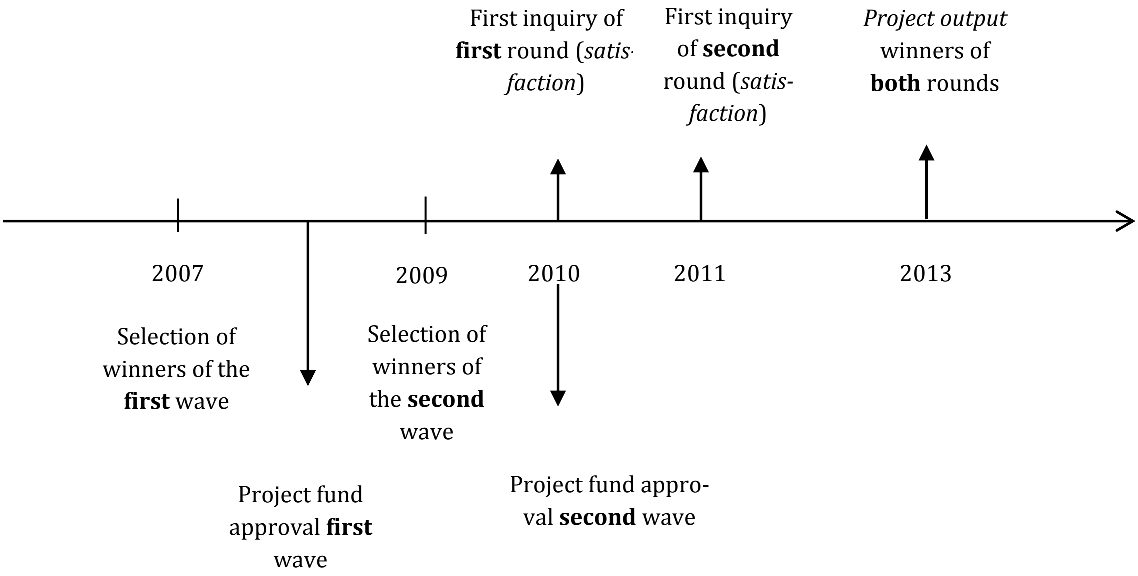

Figure 4.1 Timeline of data collection and project progress

Independent Variables

Novelty. We assume that the degree of novelty of the project determines the relevance of partners' geographical proximity for successful project accomplishment. To test this, we divide novelty into three sub aspects. First, we measure the degree of radicalness of the targeted innovation production (*radical innovation aim).* Respondents were asked to indicate on a scale from 1 (strongly disagree) to 5 (strongly agree) whether the project aimed at generating a radical novelty. Second, the familiarity with the knowledge applied in the project might shape the necessity for geographically close interaction. This aspect (*application new technology*) is measured by the respondents' agreement to the item "*The technology used in this project is completely new to us*" (same 5 point likert scale as before). Third, we also want to consider internal aspects of novelty by asking whether there have been prior projects to the current project (*previous projects*). This variable is of binary nature, indicating whether the current project continues work from previous projects (one) or not (zero). Of these three novelty aspects, only *radical innovation aim* and *application new technology* are correlated (see results section and table 4.8 in appendix).

Geographic distance. To analyse the correlation between geographical distance and project satisfaction, we employ several objective distance measures. Based on the respondents' locations, we compute the average distance in km to all partners (managers of subprojects) within the joint project (*average distance*). To also differentiate between projects that are clustered close in space as compared to projects with core-periphery structures, we calculate a relative distance measure that takes into account the distance of each respondent to a pre-defined geographical core or center of the joint project (*distance to centre*). We identify those cities as project centers where the majority of partners is located. We assume that this center hosts the core activity of the project work due to the clustering of project partners. This measure is the de facto geographical proximity of the project partners and will be coupled with the perceived importance of geographical proximity by the project managers in the analysis (*perceived relevance of geographical proximity*).

Social proximity. Social proximity comprises the "social context" of the economic relations (Boschma 2005). Basically it is understood as the level of trust between the partners and has been identified as a crucial factor in mediating the positive effects of geographical proximity on collaboration (Gulati and Gargiulo 1999, Breschi and Lissoni 2009). In the research of networks or bilateral collaborations social proximity is operationalized in terms of the numbers of previous mutual collaborations or shared inventors (inventor mobility) (Gulati, 1995, Breschi and Lissoni 2009) or some other proxy (prior indirect ties, reputation) that implies some kind of trust or familiarity of the project partners (due to prior experience) (Gulati and Gargiulo 1999). In our data, the respondents were asked with how many of the partners in the current projects they have worked before in other projects. This is a good indication for familiarity and social proximity to the actual partners, as this captures whether they had prior successful experiences with the actual partners (otherwise they would not repeat the collaboration). Moreover, since they could indicate on an increasing scale the share of partners they know, we can capture a range of social proximity (from low to high). More specifically, we measure social proximity (*social proximity*) on an increasing scale from 0 to 3. The variable is 0 when none of the current partners are known, 1 when the minority is already known, 2 when the majority is already known and 3 when all the partners from the current project are known from prior work.

Controls. Apart from these main variables of interest, we include additional variables to control for factors that might influence our dependent variables. When talking about the importance of geographical proximity, one has to control for the general goal of the project as the perceived relevance of geographical proximity for project success might differ for projects that aim at establishing regional infrastructure (qualification programs, start-up climate) as compared to ones that explicitly aim at producing novel knowledge. Therefore we differentiate between projects that aim primarily on the development of new product and process innovation (*goal product innovation, goal process innovation*), the support of start-ups (*goal business formation*) or the development of qualification and educational programs (*goal qualification program*). Since projects might pursue different goals simultaneously, each of these variables indicates the relative importance of each goal on a five point Likert scale. Closely related to that, it has been found that effects of geographical proximity on success are less pronounced for research endeavors that are basic rather than applied (Mansfield and Lee 1996). For this reason, the basic nature of each research project is proxied by the respondent's binary indication regarding the potential of the project results to be implemented directly in new products/processes (*applied results*).

In the second model, further confounding factors that might drive the variance in perceived project satisfaction are project size as measured by the number of organizations collaborating in one project (*project size*), whether the respondent was the initiator of the project (*project initiator*), the general importance (*project importance*) of the project for the respondent in terms of network activities (i.e. to identify low engagement in joint projects due to deviating targets) and whether the project would have been dismissed without funding (*project dismissal*). Larger projects might receive lower satisfaction scores since they require higher coordination, communication and transaction costs. Likewise, projects which are more important for the respondent organization might be evaluated better.

In explaining project results in terms of the generation of innovation and cross fertilization effects, we also control for R&D-input measured by the number of highly skilled employees in the project (Human Capital Input - *high skilled*).

Moreover, in all three models we control for actor type (*firm* or *public research institute* - whether the respondent is an enterprise or research institute) and cluster specific effects (to account for unobserved differences between clusters, such as technology, potential governance, overall network structure, etc.).

4.4.4 Estimation strategy

The relations that we aim to analyze are highly intertwined. Geographical proximity between the research collaborators as our main variable of interest is assumed to be a crucial determinant of project satisfaction which in turn should affect later project outcomes. The relation between geographical proximity and project success is in turn mediated by other factors. For this reason, we follow a three stage estimation strategy in which the predicted values of the previous step are integrated as independent variables in the subsequent step. Since all our dependent variables represent a set of choices (response categories), we apply discrete choice models. In these models one estimates the probability for a certain choice dependent on the characteristics of the individual respondent. For the n response categories, we estimate the following models:

Step I. In the first model, we estimate the conditions (novelty, project goals) under which geographical proximity is seen as a necessity for the successful accomplishment of the project. Since the response categories are ordered along ascending agreement we estimate an ordered logistic regression model. For each response category j from 1 to n-1[15] the ratio between the probability that the observed response is below category j and the probability that the response score is above the category j is calculated (left hand side) (Wooldridge 2002). In this step, the categories range from 1 to 5. To be more specific, we regress the response for the perceived relevance of geographical proximity $perceived\ relevance\ of\ geographical\ proximity_i$ on the radicalness of the project ($radical.inn_i$), the familiarity with the technology applied ($application\ new\ technology_i$) and whether the current project is based on previous project activities ($previous\ projects_i$). The last summation term represents further control variables.

$$ln\left[\frac{P(perceived\ relevance\ of\ geographical\ proximity_i \leq j)}{1 - P(perceived\ relevance\ of\ geographical\ proximity_i \leq j)}\right] = \beta_0$$
$$- (\beta_1 radical\ innovation\ aim_i + \beta_2 application\ new\ technology_i$$
$$+ \beta_3 previous\ projects_i + \sum_{k=1}^{n} \gamma_k\, c_{ik})$$
$$j = 1,2,\ldots,n-1$$

Step II. In the second model, we regress the satisfaction of project managers with certain aspects of the project work ($satisfaction\ with\ coop_i$) on their geographic distance ($geogr.distance_i$) to partners within the joint project, the predicted values of the perceived relevance of geographical proximity from the first model ($perceived\ relevance\ of\ geographical\ proximity_i$), their social proximity ($social\ proximity_i$) and other confounding factors. $Satisfaction\ with\ coop_i$ represents the various aspects of project work that the respondents were asked to evaluate: general cooperation satisfaction (know-how transfer, information transfer and coordination. The response options again range between 1 and 5 in ascending order. $geogr.distance_i$ stands for the two geographical distance measures *average distance* and *distance to centre*. Just as in step I, the last term represents the further control variables.

[15] n-1 because the cumulative probabilities are computed and this would equal 1 for the n^th category.

$$ln\left[\frac{P(satisfaction\ with\ coop_i \leq j)}{1 - P(satisfaction\ with\ coop_i \leq j)}\right] = \beta_0 - (\beta_1 geogr.distance_i$$
$$+ \beta_2 perceived\ relevance\ of\ geographical\ proximity_i$$
$$+ \beta_3 socical\ proximity_i + \beta_4 geogr.distance_i$$
$$* perceived\ relevance\ of\ geographical\ proximity_i + \beta_5 geogr.distance_i$$
$$* social\ proximity_i + \beta_6 geogr.distance_i * firm_i + \sum_{k=1}^{n} \gamma_k\, c_{ik})$$

Step III. In step three we finally want to elaborate, whether projects with more satisfied participants exhibit a higher success probability. Therefore we relate the predicted values of overall project satisfaction ($satisfaction\ with\ coop_i$) from the second step and the geographic distance to the partners ($geogr.distance_i$) to the project results ($results_i$) in terms of cross fertilization effects (*cross fertilization*) and innovative performance (*introduction of innovation (binary)*). The response categories j for *cross fertilization* range from 1 to 5 and we apply an ordered logit model as well. Since the responses for *introduction of innovation (binary)* are binary (0 – no innovation, 1 – innovation), we employ a binary logistic regression model. Analogue to the first two steps, the last term represents further control variables.

$$ln\left[\frac{P(results_i \leq j)}{1 - P(results_i \leq j)}\right] = \beta_0 - (\beta_1 satisfaction\ with\ coop_i + \beta_2 geogr.distance_i + \sum_{k=1}^{n} \gamma_k\, c_{ik})$$

4.5 Results

There is suggestive evidence that the probability to form a collaboration is highest when actors are located close-by and that the interaction likelihood decreases sharply above a distance of about 100 km between the partners, which equals approximately one hour of travel time between collaborators (Garcia et. al 2013).

Accordingly, as can be seen in figure 4.2 (and table 4.6 in the appendix), the geographical distance between participants in the funded R&D projects in our sample conforms to prior findings with the majority of project partners being located within (median of *average distance*) 107 km of each other. Beyond this threshold, the number of distant project members drops sharply. Additionally, the highly skewed distribution of the average distance (red line) and its concentration at rather small values (75% of observations are below 166 km) reflects the strong regional focus of the competition. Far distant partners can inflate the average distance measure of the respondents to their partners. Therefore we also calculated the distance of each respondent to the identified geographical core of the joint project (*distance to centre*). The distribution of this measure is represented by the blue line in the same figure. The median distance of partners to the center equals 20.1 km, which also mirrors the selective support of regional linkages by the program. We can see however, that the mean average distance and mean distance to the center highly varies across the clusters (see table 4.7 in the appendix which show the mean and the median of avrg_dist and cent_dist per cluster).

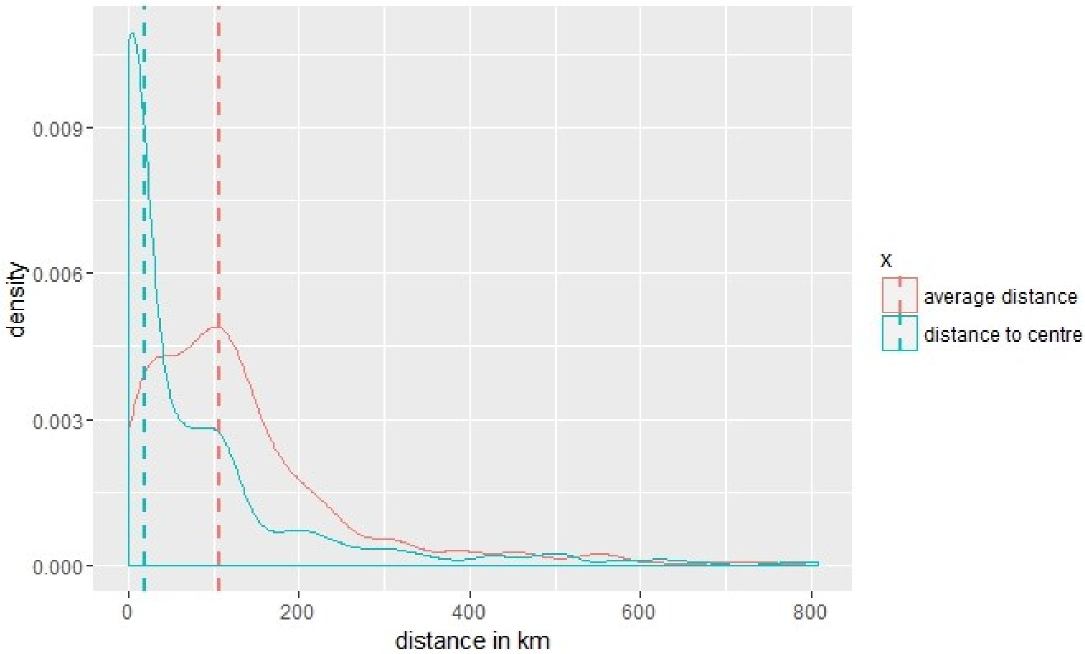

Figure 4.2 Distribution of *average distance* and *distance to centre* with respective median (dashed line)

Table 4.2 Distance between project partners by collaboration type (absolute numbers of cases per collaboration category)

	1 research-industry	2 inter-academia	3 interfirm
No. of collaborations with distance ≥ 100 km	50	2	4
No. of collaborations with distance < 100 km	33	4	8
Median of avrg_dist to project partners	118.20	73.45	56.33

Furthermore, Garcia et al. (2013) have also stressed, that geographical proximity particularly plays a role in industry-university collaborations. In their study, the majority of collaborations of this type were formed with partners that were less than 100 km away. When subdividing our sample by the type of collaboration (research-industry, inter-academia, interfirm) and comparing them in terms of their average distance between the partners in one project, reveals a somewhat deviating picture (table 4.2). Collaborations that exhibit some degree of institutional proximity, i.e. between actors of the same type as shown in column 2 and 3 are more proximate to their partners. In contrast, collaborations between research institutes and firms are more likely to include more distant partners. However, the number of industry-research collaborations in our sample is far higher than for the other cases.

These results are also mirrored in the self-reported evaluations of the project managers when asked whether geographical proximity is an important precondition for project success. Figure 4.3 shows the distribution of answers across agreement levels. In general, slightly more than half of the respondents (52%) confirm the need of being closely located to each other in order to be successful. However a non-negligible share of respondents is rather neutral or disagrees to this statement.

To elaborate further on what drives this heterogeneity concerning the perceived relevance of co-location, we regress the categorical responses on certain peculiarities of the research projects such as the novelty of the project activities, the applicability of the results as well as the targeted goals and control for actor and cluster specific effects. Table 4.3 presents the estimation results of our first model. We start by including our main variables of interest and then stepwise introduce the dummies for actor type and cluster to check the robustness of our findings.

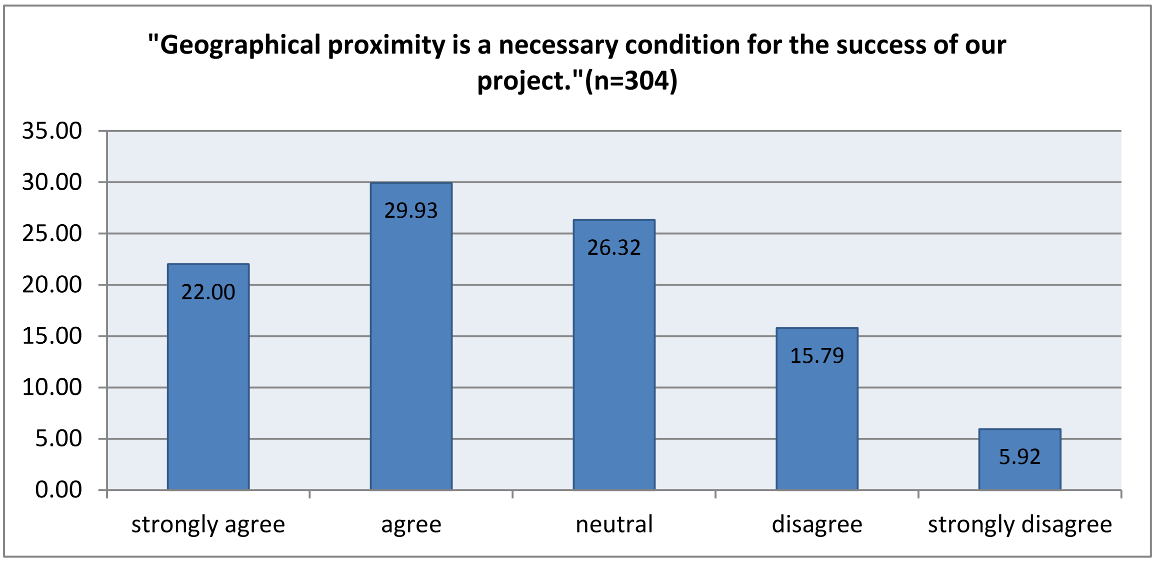

Figure 4.3 The necessity of geographical proximity for project success (own analysis based on the surveys from the LECC)

Basically, we find mixed results for the hypothesized positive relation between novelty of the collaborative research endeavor and the perceived relevance of geographical proximity to warrant success. Concerning the extent of novelty production and the familiarity with the technology applied, we find partial support for our hypotheses 1a and 1b. The perceived relevance of geographical proximity for successful project implementation increases with the exploratory nature of the project activities in terms of producing more radical innovations (*radical innovation aim*) as well as applying new technologies (*application new technology*). But this effect disappears after controlling for specific project goals, type of respondent and cluster. Instead we observe that for members of projects focusing on the development of process innovations, geographical proximity is of minor importance. This relation holds in all model specifications.

With regard to the organizational aspect of novelty, we find that projects that were established as continuation of prior project activities are more likely to rate geographical proximity more important for project success. The coefficient of *previous projects* does not show the expected sign and the result is not robust to the inclusion of actor and cluster dummy variables. Consequently we find no support for hypothesis 1c.

Another interesting and strong finding is related to the applicability of project results (*applied results*). In line with prior studies on collaborations (D'Este and Iammarino 2010, Mansfield and Lee 1996), we can assert that members of projects with a focus on basic research are less reliant on geographical proximity to their partners as compared to actors in applied research projects. Probably the solving of more applied problems in the development of a ready to implement product and/or process requires more frequent interaction due to experimentations and observations processes which in turn are facilitated by geographical proximity of the collaborators.

Concerning actor and cluster heterogeneity, we find no significant differences in the respondent behavior between research institutes and firms. It is not very surprising that controlling for cluster membership reduces the variation explained by the technological and novelty aspects of the projects since the cluster technologies differ in terms of novelty and radicalness. This can also be seen in the significant bilateral correlations of some of the cluster dummies with the *application new technology* and *radical innovation aim* variables (table 4.8 in the appendix).

Table 4.3 Estimation results Step 1: dependent variable is the perceived relevance of geographic proximity for project success (Coefficients of ordinal logistic regression)

Ordered logistic regression					
Model	1	2	3	4	Full
Dep. Var.	*Perceived relevance of geographical proximity*				
previous projects	**0.423** ** (0.216)	**0.362** * (0.219)	0.259 (0.234)	0.235 (0.245)	0.219 (0.275)
application new technology	**0.146** * (0.087)	0.134 (0.086)	0.093 (0.089)	0.091 (0.089)	0.066 (0.087)
radical innovation aim			**0.200** * (0.103)	**0.199** * (0.103)	0.157 (0.109)
goal business formation			0.175 (0.143)	0.163 (0.146)	0.240 (0.165)
goal process innovation			**-0.292** ** (0.138)	**-0.294** ** (0.138)	**-0.272** * (0.152)
goal product innovation			-0.255 (0.176)	-0.243 (0.181)	-0.152 (0.193)
goal qualification program			0.086 (0.149)	0.088 (0.150)	0.164 (0.168)
applied results		**0.612** ** (0.265)	**0.507** * (0.271)	**0.514** * (0.272)	**0.598** ** (0.277)
firm				-0.102 (0.245)	-0.043 (0.269)
BioRN					-0.927 (0.634)
CoolSilicon					0.745 (0.520)
FOE					0.371 (0.630)
Logistik					**-0.638** * (0.380)
Aviation					-0.084 (0.520)
m4					-0.316 (0.458)
MedicalValley					-0.619 (0.438)
Software					0.143 (0.412)
Solarvalley					-0.101 (0.473)
Observations	282	278	263	263	263
LR chi2	7.402	12.356	22.509	22.681	34.432
Pr(> chi2)	0.025	0.006	0.004	0.007	0.011
Pseudo-R2[16]	0.027	0.046	0.086	0.087	0.129

Robust standard errors in parentheses; *p < 0.10, ** p < 0.05, *** p < 0.01

[16] The R package *rms* which is applied here provides a pseudo R2 (Nagelkerke) for ordinal logistic regressions.

Table 4.4 Estimation results Step 2: dependent variables are project satisfaction in cooperation with research institutes and firms in general and along various dimensions (know-how transfer, information transfer, coordination) (Coefficients of ordinal logistic regression)

Ordered logistic regression												
Model	1	2	3	4	5	6	7	8	9	10	11	12
Dep. Var.	*Satisfaction with cooperation (public research)*				*Satisfaction with know-how transfer (public research)*	*Satisfaction with information transfer (public research)*	*Satisfaction with coordination (public research)*	*Satisfaction with cooperation (firms)*		*Satisfaction with know-how transfer (firms)*	*Satisfaction with information transfer (firms)*	*Satisfaction with coordination (firms)*
average distance	0.001	0.019			0.003	-0.024	0.003	**0.034** *	**0.036** *	-0.006	-0.012	0.000
	(0.001)	(0.026)			(0.018)	(0.022)	(0.016)	(0.020)	(0.020)	(0.023)	(0.022)	(0.017)
distance to centre			-0.005									
			(0.021)									
distance to centre (binary)				-1.355								
				(4.464)								
predict. perceived relevance of geographical proximity	0.428	0.568	-0.032	0.002	-0.077	-0.041	-0.344	0.600	0.358	-0.406	-0.735	-0.762
	(0.459)	(0.936)	(0.623)	(0.571)	(0.862)	(0.840)	(0.752)	(0.807)	(0.868)	(0.787)	(0.820)	(0.721)
social proximity	**0.333** *	0.055	0.369	0.336	0.389	-0.285	0.011	**0.569** *	**0.574** *	0.573	0.444	0.364
	(0.172)	(0.314)	(0.226)	(0.209)	(0.333)	(0.317)	(0.334)	(0.32)	(0.315)	(0.407)	(0.383)	(0.331)
*average distance * social proximity*		0.003			**0.005** **	**0.005** **	0.002	0.000	0.000	0.001	0.000	-0.001
		(0.002)			(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)
*distance to centre * social proximity*			-0.001									
			(0.002)									
distance to center (binary) social proximity*				-0.224								
				(0.467)								
*average distance * predict. perceived relevance of geographical proximity*		-0.003			0.000	0.005	0.000	-0.008	-0.008	0.002	0.005	0.002
		(0.007)			(0.005)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)
*distance to centre * predict. perceived relevance of geographical proximity*			0.005									
			(0.006)									
*distance to center (binary) * predict. perceived relevance of geographical proximity*				0.958								
				(1.186)								
*average distance * firm*		**-0.011** **			**-0.007** **	-0.001	-0.004	**-0.007** **	**-0.009** ***	-0.005	-0.005	**-0.006** *
		(0.004)			(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
*distance to centre * firm*			**-0.013** ***									
			(0.005)									
*distance to center (binary) * firm*				**-2.072** **								
				(0.898)								
Firm	0.140	**1.263** **	**0.749** *	0.537	-0.076	-0.514	-0.490	0.594	**0.904** *	0.375	0.000	-0.183
	(0.333)	(0.567)	(0.406)	(0.394)	(0.556)	(0.510)	(0.501)	(0.492)	(0.538)	(0.586)	(0.504)	(0.495)
project size	-0.021	**-0.091** **	**-0.097** **	**-0.082** **	0.034	-0.043	0.021	0.012	-0.023	-0.011	-0.032	-0.053
	(0.023)	(0.038)	(0.038)	(0.036)	(0.039)	(0.036)	(0.046)	(0.027)	(0.054)	(0.051)	(0.044)	(0.049)
project dismissal	0.347	0.235	0.197	0.16	0.129	**0.593** *	0.286	0.194	0.119	-0.147	0.227	0.142
	(0.318)	(0.368)	(0.374)	(0.365)	(0.348)	(0.335)	(0.365)	(0.300)	(0.337)	(0.345)	(0.325)	(0.308)
project initiator	0.203	0.119	0.156	0.157	0.040	-0.189	-0.002	-0.030	-0.098	-0.177	0.061	-0.066
	(0.304)	(0.365)	(0.359)	(0.358)	(0.371)	(0.368)	(0.334)	(0.322)	(0.353)	(0.411)	(0.355)	(0.336)
project importance	**0.375** **	**0.392** *	**0.391** *	**0.414** **	**0.416** **	**0.346** *	**0.444** **	**0.413** **	**0.381** *	0.068	**0.327** *	0.280
	(0.186)	(0.223)	(0.200)	(0.200)	(0.180)	(0.193)	(0.211)	(0.197)	(0.195)	(0.191)	(0.19)	(0.183)
Cluster dummies	N	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y
Observations	198	198	198	198	188	206	204	197	197	183	206	200
LR chi2	15.564	46.870	46.769	43.268	56.957	42.274	35.397	21.196	34.226	32.553	33.381	29.054
Pr(> chi2)	0.049	0.001	0.001	0.002	0.000	0.003	0.018	0.031	0.025	0.038	0.031	0.087
Pseudo-R2	0.089	0.248	0.248	0.231	0.290	0.209	0.182	0.116	0.182	0.177	0.167	0.153

Robust standard errors in parentheses; *p < 0.10, ** p < 0.05, *** p < 0.01

After identifying the circumstances that guide the perceived relevance of co-location for project success, we are interested whether projects with local partners are indeed outperforming the ones with distant partners. Therefore, we use the predictions for perceived relevance of geographical proximity of step 1 (Model 3[17]) along with the de-facto geographical proximity to explain the project satisfaction as an intermediate outcome of the project work. Table 4.4 provides the estimated parameters for our second model.

Overall, our estimates do not support the presumed direct relationship between the distance of collaboration partners and project satisfaction (H2a). Neither the single average distance (*average distance*) nor the single distance to the project center (*distance to centre*) turn out to play a significant role for most of the project aspects such as the general cooperation satisfaction (*satisfaction with cooperation*), the knowledge transfer (*satisfaction with know-how transfer*), the information transfer (*satisfaction with information transfer*) as well as the coordination of project members (*satisfaction with coordination*). Distance only becomes relevant with regards to overall satisfaction in cooperation with firms. However, the coefficients do not show the expected signs. Checking for a threshold distance (both the mean and the sophisticated 1 hour travel distance (100 km)) by compiling the distance values to the binary information distant (one) or close (zero) did not yield different results. Although we ran both regressions for binary *average distance* and *distance to centre*, the table only contains the model modification for *distance to center (binary)* (column 4).

Contrary to geographical distance, the individual effect of social proximity (*social proximity*) on project success is significant for the overall cooperation satisfaction, with a more pronounced effect for collaborations with firms (satisfaction with cooperation (public research) and satisfaction with cooperation (firms), column 1, 8, 9). This conforms to the ample evidence provided by a multitude of prior studies (Mora-Valentin et al. 2004, Breschi and Lissoni 2009). Projects that involve more familiar partners have higher chances to contain highly satisfied partners than projects where completely new partners interact. Consequently, our findings underpin our H2b.

Finding only partial support for a direct link between distance and satisfaction is hardly surprising, since the relation between co-location of partners and project satisfaction is very complex and mediated by project peculiarities as seen in our step one estimations. Thus, geographic proximity might affect satisfaction levels through multiple channels. First, the preference for being closely located might determine whether distant project members appoint high satisfaction scores or not. If respondents deem proximity to their partners as irrelevant, we would expect that the satisfaction scores do not decrease with geographic distance and vice versa (H2c). The inclusion of a joint effect of the perceived relevance of proximity and the actual distance of the partners on project satisfaction (*distance*predict.perceived relevance of geographical proximity*) does not support this hypothesis.

Second, the substitutive relationship between geographical proximity and social proximity has been stressed by multiple studies (Agrawal et al. 2008, Singh 2005, Breschi and Lissoni 2003, ter Wal and Boschma 2009, Boschma 2005). In our study we assume that collaboration with distant partners is easier when they already have worked together in the past and have already established communication routines and trust and therefore do not evaluate the collaboration with distant partners worse than with close ones (H2d). However, we only find weak evidence for an interaction effect between social proximity and geographic distance (*distance*social proximity*) on cooperation satisfaction. Solely with respect to know how transfer and information transfer in collaboration with research institutes (column 5 and 6) a significant relation becomes apparent, showing that socially proximate partners are more likely to award higher scores to distant partners as compared to formerly unknown partners. This relationship

[17] For the further analysis we always consider the predicted values from the reduced model either without actor and cluster dummies (step 1) or without cluster dummies (step 2).

is depicted in the left-hand side graph in figure 4.4. The mean predicted satisfaction levels for collaboration partners of research institutes are separated between previously known compared to previously unknown partners (social proximity was transformed into a binary variable) and plotted against the average distance (whether partners are located below 100km or above 100km distant from each other). The mean predicted cooperation satisfaction decreases with distance when the partners in the respective project do not share prior common work experience, i.e. are socially distant. So there is a somewhat partial evidence that collaborations over larger distances (here over 100 km) can be successful when the partners already know each other.

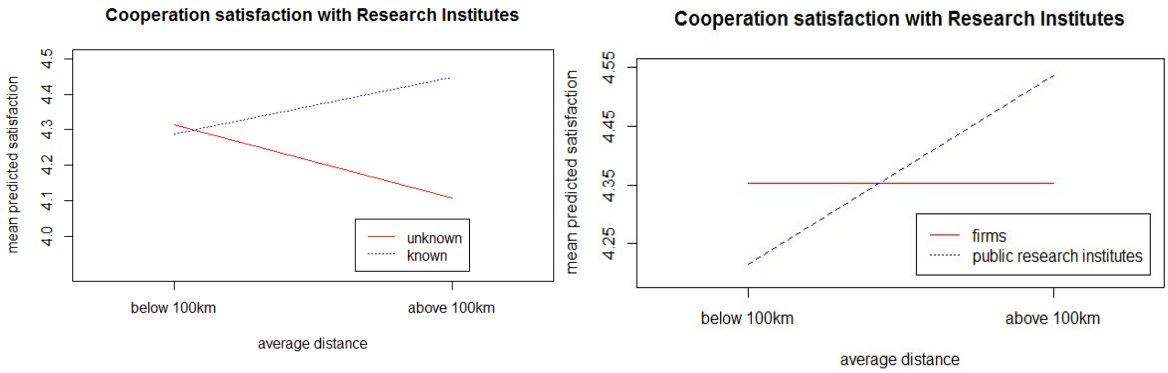

Figure 4.4 Joint/ Interaction effects of social proximity/ actor type and average distance on cooperation satisfaction

Third, if we scrutinize the influence of geographical distance on project satisfaction by actor groups, we find that the interaction effect of distance with the actor dummy (*firm*) is significant and negative. This means that if the distance to the partners increases, companies are less satisfied with the collaboration. This effect is most pronounced for overall satisfaction levels (*satisfaction with cooperation (public research)* and *satisfaction with cooperation (firms)*, column 2 – 4, 8, 9) and independent of the type of cooperation partner (so regardless whether they should evaluate cooperation with research institutes or other firms). Moreover, the observed significant relation is robust to the modification of the distance measures (column 3 & 4). These finding are visualized in the right-hand side graph in figure 4.4. The mean predicted satisfaction levels for collaboration partners from research institutes are separated by type of respondent (firms or public research institutes) and are again plotted against the average distance (below 100km or above 100km). As can be seen, the mean predicted satisfaction levels decrease slightly for firms when partners (research institutes) are located more than 100 km away. Collaborations between research institutes however, appear to perform better if they are located in geographical distance to each other. From this we can conclude that the respondent companies in our sample are more reliant on being close to their cooperation partners as compared to the research institutes in our sample.

Apart from these major findings, satisfaction levels over all project aspects are primarily driven by the main motif of the respondents to participate in the project (*project importance*). Project managers who rated the project to be of minor importance in their organization's project portfolio are less satisfied with all cooperation aspects (except *Satisfaction with know-how transfer (firms)* and *Satisfaction with coordination (firms)*).

Also respondents within larger projects in terms of number of collaboration partners (*project size*) are comparably less satisfied with the overall cooperation – at least with research institutes – than those in smaller projects. Other controls, such as initiating the project (*project initiator*) or necessity of public funding (*project dismissal*) show no robust significant influence.

Table 4.5 Estimation results Model 3: dependent variables are cross-fertilization effects (cross fertilization) and innovation production (introduction of innovation (binary)) (Coefficients of ordinal and binary logistic regression)

Model	1	2	3	4	5	6	7	8
	Ordered Logit				Logit			
Dep.var.	Cross fertilization				Introduction of innovation (binary)			
Predict.satisfaction with cooperation (public research)	**2.247** ***	**2.543** ***	**2.282** ***		-0.280	-0.087	-0.324	
	(0.829)	(0.794)	(0.811)		(1.104)	(1.144)	(1.104)	
Predict.satisfaction with cooperation (firms)				**1.263** *				0.365
				(0.718)				(1.003)
average distance		**-0.003** *				-0.003		
		(0.001)				(0.003)		
distance to centre			-0.001				-0.002	
			(0.001)				(0.002)	
high skilled	-0.029	-0.027	-0.030	-0.027	0.028	0.035	0.026	0.041
	(0.031)	(0.028)	(0.032)	(0.030)	(0.036)	(0.034)	(0.037)	(0.042)
applied results	**1.147** ***	**1.045** ***	**1.090** ***	**1.175** ***	**0.885** *	0.812	**0.856** *	0.317
	(0.349)	(0.349)	(0.352)	(0.369)	(0.505)	(0.500)	(0.498)	(0.503)
public research institute	**1.046** ***	**0.928** **	**0.964** **		**1.018** **	0.775	**0.858** *	
	(0.373)	(0.376)	(0.381)		(0.489)	(0.516)	(0.492)	
Firm				**-1.016** ***				**-1.349** ***
				(0.381)				(0.513)
BioRN	0.599	0.132	0.444	**1.446** **				
	(0.523)	(0.541)	(0.519)	(0.736)				
CoolSilicon	**1.341** *	1.144	**1.293** *	0.779	**6.750** ***	**6.969** ***	**6.821** ***	0.278
	(0.706)	(0.697)	(0.706)	(0.624)	(1.251)	(1.239)	(1.231)	(1.538)
FOE	-0.098	-0.239	-0.106	-0.011	**5.325** ***	**5.824** ***	**5.590** ***	-1.428
	(1.015)	(1.028)	(1.012)	(0.924)	(1.510)	(1.543)	(1.501)	(1.684)
Logistic	0.516	0.478	0.478	0.464	**7.442** ***	**7.929** ***	**7.584** ***	1.381
	(0.443)	(0.444)	(0.447)	(0.395)	(0.930)	(1.028)	(0.938)	(1.264)
Aviation	-0.684	-0.848	-0.723	-0.36	**6.486** ***	**6.798** ***	**6.647** ***	-0.044
	(0.488)	(0.537)	(0.513)	(0.595)	(1.157)	(1.172)	(1.178)	(1.581)
m4	**1.257** *	**1.179** *	**1.276** *	0.949	**6.928** ***	**7.446** ***	**7.193** ***	0.126
	(0.679)	(0.679)	(0.675)	(0.902)	(1.001)	(1.011)	(0.987)	(1.465)
MedicalValley	**-1.523** *	**-1.909** **	**-1.610** **	**-1.112** **	-0.457	0.108	-0.114	**-6.119** ***
	(0.793)	(0.811)	(0.797)	(0.510)	(1.397)	(1.458)	(1.417)	(1.641)
Software	**1.398** ***	**1.209** ***	**1.346** ***	**1.126** ***	**8.877** ***	**9.134** ***	**8.972** ***	**2.696** *
	(0.454)	(0.462)	(0.456)	(0.404)	(1.135)	(1.152)	(1.150)	(1.404)
Solarvalley	0.234	0.292	0.234	0.054	**8.825** ***	**9.459** ***	**9.043** ***	2.501
	(0.539)	(0.509)	(0.528)	(0.538)	(1.557)	(1.522)	(1.562)	(1.759)
MicroTec					**7.066** ***	**7.677** ***	**7.280** ***	1.057
					(0.930)	(1.035)	(0.937)	(1.256)
Observations	189	189	189	190	104	104	104	111
LR chi2	56.446	61.017	58.326	46.201	22.146	24.303	23.679	24.798
Pr(> chi2)	0.000	0.000	0.000	0.000	0.053	0.042	0.050	0.025
Pseudo-R2	0.274	0.293	0.282	0.231	0.256	0.278	0.272	0.268

Robust standard errors in parentheses; *p < 0.10, ** p < 0.05, *** p < 0.01

In the last step we want to clarify if geographical proximity has a direct effect on project results and if project satisfaction is indeed an appropriate indication for later projects success in terms of producing valuable results[18]. Therefore we regress two success variables on both geographic distance and the predicted cooperation satisfaction from step II (from Model 2 for RI and Model 8 for Firm Table 4.4) while controlling for the application of project results (*applied results*), human capital input, actor type and cluster differences. The first success variable relates to the cross-fertilization effects of the funded projects on other projects in the same organization (*cross fertilization*). The second output variable captures whether project activities already resulted in novel products, services or processes (*introduction of innovation (binary)*). Since the two success variables are of different scale, we first estimate an ordered logit model for *cross fertilization* and then a binary logistic regression model for *introduction of innovation (binary)*. The resulting parameter estimates can be found in table 4.5.

Overall, we find that the relation between project satisfaction and project outcome only holds for potential cross-fertilization effects but not for the probability of introducing an innovation. The estimations support hypothesis 3b in that projects that receive a higher rating on the satisfaction scale are more likely to report project results that can be applied in and fertilize other project (*cross fertilization*). This effect is robust against the inclusion of all control variables including actor type and cluster dummies. Likewise and in accordance with H3a, geographical proximity is also only relevant for projects in terms of the production of the cross-usage of results but not for innovative outcome. Here, the average distance to partners hampers the appearance of cross-fertilization effects. This effect does not appear for distance to centre (the distance to the project center). However, the responses also vary significantly between applied and basic research projects, between research institutes and companies as well as between the individual clusters. Project managers who do research in rather applied areas are more likely to report cross-usage of project results in other projects. Furthermore, research institutes are more likely to report that project results add value to other projects as compared to companies. Since we can assume that the main activities of research institutes are within earlier phases of the innovation process this result is not surprising. The projects within the LECC are required to be at a pre-market stage and effects for firms might show somewhat later. In contrast, projects with higher satisfaction ratings do not necessarily manifest in superior innovative performance (*introduction of innovation (binary)*). The reporting of innovative outcome is also quite heterogeneous across clusters and actor types. Managers of applied research projects are again more likely to report innovations and research institutes are also more likely to introduce a novel product, service or process as a result of the project as compared to respondent firms. Consequently we find only partial support for hypothesis 3b.

4.6 Conclusion

The purpose of this study was to reassess the justification for the strong focus of regional innovation policies on fostering regional networking. Since the political support of local collaboration bases on the assumption that geographical proximity has beneficial effects for research collaboration, we wanted to reassess this assumption and confront it with new empirical evidence. Furthermore, we also add to the rare empirical evidence on the relationship between geographical proximity of collaboration partners and the performance of these collaborations. While the constituent role of geographical proximity for the formation of research alliances came to the fore on the innovation research agenda, the consequences for subsequent performance of joint research were still underexplored.

To address this matter, we utilized data from a unique survey conducted with beneficiaries from the German “Leading-Edge Cluster Competition“, one of the main national cluster funding

[18] Some of the projects were still running while the survey was conducted.

programs in recent years. In detail, we analyzed the simultaneous effects of geographical along with technological aspects, social proximity and actor heterogeneity on intermediate outcome in terms of project satisfaction and final project output in terms of cross-fertilization effects and the introduction of a product or process innovation.

We find that geographical proximity of collaboration partners is not a universal precondition for project success. In fact, the picture on how the individual respondents perceive the necessity of being closely located in order to be successful is quite heterogeneous. Our findings suggest that the nature of knowledge involved determines the degree to which collaborators are reliant on being closely located to each other. Geographical proximity between partners is deemed especially important in exploration contexts when projects aim at the production of radical novelty or experiment with new technologies. Contrariwise but in line with prior findings, this effect is less pronounced for projects focusing on basic research (Mansfield and Lee 1996, D'Este and Iammarino 2010, Garcia 2013). Furthermore, we find significant actor specific differences concerning the role of geographical distance to the project partners for project satisfaction levels. The project satisfaction of firms decreases significantly as compared to research institutes the more distant they are located from their collaboration partners. In line with prior studies we further observe that prior common work experience has a significant explanatory power for project satisfaction levels. Contrariwise, we only find little evidence for the often suggested substitutive relationship between geographical proximity and social proximity. However, we only looked at possible substitution effects of both types of proximity at any level of each of the proximity dimensions. A deeper analysis on the interrelations of proximity depending on the prevalent level of each dimension in the fashion of Fidjar et al. (2015) would be an interesting follow up to our study. They analyze in detail when (at which level) geographical proximity can be substituted or complemented by other types of proximities. In other words, they elaborate if substitution or overlap with other types is only efficient at optimal levels of proximity.

With regard to final project results, we find that both, geographical proximity and project satisfaction foster the cross-fertilization of other projects.

Conforming to findings of D'Este and Iammarino (2010), our results leave us to the conclusion that the link between geographical proximity and project success is rather complex and characterized by strong interdependencies with other contextual factors. Consequently, not only the connection to the nearest partners should be supported, but also that the "right" actors have to be chosen. Our results speak against a one-fits-all type of policy which merely strengthens regional linkages, since other important contextual factors might be overlooked and the policy program will not yield the ex-ante expected effects (Crescenzi 2014, Koschatzy 2000). In consideration of the relative importance of other proximity dimensions and contextual factors, policy makers should shift their focus away from this restrictive view and include these factors into their decision. Regional proximity per se might not always be a warrant for successful research, as the benefits of the expertise might outweigh the cost for the collaboration with a distant partner (Garcia et al. 2013). Moreover, geographical proximity can be even detrimental when regional knowledge has been exploited and there is not access to fresh outward knowledge (Bathelt et al. 2004). Extraregional connections might serve as a source for new knowledge to overcome these critical situations. Also geographical distance can be substituted by other forms of proximities between actors (Boschma 2005, Cerscenzi 2014).

Furthermore policy has to find a balance between funding research with new partners for the reason of access to novel knowledge and the exploiting the benefits of conducting joint R&D with old acquaintances based on established trust and institutions. Therefore, the stage of the technology of projects and the prevailing network structures should be taken into consideration as the growth of regions specialized on old technologies might be hindered by the mere focus on regional networking.

Besides these findings, the analysis in this chapter faces some limitations and accordingly leaves room for further research endeavors. The main limitation of this study is the focus on publicly funded R&D projects due to the data availability. The extent of the generalizability of our results needs to be tested on the basis of comparable data from non-funded projects. Moreover, the static nature of the analysis does not allow for any conclusions on causal mechanisms or statements about the development of the necessity for proximity over time. More dynamic approaches are needed to further understand, whether the mechanisms of proximity exhibit stability over time and how their interrelations change when collaborations end or persist.

As a last limitation, we have to mention that our performance measures all base on self-reported information by the project managers. When interpreting the results, one has to bear in mind that there is a risk for a positive bias in the replies by the managers and they tend to be overly positive about their project work. However, in our data we have a reasonable amount of variation and also shares of low values in our project performance variables (project satisfaction and the project results variable) which show that not all managers were completely positive about their projects. In fact, it would be an interesting extension of our analysis and a further check for reliability to mirror our results to the actual performance (patents, publications etc.) of the funded R&D projects. However, due to the time lag between research project and observable outcome, it is still too early to get reliable secondary data on the performance of these projects. This is why we here focused only on the early indicators as collected by the accompanying survey data.

4.7 Appendix

Table 4.6 Description of Variables

Concept	Code	Description	Scale	Obs	Min	Max	Mean	Std.Dev
Geogr. prox and project success	*perceived relevance of geographical proximity*	Projects managers' reply to the item "Geographical proximity is a central precondition for the successful accomplishment of our project."	Categorical (1=strongly disagree, 5=strongly agree)	304	1	5.00	3.46	1.17
Project satisfaction in collaborations with companies and research institutes	*satisfaction with cooperation (public research)*	Satisfaction with the cooperation during the implemenation of the project. (with research institutes as cooperation partners)	Categorical (1=very low, 5=very high)	398	2	5.00	4.28	0.70
	satisfaction with cooperation (firms)	Satisfaction with the cooperation during the implemenation of the project (with companies as cooperation partners).	Categorical (1=very low, 5=very high)	402	2	5.00	4.19	0.76
	satisfaction with know-how transfer (public research)	Satisfaction with the know how transfer into the own organsation (with research institutes as cooperation partners).	Categorical (1=very low, 5=very high)	377	1	5.00	3.92	0.85
	satisfaction with know-how transfer (firms)	Satisfaction with the know how transfer into the own organsation (with companies as cooperation partners).	Categorical (1=very low, 5=very high)	376	1	5.00	3.75	0.89
	satisfaction with information transfer (public research)	Satisfaction with the information transfer between the project partners (with research institutes as cooperation partners).	Categorical (1=very low, 5=very high)	409	1	5.00	4.08	0.76
	satisfaction with information transfer (firms)	Satisfaction with the information transfer between the project partners (with companies as cooperation partners).	Categorical (1=very low, 5=very high)	414	1	5.00	3.96	0.82
	satisfaction with coordination (public research)	Satisfaction with the coordiantion with the project partners (with research institutes as cooperation partners).	Categorical (1=strongly disagree, 5=strongly agree)	403	2	5.00	4.15	0.76
	satisfaction with coordination (firms)	Satisfaction with the coordiantion with the project partners (with companies as cooperation partners).	Categorical (1=very low, 5=very high)	406	1	5.00	4.06	0.78
Project Output	*cross fertilization*	We already can/ could use the project results as inputs for other current projects and planned projects.	Categorical (1=strongly disagree, 5=strongly agree)	326	1	5.00	3.64	1.15
	introduction of innovation (binary)	Has your organization so far introduced a novel product, service or process as a result of the work in this project?	Binary (0=no,1=yes)	191	0	1.00	0.55	0.50
Novelty	*radical innovation aim*	Did the project aim at developing a radical novelty?	Categorical (1=strongly disagree, 5=strongly agree)	317	1	5.00	2.79	1.30
	application new technology	The technology that is used in this project is new to us.	Categorical (1=strongly disagree, 5=strongly agree)	322	1	5.00	3.24	1.41
	previous projects	Does this project base on prior research projects ?	Binary (0=no,1=yes)	455	0	1.00	0.47	0.50
Project Goals	*goal product innovation*	How important is the development of product or service innovation as a result of your project?	Categorical (1=not important, 5=very important)	468	1	5.00	4.57	0.76
	goal process innovation	How important is the development of process innovation as a result of your project?	Categorical (1=not important, 5=very important)	462	1	5.00	4.31	0.83
	goal business formation	How important is the support of new business formation as a result of your project?	Categorical (1=not important, 5=very important)	461	1	5.00	2.92	1.03

Table 4.6 Description of Variables (continued)

Concept	Code	Description	Scale	Obs	Min	Max	Mean	Std.Dev
Project Goals	*goal qualification program*	How important is the development of educational and qualification programs as a result of your project?	Categorical (1=not important, 5=very important)	462	1	5.00	2.92	1.00
Geographical distance	*average distance*	Average distance of the respondent to the project partnersin km.	Continous	475	0	754.50	106.96 [19]	122.04
	distance to centre	Distance in km to the project's geographical center.	Continous	475	0	809.00	20.10[20]	127.15
	distance to centre (binary)	Is the respondent more than 100 km away from the project's geographical center?	Binary (0=no,1=yes)	475	0	1.00	0.24	0.43
Social proximity	*social proximity*	Did you work with some of your partners previously?	Categorical (0=no,1=yes, with less than 50% of them, 2=yes, with more than 50% of them, 3=all)	468	0	3.00	1.34	0.89
Controls	*project size*	Project size in number of organisations involved	Count	475	2	24.00	9.04	6.04
	applied results	The project results can/ could be directly implemented into new products/ processes.	Binary (1=yes ,0=no)	323	0	1.00	0.29	0.45
	project importance	What is the relevance of the project in your general project portfolio? The project itself is of minor importance to us.	Categorical (1=strongly agree, 5=strongly disagree)	290	1	5.00	4.49	0.87
	project initiator	Was the project initiated by your organization?	Binary (0=no,1=yes)	475	0	1.00	0.44	0.50
	project dismissal	The project would have not existed without the funding.	Binary (0=no,1=yes)	475	0	1.00	0.29	0.45
	high skilled	Number of highly skilled researchers working in the project (university degree).	Count	423	0	50.00	4.00	4.72
	firm	Is the respondent a company?	Binary (0=no,1=yes)	475	0	1.00	0.64	0.48
	public research institute	Is the respondent a research institute (university, public research institute)?	Binary (0=no,1=yes)	475	0	1.00	0.36	0.48
	BioRN	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.05	0.21
	CoolSilicon	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.07	0.25
	FOE	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.06	0.24
	Logistic	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.21	0.41
	Software	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.06	0.23
	MicroTec	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.19	0.39
	Solarvalley	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.10	0.30
	MedicalValley	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.10	0.30
	m4	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.09	0.28
	Aviation	Dummy variable for Cluster of respondent	Binary (0=no,1=yes)	475	0	1.00	0.08	0.27

[19] This is the median. The mean for avrg.dist equals 130.84.

[20] This is the median. The mean for cent.dist equals 74.73.

Table 4.7 Average distance (avrg_dist) and Distance to the Center (cent_dist) per Cluster

	Avrg_dist		Cent_dist		
Cluster	Mean	Median	Mean	Median	n
BioRN	31.64	27.44	18.45	0.00	23
CoolSilicon	92.31	85.30	53.32	0.00	33
FOE	96.17	80.03	54.31	40.20	28
Logistik	143.76	111.54	75.20	26.05	98
Luftfahrt	115.46	39.00	68.14	0.00	39
m4	136.66	105.00	85.87	0.00	41
Medical Valley	87.48	73.67	49.09	0.00	49
MicroTec	156.97	141.67	86.75	35.40	89
Software	95.18	94.21	68.31	70.10	27
Solarvalley	222.09	199.90	130.66	93.30	48

Table 4.8 Cluster deviations per dependent variable (*perceived relevance of geographical proximity, satisfaction with cooperation (public research), cross fertilization, introduction of innovation (binary)*) [21] - Basis for the choice of the reference category (*cluster*)

	Cluster	BioRN	CoolSilicon	FOE	Logistic	Aviation	m4	Medical Valley	MicroTec	Software	Solarvalley
RQ 1	perceived relevance of geographical proximity mean	3.077	3.840	3.750	3.178	3.367	3.679	3.333	3.507	3.840	3.250
	abs.mean.dev	0.387	0.376	0.286	0.286	0.097	0.215	0.130	0.044	0.376	0.214
	n	13	25	20	73	30	28	3	67	25	20
RQ 2	satisfaction with cooperation (public research) mean	4.333	4.226	4.348	4.333	4.412	4.424	4.342	4.360	4.185	3.864
	abs.mean.dev	0.049	0.058	0.064	0.049	0.128	0.140	0.058	0.076	0.099	0.420
	n	9	31	23	84	34	33	38	75	27	44
RQ 3	cross fertilization mean	3.250	4.148	3.286	3.737	2.794	3.914	2.250	3.657	4.040	4.000
	abs.mean.dev	0.394	0.504	0.358	0.093	0.850	0.270	1.394	0.013	0.396	0.356
	n	16	27	21	76	34	35	4	67	25	21
	introduction of innovation (binary) mean	0.545	0.647	0.154	0.625	0.588	0.414	0.000	0.514	0.800	0.867
	abs.mean.dev	0.010	0.092	0.401	0.070	0.033	0.141	0.555	0.041	0.245	0.312
	n	11	17	13	40	17	29	2	37	10	15

[21] The table contains all mean responses per cluster and the respective absolute deviations from the mean. The grey cells represent the minimal deviation in each row. The cluster with the minimal deviation from the overall mean was chosen to be the reference cluster in the estimations.

Table 4.9 Correlation tables

Model 1/ RQ 1

	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.	XIII.	XIV.	XV.	XVI.	XVII.	XVIII.	XIX.
I. perceived relevance of geographical proximity	******	0.104*	0.102*	0.139**	-0.06	-0.13**	0.104*	0.062	0.127**	-0.084	-0.074	0.099	0.051	-0.128**	0.103*	-0.064	-0.013	0.011	-0.047
II. application new technology		******	0.017	0.034	-0.051	0.008	-0.032	-0.045	0.24***	-0.058	-0.122**	0.085	0.172***	0.03	0.04	-0.168***	-0.001	-0.063	0.057
III. previous projects			******	0.084	0.072	-0.103*	0.145**	-0.02	0.079	-0.236***	0.075	0.086	-0.105*	-0.083	0.044	-0.1	0.037	0.172***	-0.021
IV. applied results				******	-0.008	-0.021	0.109*	0.036	0.037	0.005	0.113*	-0.06	-0.055	-0.015	-0.067	0.062	-0.065	0.095	-0.099
V. goal product innovation					******	-0.067	0.16***	0.011	0.086	0.121*	0.097	-0.082	-0.214***	0.132**	0.066	-0.093	0.059	0.078	-0.176***
VI. goal process innovation						******	0.069	0.041	-0.036	-0.037	-0.225***	-0.075	0.024	0.209***	-0.095	0.082	-0.132**	-0.007	0.084
VII. goal business formation							******	0.545***	-0.052	-0.238***	-0.072	-0.278***	-0.085	0.294***	0.183***	-0.244***	0.04	0.226***	-0.349***
VIII. goal qualification program								******	-0.171***	-0.108*	-0.108*	-0.343***	-0.085	0.271***	0.148**	-0.181***	0.009	0.132**	-0.277***
IX. radical innovation aim									******	0.006	-0.017	-0.008	0.128**	-0.167***	0.121*	-0.094	-0.016	-0.044	0.166***
X. Firm										******	0.135**	-0.016	-0.047	-0.022	0.051	-0.112*	0.011	-0.117*	0.095
XI. BioRN											******	-0.066	-0.057	-0.121**	-0.068	-0.061	-0.023	-0.071	-0.075
XII. CoolSilicon												******	-0.079	-0.168***	-0.094	-0.084	-0.032	-0.098	-0.104*
XIII. FOE													******	-0.146**	-0.081	-0.073	-0.028	-0.085	-0.091
XIV. Logistic														******	-0.172***	-0.155**	-0.06	-0.18***	-0.192***
XV. Software															******	-0.086	-0.033	-0.1	-0.107*
XVI. Solarvalley																******	-0.03	-0.09	-0.096
XVII. MV																	******	-0.035	-0.037
XVIII. m4																		******	-0.112*
XIX. Aviation																			******

Model 2/ RQ 2

	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.	XIII.	XIV.	XV.	XVI.	XVII.	XVIII.	XIX.	XX.	XXI.	XXII.
I. satisfaction with cooperation (firms)	******	0.605***	0.017	0.222***	-0.081	-0.06	0.134*	-0.002	0.077	0.045	0.038	0.064	-0.106	0.035	0.08	0.102	0.092	-0.088	-0.088	0.119*	-0.073	0.014
II. satisfaction with cooperation (public research)		******	0.085	0.171**	0.007	-0.073	0.172**	0.094	0.115	0.062	-0.056	0.052	-0.012	0.055	0.09	-0.004	0.11	-0.028	-0.268***	0.21***	0.019	0.096
III. average distance			******	-0.043	0.186***	-0.107	-0.052	-0.064	0.002	-0.093	-0.165**	-0.044	0.059	-0.033	-0.02	-0.095	0.215***	-0.116	0.089	0.765***	0.829***	0.992***
IV. social proximity				******	-0.118*	-0.128*	0.159**	0.194***	0.219***	-0.119*	0.08	-0.034	-0.143**	-0.054	0.088	0.105	0.111	-0.065	-0.014	0.489***	-0.098	-0.023
V. Firm					******	0.003	-0.05	-0.224***	-0.243***	0.047	-0.031	-0.161**	0.053	0.082	-0.149**	0.008	0.093	0.045	-0.092	0.074	0.569***	0.161**
VI. project size						******	-0.029	0.11	0.072	-0.004	-0.217***	-0.119*	-0.178**	0.029	0.423***	0.078	-0.346***	0.565***	-0.074	-0.117	-0.08	-0.091
VII. project importance							******	0.038	0.12*	-0.016	0.044	0.048	-0.209***	0.089	-0.003	0.072	0.048	0.016	0.005	0.076	-0.07	-0.048
VIII. predict.perceived relevance of geographical proximity								******	0.141**	-0.083	-0.072	0.089	-0.117	-0.098	0.072	0.027	0.064	0.17**	-0.172**	0.057	-0.151**	0.036
IX. project initiator									******	0.061	-0.008	-0.105	-0.076	0.175**	0.169**	0.144**	-0.105	-0.056	-0.074	0.146**	-0.144**	0.023
X. project dismissal										******	-0.11	0.217***	0.055	0.132*	-0.067	0.015	0.056	-0.154**	-0.15**	-0.133*	-0.055	-0.099
XI. CoolSilicon											******	-0.071	-0.178**	-0.094	-0.106	-0.038	-0.161**	-0.111	-0.074	-0.147**	-0.152**	-0.162**
XII. FOE												******	-0.134*	-0.071	-0.079	-0.029	-0.121*	-0.084	-0.056	-0.042	-0.119*	-0.036
XIII. Logistic													******	-0.178**	-0.2***	-0.072	-0.306***	-0.211***	-0.141**	-0.042	0.053	0.053
XIV. Aviation														******	-0.106	-0.038	-0.161**	-0.111	-0.074	-0.03	0.044	-0.04
XV. m4															******	-0.043	-0.181**	-0.125*	-0.084	0.084	-0.037	-0.013
XVI. MedicalValley																******	-0.065	-0.045	-0.03	-0.079	-0.087	-0.092
XVII. MicroTec																	******	-0.191***	-0.128*	0.244***	0.222***	0.214***
XVIII. Software																		******	-0.088	-0.121*	-0.072	-0.102
XIX. Solarvalley																			******	0.046	-0.015	0.069
XX. average distance * social proximity																				******	0.572***	0.774***
XXI. average distance * Firm																					******	0.804***
XXII. average distance * predictperceived relevance of geographical proximity																						******

Model 3/ RQ 3

	I.	II.	III.	IV.	V.	VI.	VII.	VIII.	IX.	X.	XI.	XII.	XIII.	XIV.	XV.	XVI.	XVII.	XVIII.	XIX.
I. Cross	******	-	0.196**	0.271***	-0.184**	-0.141*	-0.128	0.202***	0.275***	0.025	0.106	-0.063	-0.021	0.123	0.037	-0.08	0.128	-0.224***	-
II. Introduction of innovation (binary)		******	0.029	0.072	-0.082	-0.095	0.028	0.08	0.065	-	-0.097	-0.153	0.036	0.199*	0.197*	-0.109	0.067	-0.133	-0.045
III. Predict.satisfaction with cooperation (public research)			******	0.743***	0.265***	0.09	0.117	0.244***	0.000	0.068	-0.019	0.102	-0.073	-0.192**	-0.029	0.028	-0.137*	0.051	0.157
IV. Predict.satisfaction with cooperation (firms)				******	0.007	-0.052	0.047	0.113	0.229***	0.042	0.03	0.05	-0.138*	-0.025	0.092	0.094	-0.023	-0.015	-0.06
V. Average distance					******	0.846***	0.055	0.022	-0.205***	-0.117	-0.124	-0.062	0.041	-0.152*	0.087	-0.08	-0.01	0.044	0.211**
VI. Distance to centre						******	-0.016	-0.036	-0.16**	-0.066	-0.051	-0.022	-0.058	-0.035	0.025	-0.021	0.089	0.045	0.064
VII. high skilled							******	-0.016	-0.254***	0.037	0.041	-0.077	0.012	0.083	-0.107	0.094	-0.042	0.256***	-0.174*
VIII. Applied results								******	-0.053	0.073	-0.095	-0.076	0.035	-0.049	0.089	-0.06	-0.039	-0.095	0.079
IX. public research institute									******	-0.09	0.105	0.156**	-0.087	-0.079	0.079	0.023	0.248***	-0.086	-0.068
X. BioRN										******	-0.031	-0.028	-0.063	-0.045	-0.03	-0.012	-0.031	-0.031	-
XI. CoolSilicon											******	-0.071	-0.158**	-0.113	-0.075	-0.031	-0.078	-0.078	-0.164
XII. FOE												******	-0.144*	-0.102	-0.068	-0.028	-0.071	-0.071	-0.148
XIII. Logistic													******	-0.228***	-0.151*	-0.063	-0.158**	-0.158**	-0.327***
XIV. Software														******	-0.108	-0.045	-0.113	-0.113	-0.216**
XV. Solarvalley															******	-0.03	-0.075	-0.075	-0.178*
XVI. MedicalValley																******	-0.031	-0.031	-0.065
XVII. m4																	******	-0.078	-0.191*
XVIII. Aviation																		******	-0.178*
XIX. MicroTec																			******

Chapter 5

5. Does public support increase interdisciplinarity and innovation? Evidence from publication data[22]

5.1 Introduction

The support of collaborative R&D across disciplines has become an important topic on modern policy agendas and increasing emphasis has been put on interdisciplinarity as a precondition for the distribution of public research funds (Wagner et al. 2011). These developments are stirred by the mostly theoretically grounded expectations about the benefits arising from interdisciplinary research for the production of novel and innovative ideas (Nissani 1997). There is a widespread discernment that the solutions to complex modern societal problems lay beyond disciplinary boundaries (Gibbons et al. 1994). The pooling and integration of diverse, complementary knowledge is deemed to constitute the great potential of interdisciplinary research for radical novelty and innovation. However, the research environment is evidentially hostile to interdisciplinary research. It is evaluated as unconventional and not meeting standards in peer reviews (Laudel and Origgi 2006, Rafols et al. 2012), it is associated with low career prospects, high communication costs, and highly uncertain outcomes. Thus, interdisciplinary research is costly compared to research within discipline boundaries. On this account policy support is essential in compensating for risks and costs involved and incentivizing interdisciplinary research. Yet, the outcomes of awarding supplementary public grants to research in terms of interdisciplinarity have not been explored so far. Moreover, a conceptual equivocality and equal dissent about operationalization render the evaluation of interdisciplinary projects challenging (Huutoniemi et al. 2010). The aim of this study is to shed light on the unsought role of public funding in stimulating interdisciplinary research. While input interdisciplinarity has already been subject to a couple of studies, the interdisciplinarity of the outcome has rarely been examined hitherto. We analyze the knowledge diffusion processes as measured by forward citations to scientific publications emanating from publicly funded research projects and compare it to the outcome of projects that indicated no supplementary financial support. Particularly, we analyze three interrelated aspects of the knowledge diffusion of publicly funded research: *interdisciplinarity*, *novelty* and *impact*.

Building on the *state-of-the-art* bibliometric indicators to assess the integrative feature of interdisciplinary research (Leydesdorff and Rafols 2011), we run large scale analyses exploiting the rich and relatively unexplored data of funding acknowledgements in the Thomson Reuters Web of Science (Rigby 2013). This data allows to explicitly drawing a link between the funding source and the respective outcome. We extract information from the funding acknowledgements from articles that were published between 2007 and 2013 in the field of Medical Devices

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to compare the citation structure of funded and non-funded publications. Via propensity score matching we reduce the pre-treatment heterogeneity between funded and non-funded projects and explore whether the ideas of funded projects disseminate over a larger variety of scientific disciplines, are more likely to connect distant disciplines, and yield a higher overall impact than their non-funded equivalents.

Our results reveal that projects awarded with supplementary public funds are more likely to be spread out over diverse bodies of knowledge and to cross-fertilize distant disciplines. Moreover, interdisciplinarity seems to be a phenomenon that is located in basic research. Furthermore, interdisciplinary research seems to be conducted in international teams of experts. With respect to impact, our results are less univocal. While articles from publicly funded projects are favored by prestigious journals and exhibit a higher likelihood to be cited at all, breakthrough results are rather achieved by larger teams, international cooperation and the expertise of the researchers in the team than with public support. Moreover, we find that researchers have a significantly higher propensity to produce cited publications when they are associated to an interdisciplinary research organization while the knowledge variety of a team seems to be rather harmful for the subsequent impact of the research ideas.

This chapter is organized as follows: section **5.2** positions our study into existing work on this topic and provides the main arguments and hypotheses that build the basis for our analysis. In section **5.3** we introduce our empirical strategy and explain the steps of our estimation procedures. Section **5.4** contains the presentation and discussion of our results. Section **5.5** concludes and provides potentials for further research desiderata.

5.2 Prior work and related literature

5.2.1 The complexity of defining and measuring interdisciplinarity

The phenomenon of interdisciplinary research (IDR) has been subject to many scientific studies in the last decades. First few attempts to study and promote this particular theme have already been made in the 70th (Wagner et al. 2011, Rinia 2007, Larivière and Gingras 2010)[23]. A significant increase in the number of R&D collaborations since the early 1990th has entailed an extensive discussion about the benefits of knowledge sharing and has specifically rekindled the debate on knowledge exchange in cooperations that span disciplinary boundaries as a source of innovation (Katz and Martin 1997, Haagedorn 2002). Likewise, this development was stirred by a shift in the orientation of science towards problem solving and the applicability of research results (Gibbons et al. 1994, Rinia 2007, Schmidt 2008). The strengthened link between science and society has been described in the seminal book by Gibbons et al. (1994) as a „new mode“ of knowledge production. This new paradigm involves overcoming established discipline boundaries and is characterized by interdisciplinarity as a means to challenge increasingly complex problems that humanity has to face in modern times and for which disciplinary solutions are not sufficient (Tress et al. 2005, Bruce et al. 2004, Gibbons et al. 1994, Brewer 1999, Klein 2004, Lyall et al. 2013). The growing awareness about the potentials of IDR has also fertilized the political development. The promotion of interdisciplinarity has become a main target of national and international funding agencies (in Europe the European Research Council emphasizes the support of IDR since the 5th European Framework Program (Bruce et al. 2004) and a precondition for successful grant proposals (Rafols et al. 2012, Cummings and Kiesler 2005, Steele and Stier 2000, Tress et al. 2005).

[23] For a comprehensive overview of the development of the term, please see Wagner et al. (2011) and Rinia (2007).

Despite the prioritization of IDR and due to the complexity of IDR no consensus has been reached so far on a clear-cut definition of IDR as well as on an adequate assessment of the quality of IDR neither among the funding authorities (Tress et al. 2005) nor among the scientific community (Tress et al. 2005, Laudel and Origgi 2006, Wagner et al. 2011, Huutoniemi et al. 2010). Both issues are highly intertwined, since a fruitful debate about the appropriate measurement of IDR requires an agreement on a solid conceptual basis. Huutoniemi et al. (2010) summarize the dual problem of existing literature concluding that prevailing sophisticated conceptual understandings of IDR lack a proper empirical implementation or, reversely, existent empirical measurements are not grounded on an elaborated theoretical foundation.

On the conceptual level, scholars have stressed that the definition of a *discipline* or *scientific field* should mark the starting point for a proper analysis of IDR (Wagner et al. 2011). The rare studies that follow this advice understand a scientific discipline or field as a "community of experts" (researchers) (Nissani 1997) whose boundaries are defined by realm specific problems, beliefs, data, methods, vocabulary, habits, and practices (Huutoniemi et al. 2010, Bruce et al. 2004, Wagner et al. 2011). Building on that, a relatively general but widespread definition comprehends interdisciplinary research just as each research activity that is conducted at the (knowledge) boundaries of several of these disciplines (Cummings and Kiesler 2005, Bewer 1999, Nissani 1997, Morillo et al. 2003). However, this definition has been heavily criticized in recent years as too vague, simplistic and therefore neglecting the complex, integrative and dynamic character of IDR (Huutoniemi et al. 2010, Wagner et al. 2011). Wagner et al. (2011) and other researchers (Laudel and Origgi 2006, Huutoniemi et al. 2010, Porter and Rafols 2009, Bruce et al. 2004, Porter et al. 2006, Feller 2006) propose to go for a more holistic perspective that corresponds to the multifaceted nature of IDR.

In the plethora of definitions and concepts, the three following notions have become emergent and have been mostly used simultaneously: *multi-, trans-* and *interdisciplinarity* (Bruce et al. 2004). All three notions refer to joint research that is conducted by researchers from different disciplines (Horlick-Jones and Sime 2004). However, the integration of the generated knowledge as a result of the research activity has been identified as the key feature that differentiates interdisciplinary research from the other two modes of boundary crossing. Brewer (1999) for instance states that for IDR the value of the total system is more than the sum of the individual parts because knowledge from different specialties is combined. Yet, he does not qualify further the process of combination. Other authors are more specific (Schummer 2004). They identify *multidisciplinarity* as cooperation and interaction of researchers from different (mostly related) disciplines, but the produced theories, methods and results stay in their discipline boundaries and do not find their application across disciplines or the resulting knowledge is not overarching disciplines. In short, multidisciplinary research is rather a form of 'division of labor' (Horlick-Jones and Sime 2004) in which each researcher mainly operates in his realm boundaries. In other words, the outcome of multidisciplinary research equals the sum of its individual parts (Wagner et al. 2011).

In contrast, *interdisciplinarity* is understood as each research project that integrates knowledge from more than one disciplines or community of experts. The knowledge can comprise methodologies, concepts, beliefs, theories, data, and paradigms from diverse disciplines (Huutoniemi et al. 2010, Wagner et al. 2011, Bruce et al. 2004, Porter et al. 2007). This knowledge is pooled to create overarching approaches to problem solutions. Further refinements for different degrees of IDR have been proposed such as the differentiation of research with respect to the cognitive distance between the spanned disciplines: small and large (Morillo et al. 2003, Schmoch et al. 1994) or narrow and broad IDR (Huutoniemi et al. 2010). Likewise, the degree of interaction and integration motivates further distinctions (Huutoniemi et al. 2010, Bruce et al. 2004). However, the aim of our study is not to purify established definitions, but to provide a large scale empirical analysis of the diffusional aspect of interdisciplinary research supported by public funds. We focus our analysis on knowledge integration as it has been persistently described as the main distinctive characteristic of IDR and received the largest agreement among scholars in the status quo research on ID (Wagner et al. 2011).

Finally, *transdisciplinary* refers to research that focuses on problems that dissociate from any disciplinary attribution and knowledge is organized in a broader scope and around more complex domains (Bruce et al. 2004). Transdisciplinary is understood as generating a new autonomous interdisciplinary realm by combining two or more disciplines. Also, the list of main actors includes researchers as well as practitioners and stakeholders (Wagner et al. 2011).

At the empirical frontier, the necessity for more elaborate indicators to assess the outcome of interdisciplinary research was demonstrated by a bias in research evaluation towards disciplinary research (Laudel and Origgi 2006). Owing to its complex nature, the review of interdisciplinary research is misguided when only considering standard disciplinary metrics. Interdisciplinary approaches are perceived as unconventional by reviewers and peer reviews in journals and grant proposals lack adequate quality standards to benchmark interdisciplinary research (Lyall et al. 2013, Laudel and Origgi 2006, Feller 2006). Rafols et al. (2012) have empirically detected the neglect of interdisciplinary research by applying traditional citation based indicators such as journal rankings in the field of economics. They conclude that the suppression of interdisciplinary research would potentially lead to a reorientation of science away from solving essential societal problems. However, this phenomenon seems to be quite heterogeneous. In contrast to Rafols et al. (2012), Rinia et al. (2001) do not find a general bias in peer review and quantitative bibliometric indicators against interdisciplinarity for the case of physics. The field heterogeneity may depend on the custom of interdisciplinary research in the field. The bias is potentially more pronounced in fields where interdisciplinarity is generally not a routine practice.

To address this issue and in correspondence to more sophisticated definitions of interdisciplinarity, advanced measures have been developed by experts in the fields of scientometrics that capture the multiple dimensions of interdisciplinarity (Rafols et al. 2012, Rafols and Leydesdorff 2011, Porter and Rafols 2009, Rafols and Meyer 2010, Porter el al. 2007, Mansila 2006, Feller 2006). These dimensions comprise the variety of disciplines (the multidisciplinarity), the balance of the disciplines covered, and the disparity of the disciplines covered by the research. In principle, interdisciplinarity is mapped on the basis of a web of linkages between different bodies of knowledge, where the disciplines are the components that are linked by cross-citations from scientific publications. Knowledge integration is thus defined as a link between distinct bodies of knowledge and is quantified by network metrics such as centrality measures and measures of diversity and entropy (Leydesdorff and Rafols 2011). Although these newly developed indicators have been increasingly utilized to empirically analyze the phenomenon of interdisciplinarity (Rafols et al. 2012, Porter and Rafols 2009, Yegros-Yegros et al. 2015), a comprehensive comparison of the existing indicators has been lacking to date (Wagner et al. 2011).

5.2.2 The relation between interdisciplinarity, innovation and policy support

In a knowledge driven economy where knowledge is the main ingredient for innovation and its diffusion processes are of crucial importance (Cowan and de Paal 2000, Lundvall and Johnson 1994), the access to a diverse pool of knowledge through collaboration is essential. The growing emphasis of policy makers in supporting collaborative and interdisciplinary research has been grounded on the expectation about the benefits arising from collaborative research activities that span the boundaries of multiple disciplines (Katz and Martin 1997, Nissani 1997). In fact, the link between collaboration and the productivity and innovativeness of researchers has been observed in many studies (Teece 1992, Uzzi und Spiro 2005, Singh and Fleming 2010, Bercovitz and Feldman 2011). However, the arguments about the benefits of interdisciplinarity for innovation are primarily theoretically grounded (Brewer 1999, Gibbons et al. 1994). The main advantage that collaborative, interdisciplinary research offers over disciplinary activities is the access to complementary and diverse knowledge sources (Katz and Martin 1997). The naturally constrained capacity of individuals to learn and accumulate knowledge establishes a tradeoff between gaining a profound, deep expertise in one discipline or being a jack of all trades with a broad, but not in-depth knowledge in multiple disciplines (Nissani 1997). Interdisciplinary research offers a fruitful platform for a satisfaction of this tradeoff by combining the strength of knowledge accumulation (expertise) and diversity. Furthermore, the access to fresh and complementary knowledge increases the possibilities for novel recombination and is thus associated with higher probability to generate radical ideas and path breaking innovations (March 1991, Nooteboom et al. 2007, Carayol and Thi 2005, Lee et al. 2015). Contrarily, specialized research is limited by the cognitive boundaries of the specific disciplines and discoveries might be the result of rather exploitative than explorative search process and produce comparably incremental results (March 1991). Furthermore, specialization bears the danger of a cognitive lock-in causing the ignorance of main developments in other adjacent disciplines (March 1991). Accordingly, scientists that work at the intersection of scientific communities have been found to be more innovative (Goossen 2013).

With respect to the link between interdisciplinarity and innovation, Rinia (2001) differentiates two types of innovation. Depending on the source of the innovation, originating from basic science or being the product of applied research, he distinguishes scientific innovation and social or technological innovations. He argues that 'small interdisciplinarity' - crossing boundaries of disciplines in basic research - is more closely related to scientific innovation while 'big interdisciplinarity' - aiming at solving urgent societal or technological advances - has a stronger link to technological innovation. According to Rinia's taxonomy, we put our research focus on scientific innovations since we observe inventions as the pre-product to innovation on the basis of scientific output (publications). Contrariwise, Mansfield (1998) has observed an increasing relevance of academic research for the generation of industrial innovations and a decrease in the lag between the event of academic invention and its commercialization. In the same vein, a strong correlation has been found between the publication propensity of a researcher and the amount of patents that he holds (Beaudrey and Allaoui 2012). Furthermore, we focus our analysis on the publications from the field of Medical Devices (all articles published in Biomedical Engineering and Medical Laboratory Technology). The peculiarity of the field of Medical devices is the collaboration on the boarders of different disciplines, namely medical research and engineering (Goosen 2013, Metcalfe et al. 2005). This technological focus implies that the publications in our sample have a high likelihood to be associated with technological innovations than to purely scientific innovations. In fact, Goosen (2013) has found that possessing an intermediate position between both communities in the co-author and co-inventor network increases the innovative outcome of the scientist.

However, the quantitative analysis of the impact of interdisciplinary research has been restricted to the contribution of interdisciplinarity to scientific advance. Bordons et al. (1999) find that interdisciplinarity as measured by the authors' affiliations from different fields has a positive influence on the propensity to publish. Likewise, Steel and Stier (2000) show that interdisciplinarity as measured by author diversity, diversity of cited references and in the categories of the articles leads to higher citation counts. Rinia (2001) also applies citation analyses and finds, that cross-disciplinary linkages take more time to establish, i.e. the citation lag is much larger as compared to within-disciplines citations. Yegros-Yegros et al. (2015) employ more complex measures of diversity and entropy and demonstrate that the degree of interdisciplinarity as measured by the disparity of the disciplines covered matters for citedness. Lee et al. (2015) analyze the relationship between author diversity and field and task variety on the generation of novelty and impact which they summarize as creativity. They find an inverse u-relationship between team size and novelty and explain it by the existence of an optimal level of team variety (Lee et al. 2015, Hollingsworth 2006). These findings are supported by Larivière and Gingras (2010), who also provide evidence on an optimal level of interdisciplinarity measured on the basis of cited references. Additionally they denote that the relationship between interdisciplinarity and impact is field specific. Citation rates for interdisciplinary research have been found highest in biomedical sciences.

In light of the theoretical considerations and the empirical evidence, it is comprehensible that policy makers perceive interdisciplinary research as attractive to be financially incentivized. The effective nurture of interdisciplinary research requires a profound understanding of the determinants and environments in which it takes place to adopt adequate measures (Bruce et al. 2004, Lyall et al. 2013, Lee et al. 2015). Particularly, the need for public financial support of interdisciplinary research originates from the costs that this type of research imposes on the researcher. First, the outcome of interdisciplinary research projects is highly uncertain and hard to predict due to its novel and explorative nature (March 1991), it takes long time to establish and it comes with high communication and coordination costs (Brewer 1999, Nissani 1997). Moreover, the academic environment and disciplinary institutions (peer review process, skepticism against unconventional research, career obstacles) render interdisciplinary research unattractive to researchers and therefore circumvent interdisciplinary research (Lyall et al. 2013, Rafols et al. 2012, Laudel and Origgi 2006, Feller 2006, Carayol and Thi 2005, van Rijnsoever and Hessels 2011). Thus, policy support plays an important role in serving as a risk premium and compensating for these opportunity costs and thus inducing interdisciplinary research (Lyall et al. 2013). In this regard, the assessment of the success of policy support in achieving an increase in interdisciplinarity is of vital importance. First case studies on the evaluation of the effects of the establishment of an interdisciplinary university research center have revealed, that researchers have used the opportunity to collaborate with other researchers with whom they would have not collaborated otherwise (Bishop et al. 2014). However, a systematical, large scale analysis on the role of public grants as a decisive input factor to the outcome of interdisciplinary research is still pending and has not been explored hitherto (Wagner et al. 2011). Our study aims to fill this gap by an empirical examination of the role of policy in fostering the interdisciplinarity of research projects, the production of novel ideas, and the scientific impact of the research publications.

In general, policy support to research is a fundamental ingredient for the scientific landscape of a country. A strong science base provides the breeding ground for the generation and diffusion of new knowledge and innovation. In Germany, three types of research funding can be differentiated: institutional, infrastructure and project specific third party funds (Geuna and Martin 2003). Rigby (2013) summarizes the first two as implicit and the latter as explicit funding. As basic research does not materialize in immediate commercial benefits and returns are hardly appropriable, policy secures the general core budget for the main producers of basic research: universities and non-university research organizations by providing institutional funds (Geuna and Martin 2003, Lepori et al. 2007, Rigby 2011, Fier & Harhoff 2003). These funds are provided without a time limit and topical focus to warrant the autonomy of the basic research. This core funding is complemented by supplementary funds from funding agencies that are allocated for specific research projects with time, scope and budget constraints (Leporit et al. 2007, Rigby 2011).

Supplementary project funds are the appropriate means to prompt specific research desiderata and avenues such as interdisciplinarity. Therefore, we focus our analysis on the evaluation of explicit projects funds to stir interdisciplinary research. Moreover, the impacts of a goal-orientied funding are easier to assess since outcomes can be better attributed to the specific funding source as compared to institutional funding (Lepori et al. 2007). The information about supplementary funds can be found in the acknowledgement sections of the papers that result from the projects. This information has mostly been used to analyze the interplay between funding and scientific impact as measured by publications, citation counts or journal prestige (Wang and Shapira 2011, Cronin and Shaw 1999, Zhao 2010, Rigby 2011, Rigby 2013, Costas and Leeuwen 2012, Boyack and Börner 2004, Wang et al. 2012, Butler 2001, Fedderke and

Goldschmidt 2015) across a variety of disciplines. The results remain ambiguous. Some find a positive relation (Wang and Shapira 2011, Zhao 2010, Costas and Leeuwen 2012, Allen et al. 2009) others no univocal link (Cronin and Shaw 1999, Rigby 2011, Fedderke and Goldschmidt 2015). However, the particular diffusion processes of the knowledge generated in publicly funded research have not been explored in detail. Or in other words, a central question that is left unanswered is, where the knowledge as indicated by citations from publicly funded projects flows. Are publications from publicly funded projects often cited but only by a very specific part of the scientific community or do the results cross-fertilize other disciplines? Does public funding support the interdisciplinary application of research results? This question is particularly important in light of the increased awareness of policy towards interdisciplinarity.

In a nutshell, scholars have developed advanced metrics to adequately asses the quality of interdisciplinarity research and thus offer the opportunity to evaluate the drivers of successful IDR. Though, prior work hints to that if not incentivized and financially supported, then exploratory interdisciplinary research might be unattractive for researchers. In fact, there is ambiguous evidence that public support stimulates research productivity and the creation of breakthrough ideas. Yet, the resultant question about the knowledge diffusion of publicly funded research projects into diverse disciplines has not been explored so far. To analyze the link between public support to research projects and interdisciplinarity, novelty and impact, we draw on the recent developments in the literature on the empirical examination of interdisciplinarity, bibliometric policy evaluation and exploit the recent enhancement of the publication database by the systematic collection of funding information.

We analyze the knowledge diffusion of publicly funded research by three aspects: the cross-fertilization of diverse disciplines - *interdisciplinarity*, the combination of distant bodies of knowledge -*novelty* and the general amount of scientific advance - *impact*.

First, we assume that by compensating for the opportunity costs in terms of increased communication costs to interdisciplinary research, career obstacles and publication bias, public financial support increases the propensity for engagement in interdisciplinary research. Moreover, the receipt of additional funds might change the risk attitude of the researchers and they are more likely to invest into more risky projects. A higher degree of interdisciplinarity becomes evident in forward citations that span a broader variety of disparate disciplines. Therefore, we suppose that:

Hypothesis 1: *Publicly funded projects exhibit a higher degree of interdisciplinarity than non-funded projects.*

Second, novelty can be understood as the novel combination of prior unrelated knowledge (Uzzi et al. 2013, Lee et al. 2015). The concept of novelty is therefore strongly related to the aspect of disparity between bodies of knowledge. To assess the inventive nature of the research output, we evaluate the degree of integration from knowledge from disparate disciplines. We assume that a knowledge link (the citation) is novel and inventive, when it was highly unlikely to be established and only rarely appeared before. Novelty is associated with the exploration of new possibilities rather than exploiting already existing paths (March 1991). Thus, exploratory research is characterized by a high uncertainty since the future success is hardly predictable. The uncertain outcome prospects deter researchers to engage in radical and novel endeavors. In fact, it has been found that researchers prefer to work closer to what already has been done and more on established topics. The “fear of novelty” is caused by rejection and criticism when the research is too distant from main research trajectories (Besancenot and Vranceanu 2015). Consequently, researchers lack the incentives to engage in novel research. The award of supplementary public funds might serve as a risk premium and incentivize researchers to explicitly explore novel research paths. Therefore, we expect that:

Hypothesis 2: *Publicly funded projects are more likely to produce novel ideas than non-funded projects.*

Third, impact as understood as widespread diffusion of the novel idea codified in a scientific publication into the scientific community. A high impact publication is detected by the number of citations that it receives. The assumption is that an important and influential work is cited by many following scholars that built upon this idea. The larger the citations, the more the idea is recognized in the scientific community and the larger is its impact. Some scholars have analyzed the citation counts as a measure of research quality. However, the citation counts did not correlate to the peer review and other factors, mainly the journal prestige and the author's networks, were more influential on the count of forward citations (Bornmann and Leydesdorff 2015). However, the main mechanisms for knowledge diffusion in science are conferences, workshops, scientific discussions and so forth. Via conferences and other exchange platforms, researchers usually establish connections to the scientific community increase their professional network, and present their ideas to the peers. Public grants might be accompanied by a higher travel budget and therefore more resources to go to important conferences and workshops. Thus, researchers in publicly funded projects might have more possibilities to make their idea public and visible to the scientific community. In turn, the publication concerning this idea might be more cited. Moreover, scholars argue that projects that received public funding went through extensive peer review and are therefore more relevant and of superior quality which automatically increases the citation counts (Geuna and Martin 2003, Rigby 2013, Lewison and Dawson 1998, Lewison and Devey 1999). Additionally, because of the knowledge about the selectivity of funding agencies and the peer review, the receipt of public funding might serve as a signal of importance of the idea to the research community and therefore it exhibits a higher propensity to be cited. Also, funded projects might be favored by prestigious journals. The publication in a prestigious journal in turn increases the chances of being cited (Bornmann and Leydesdorff 2015). On the basis of these arguments, we assume that:

Hypothesis 3: *Funded projects produce publications with a higher impact than non-funded projects.*

5.3 Methodology

5.3.1 Data

In order to analyze the relation between the investment of public funds and interdisciplinarity, novelty and impact of the outcome, we observe outcome on the basis of scientific publications. Scientific publications are the codification of the output of a specific research project (van Raan and van Leeuwen 2002). Articles in peer reviewed journals are the main instrument to make the outputs of research accessible to the public, to protect the intellectual property, to distribute the novel idea and to diffuse the knowledge to the scientific community. Therefore, they represent an appropriate indication for scientific progress (Allen et al. 2009). The advantages of the use of scientific publications for the evaluation of research output and inventive processes are numerous. Apart from the detailed description of the scientific work they also provide information about inward and outward knowledge flows. Knowledge inflows can be observed by the articles and sources that authors refer to in their publications (citations of prior work that the research draws upon). Outward knowledge flows can be traced by the citations that the particular article receives from subsequent articles, the so called forward citations. Those citations as indicators of knowledge linkages are an adequate measure for depicting the application of the published results in subsequent research projects. On their basis, we can evaluate the quality of the application in terms of interdisciplinarity, novelty and general impact. Furthermore, co-authorship serves as an indication for collaboration and author-specific information allow for the qualification of the characteristic of the author team (Katz and Martin 1997).

Another crucial argument for the exploitation of publication data within our framework is the possibility to detect the funding sources that have substantially influenced the work at hand. Funding sources are indicated in two ways. The information on core funding of the researchers can be retrieved from the affiliations that each author has to indicate on the publication. Since we are interested in the analysis of supplementary project funds, the information from the acknowledgement sections as a second indication for financial support is of vital importance to us. Acknowledgements in publications are typically a means for researchers to express their gratitude towards the financial, material and intellectual support which the project received apart from co-authorship (Costas and Leeuwen 2012). The possibility to directly link the funding source(s) of the research projects to their specific outcome (in terms of publications) constitutes the main advantage of this information.

The data on publications is gathered from the Thomson Reuters Web of Science[24]. Given the broad coverage of scientific publications from a variety of disciplines – especially in the natural sciences, the Web of Science (WoS) offers a rich database for bibliometric purposes. Another main merit that the Web of Science features for our analysis is the systematic inclusion of funding acknowledgements since August 2008. Before the enhancement of the WoS-database, information on financial support could be only manually retrieved from the acknowledgement sections, which is a cumbersome and time consuming task if one wants to achieve a reasonable sample size. Owing to the existence of these systematic data, the necessity of cross-checking or matching with other funding databases is decreased and efficiency gains have paved the way for more widespread analyses comprising larger samples. Some pioneer studies have begun to use this information to analyze the general influence of funding respectively the number of funding sources and peer interactive communication (acknowledged intellectual input from other persons than the authors) (Costas and Leeuwen 2012, Wang and Shapira 2011, Rigby 2013) on the impact of these publications.

Even though this new data entails multiple new opportunities for analysis, it also comes with some potential drawbacks that have to be acknowledged. The main concern when working with funding acknowledgments is the reliability of the contained information and the comprehensiveness of the revealed picture. A potential bias is introduced by false identification of funded projects. It might occur that projects due to certain circumstances omit their funding sources (false negatives) or funding sources are acknowledged while projects have not received additional funds (false positives). The voluntary character of acknowledgements might entail this "acknowledgement amnesia" (Costas and Leeuwen 2012) that can be simply caused by an unintended non-remembrance by the authors or is the result of an intentionally neglect of funding sources. Rigby (2011) points to intentionally non-indication of financial sources due to strategic behavior of authors. Since researchers are also evaluated based on their scientific output, the self-perceived quality of the work might determine the acknowledgement of funding sources. Low quality papers might omit the funding sources because they are perceived not sufficient for policy evaluation. The same holds for the reverse case: in expectation of potential future funds, papers that are perceived to be of high quality might acknowledge important funding agencies which actually had no direct influence on the project (Rigby 2011).

However, the commitment to acknowledge funding sources has increased in the last years and varies widely across disciplines. Funding acknowledgements have become a crucial means for policy evaluation (Wang and Shapira 2011, Rigby 2013) which induced policy makers to

[24] Thomson Reuters has announced the sale of Web of Science and Journal Citation Reports to an independent company named Clarivate Analytics on October 3, 2016. We gathered the data long before this event has taken place and therefore we still refer to it as belonging to Thomson Reuters. (http://ipscience.thomsonreuters.com/news/ip-and-science-launched-as-independent-company/- accessed October 10, 2016)

mandate the acknowledgement of funding sources (Coppin 2013). Moreover, in the natural science, where financial resources play an essential role compared to other disciplines (Costas and Leeuwen 2012), a scientific norm has developed to disclose the "conflict of interest" that arises from the crucial influence of funding parties or prior employers on the objectivity of the interpretation of scientific results (Smith 2002). Furthermore, Butler (2001) has cross-checked the information contained in publication acknowledgements with data from grant databases and found a strong association between the receipt of funds and their acknowledgment in scientific publications. Another potential source for systematic error when working with publication data are field-specific citation propensities (Marx and Bornmann 2012).

Being aware of these shortcomings, we try to minimize the bias stemming from heterogeneity in the propensity to cite and to acknowledge financial support across countries and disciplines by only including papers from one research field (Medical Devices) that were published by at least one author affiliated to an organization located in Germany. We focus on medical devices since problem solving in this research area requires frequent and intensive collaboration across the boundaries of multiple disciplines such as biology, engineering, electronics, and medicine (Lindner 2010, Goossen 2013). Additionally, publications in this domain exhibit a relatively high propensity for acknowledging financial support due its relative importance (Costas and Leeuwen 2012, Hellerstein 1998). In case of ambiguity of funding sources we cross checked with information from the internet to improve the quality of the funding information. To diminish distortions in the citation patterns caused by different types of publications (reports, conference proceedings, books), we only include citable items in English language, namely articles published in peer reviewed journals. These items are made public and therefore have equal chances to be cited. Journal-specific citation patterns are accounted for by taking citation counts normalized by the journal citation average.

We define Medical Devices as *"Medical Engineering"* on the basis of the OECD field of science and technology (FOS) classification in the Frascati Manual (OECD 2006). To relate publications to disciplines we rely on the Web of Science Categories which Thomson Reuters assigns to each journal. A concordance between the Web of Science subject categories (Web of Science categorizes journals according to their thematic focus) and the FOS provided by Thomson Reuters allows us to extract all publications that belong to the field of *Medical Engineering*. This comprises all publications that were at least assigned to one of the following two WoS categories: *Biomedical Engineering* and *Medical Laboratory Technology*. Furthermore, we include only publications that have been published between 2007 and 2013 since funding data is only systematically available from 2007[25] onwards and articles need to be published a certain time to establish their impact in terms of citations. The data on journal citation indexes were collected from the Thomson Reuters Journal Citation Reports.[26]

An alternative approach to analyse the effects of public support on interdisciplinarity and novelty would be to focus on the authors as observational units rather than publications. However, collecting data on the level of authors is time consuming and the attributes of publications in terms of citations and funding can hardly be related to a single author as most publications are co-authored.

Contingent on the selection criteria outlined above, our original sample comprises 6661 publications of which 3130 (47%) acknowledge funding sources. This distribution is in accordance with results from prior studies that find a general funding acknowledgment rate of 43% over all categories and countries and a rate ranging between 20% and 50 % in applied/clinical sciences

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[25] Thomson Reuters provides the data of funding acknowledgements from 2008, but we complemented them by manual search for the year 2007.

[26] The access to the raw data from both databases was kindly provided by the *Institute for Research Information and Quality Assurance Berlin* (since January 1, 2016 *Department 2 "Research System & Science Dynamics" of the German Centre for Higher Education Research and Science Studies"*). Their support is gratefully acknowledged.

(Costas and Leeuwen 2012, Lewison et al. 2003, Cronin et al. 2004). Comparably, only 25% of the authors of publications in our dataset acknowledge public funding sources.

5.3.2 Variables

To evaluate whether funded projects exhibit a higher degree of interdisciplinary application and novelty as well as an increased probability for breakthrough publications, we apply sophisticated bibliometric indicators mainly based on citations that an article received. The funding information is taken from the articles' acknowledgement sections. Summary statistics of the incorporated variables and their bilateral correlations can be found in table 5.6 in the appendix[27].

Dependent Variables

Novelty. In general, novelty is an immanent feature of invention. An invented artifact is novel when it was not existent before and differs to a significant extent from the status quo articfacts (Arthur 2007, Freeman and Soete 1997). With regards to science and technical progess, the generation of novel knowledge through recombination of prior existent knowledge can be interpreted as inventive. Current research has developed approaches to assess the novelty of technologies (Verhoeven et al. 2015, Strumsky and Lobo 2015) or scientific results (Lee et al. 2015, Uzzi et al. 2013). While they differ in the method and the basic information they use, they have a common understanding of novelty as a kind of a new combination of prior unrelated knowledge. To analyze technological novelty, Verhoeven et al. (2015) use patent data and explore the co-occurrence of technology classes and backward citations on a patent. A patent is novel, if it combines components (classes) of knowledge that were not combined before by either citing unconnected components or indicating them on the patent publication. Strumsky and Lobo (2015) apply a similar taxonomy and define novelty by novel combinations of prior unrelated technology classes. However, relying on patent data only captures novel inventions that are related to technologies. Since we are using publication data, which allows us to directly combine funding source and output and comprises a broader concept of inventions (scientific ideas), we follow the approach by Lee et al. (2015) and Uzzi et al. (2013). They assess the novelty of scientific artifacts or ideas on the basis of publications listed in the Web of Science. Novelty is operationalized as the relative unrelatedness of journal pairs that the paper under review cites. The relatedness of journal pairs is calculated based on the frequency of their co-ocurrence on all publications in the Web of Science. Building on Lee et al. (2015), we apply a modified version of their novelty indicator in order to analyze the novel combination of disciplines as measured by citations between prior unrelated disciplines. We deviate from their approach by analyzing forward-citations to papers rather than co-occurences on the papers (backward citations) and the units for which novelty is calculated are the categories of the journals (disciplines) rather than the journals themselves. Novelty (*Novel*) is defined as a novel combination of prior unrelated knowledge. Therefor, our aim is to detect rather rare citations between cited and citing categories. We proceed in two steps: first, we calculate a measure of commonness or similarity of the citing and cited disciplines. To do so, we follow a widely used procedure in the bibliometric analysis of interdisciplinary research. The frequency of cross-citations between categories is used as a proxy for their similarity (Leydesdorff and Rafols 2011). The basic assumption underlying this procedure is that the more often one category is cited by another category, the more similar the knowledge in these categories is. To receive the citation frequency between two categories, we retrieve all publications from the Web of Science that are published in Medical Devices journals since 1972 and the citations that these publications received

[27] Correlation tables can be accessed upon request. Owing to their size, they do not fit in standard publication schemes.

until recently.[28] From this set of publications we construct for each year t a cumulated citation matrix, where the cells contain the frequency of citations received by the cited category (rows of the matrix) from the citing categories (columns) until t. Since we only look at cited-citing relations, the resulting matrix is asymmetrical. Furthermore, we consider the citation propensity as shares (we divide the absolute number of citation between category i and j by the total sum of citations that articles in category i receive over all citing categories). The yielded values can be interpreted as a citation probability, namely the probability of an article in category i being cited by an article in category j. The more frequent an article in a certain category is cited by an article in another category, the higher is the citation probability and the more similar are these categories.

After retrieving the similarity values, we assign to each article in our sample the citation frequencies for all cumulated publications that were published until t-1 with t as the year of publication of the article under review. Since we are interested in the rarity of the event of a citation between two categories, we take the inverse of the citation frequency, which yields the distance (1-similarity). These distance measures are also later used in the calculation of the interdisciplinarity metrics. To obtain our final novelty measure *Novelty*, we then compute the 10% percentile of the distance distribution per article. Lee at al. (2015) and Uzzi et al. (2013) have shown that the 10% percentile is a more robust measure than the minimum value. The final variable *Novel* is continuous and ranges between 0 and 1. Larger values correspond to higher degrees of novel citation linkages.

For robustness and comparability, we also included an alternative measure of similarity, which is often applied by leading scholars in scientometrics and quantitative analyses of IDR (Leydesdorff and Rafols 2011, Porter et al. 2007, Rafols et al. 2012). They usually calculate the cosine similarity based on citations between different categories[29]. However, we faced some severe limitations with this data in combination with our particular sample. First, similarly to the Eigenfactor and Article influence, not all categories in our sample were fully covered, which introduced a non-negligible account of missing data. Second, we could only retrieve citation matrices for two years (2006 and 2010). Since our sample includes all publications between 2007 and 2013, for the sake of accuracy, it was desirable to also have citation matrices for all years in this time span. To test the reliability of our similarity measure, we ran correlation tests on the cosine similarity values and our calculated citation probability and found that they were significantly and highly positive related. Furthermore, for robustness checks, we also exchanged both variables and the results remained stable.

Impact. Besides the relationship between financial support and interdisciplinarity, we are also interested to see whether additional funds may also increase the likelihood of success in terms of scientific breakthroughs. In general, the number of forward citations that an article received until the reporting period serves as an appropriate indication for scientific success or breakthrough since citations to papers can be interpreted as the extent of usage or the impact of the published ideas in the scientific community (Allen et al. 2009). However, the raw sum of the total citations received by an article varies widely with the age of the article and the scientific discipline it belongs to (Cronin and Shaw 1999). Thus, the raw number of total citations per article without proper adjustment is not directly comparable for articles from different journals, fields or age. Usually bibliometric measures are normalized by years and aggregated field measures (approximately aggregated on the level of the corresponding Web of Science category) to reduce this heterogeneity in citation propensity. Yet, very recent findings suggest that the prestige of the journal in which the article is published, as measured by its impact factor, has an equally substantial influence on the citations (Bornmann and Leydesdorff 2015, Bosquet and

[28] The data includes all citations up to the year 2014, which was the date of data acquirement.

[29] We gathered the co-citation matrices and the associated cosine similarities for 2006 and 2010 from the personal page of Loet Leydesdorff: http://www.leydesdorff.net/.

Combes 2013). We follow these arguments and calculate a measure of *relative citations* (*RelCit)* that accounts for year and journal differences in one field. The yearly average journal citations are used for normalization. To calculate our measure of relative citations we divide the total citations $c_{i,j,t}$ of the focal article *i* published in the journal *j* in year *t* by the average citations to articles published in the same journal *j* and year *t* as the article under consideration. The average citation is calculated as the sum of all citations $c_{i,j,t}$ divided by the number $n_{j,t}$ of all articles published in journal *j* and year *t*. The value of our citedness measure is larger than one, when the article receives above average citations whereas it is less than one when the article is cited below average.

$$RelCit_i = \frac{c_{i,j,t}}{\left(\sum_{k=1}^{n} c_{k,j,t}\right) / n_{j,t}}$$

To not simply control for the influence of the journal prestige on subsequent article citation, we also analyze further, whether articles from funded projects are more likely to be accepted by prestigous journals. Therefore, we treat the journal impact factor itself also as a dependent variable (*ImpactFact)* and regress the funding variables on it. It is computed as the arithmetic mean of the citations that articles received in the prior two years. Even though the impact factor is one of the most prominent bibliometric indicators for journal quality, it has been subject to many critical discussions. A main criticism is that the distribution of citations to articles is highly skewed (few articles are highly cited) and the arithmetic mean is not appropriate to represent the average value of the citation distribution. Other critical points are that the citations included comprise all citations from many different kinds of publications and not only citations from other peer reviewed articles. Moreover, it is also equally affected by the discipline-specific citation propensity, breadth of the topic (mainstream, hot topic) and time (for further discussion see Marx and Bornmann 2012). To encounter this criticism, we also gathered recently developed, alternative metrics such as the *Eigenfactor*[30]*,* which characterizes the journal's position in the overall citation network*,* or the *Article Influence,* which calculated the average influence of an article in a particular journal (Bergstrom 2007). Both are comparable across disciplines and are also now offered by the Journal Citation Report database. However, the data coverage for our sample was very insufficient and would have resulted in a bunch of missing data and thus introduces a larger bias. For reasons of data availability, we decided to still consider the impact factor despite its shortcomings, but to control for year-specific effects. Our *relative citations* measure *RelCit* is additionally adjusted for field-specific differences.

Interdisciplinarity. Interdisciplinarity has been operationalized in manifold ways in scientometric studies in the past. Prior approaches to gauge interdisciplinarity can be distinguished by the unit of analysis, the stage of production of scientific results or the complexity of the interdisciplinarity index. First, contingent on the research question, researchers (Porter et al. 2012), articles (Rafols and Meyer 2010), journals (Leydesdorff and Rafols 2011, Rafols et al. 2012, Leydesdorff and Rafols 2012) or the whole scientific landscape (Porter and Rafols 2009) is considered as the unit of analysis for which the extent of interdisciplinarity is analysed. With regards to the interdisciplinarity of the production process, one could either consider *input*-related measures such as the diversity of the cited references on an article or backward citations to journals from other disciplines (Steele and Stier 2000, Larivière and Gingras 2010, Rafols et al. 2012, Leydesdorff and Rafols 2011, Porter and Rafols 2009, Schummer 2004, Rafols and Meyer 2008, Porter et al. 2007) or the diversity of the author affiliations (Bordons et al. 1999, Carayol and Thi 2005, Steele and Stier 2000, Schummer 2004). Whilst output-based measures focus on the paper trail of the research output such as the publications, the forward citations to these publications (Carayol and Thi 2005) or the multiassignment of publications to

[30] For more details on the Eigenfactor and Article Influence metrics see http://www.eigenfactor.org.

Web of Science categories (Morillo et al. 2008, Morillo et al. 2003, Steele and Stier 2000, Schummer 2004, Porter et al. 2007).

With respect to the complexity of the ID index, the last years have seen advances in the development of measures for ID (Wagner et al. 2011). While traditional indicators aggregate the information into one indicator, either by taking the shares of citations from articles published in divergent fields, as originally proposed by Porter and Chubin (1985), sum up the number of disciplines involved or calculated the concentration of the distribution of publications or citations over field categories (Leydesdorff and Rafols 2011). In the course of the ongoing in-depth conceptual understanding of interdisciplinary research, these classical measures have been heavily criticized for being too simplistic and not pertinent to fully capture the integrative nature of interdisciplinarity. Novel approaches incorporate citation-based network metrics and diversity indicators that combine several aspects of interdisciplinarity, particularly the knowledge integration aspect as well as the disparity of disciplines, in order to reflect the multifaceted nature of interdisciplinary research (Rafols and Meyer 2008, Wagner et al. 2011).

In this study, we apply these state of the art measures which have been recently developed by leading scholars in the bibliometric research on interdisciplinarity. Following the arguments by Porter and Rafols 2009 and Rafols and Meyer 2007, who emphasize that the assessment of interdisciplinarity is only reasonable when analyzing research outcomes, we identify and measure the interdisciplinarity of funded research projects on the basis of their outputs in terms of the forward citations that the articles under review received. Interdisciplinarity might be the decisive cause for the selection into funding as well as the result of funding, so that the causal order of events is not clear and the mere focus on input-related measures might induce endogeneity issues. Analyzing input measures, we cannot clearly disentangle whether the team composition has been the reason for or the result of the funding. Output-based indicators are more likely to fulfill the temporal precedence criterion. We assume that funding is a research input and it was received before the research results became manifest in the citable item and even before forward citations became existent. For this reason, we chose to explain the interdisciplinary output of research projects by funding and include interdisciplinary input measures as control variables.

Another argument for the usage of output based measures, particularly forward citations, is the emphasis on the feature of knowledge integration in the conceptual discussion of interdisciplinarity. To differentiate interdisciplinarity from multidisciplinary research and to spot knowledge integration, it is necessary to look at the application and diffusion of the knowledge which can be displayed via forward citations. The pure variety of author affiliations for instance indicates cooperation between researchers from different disciplines, but it does not warrant that the knowledge was exchanged intensively and knowledge integration has taken place (Porter et. al 2008). Co-authorship with researchers from different fields can also be only a reference for multidisciplinary research. Thus, forward citations are a more suitable indicator for interdisciplinary knowledge flows. Furthermore, the quality of the information on author affiliations on the publications has been criticized (Katz and Martin 1997, Wagner et al. 2011).

The analysis of forward citations allows us to extract information about three aspects of interdisciplinarity: the breadth of the application of the generated knowledge in diverse disciplines as a result of the research project which corresponds to the number of different categories that cited the particular article, the degree of specialization which is measured by the concentration of citations over the particular citing categories and the cognitive distance between the cited and the citing categories. The latter aspect also includes the novelty of the knowledge application if cognitive distant disciplines cite the article under review. To combine these aspects, we borrow indices that have been widely applied in ecology to measure the diversity in populations (the distribution of individuals over species), but have also found their way into the economic literature on diversity (Stirling 2007) and was subsequently used in the research on interdisciplinarity (Stirling 2007, Leydesdorff and Rafols 2011). Conceptually, diversity is composed of three components that drive the degree of diversity: *Variety* which comprises the number of different species or categories, the *balance* or evenness of the distribution of observations across these species or categories and *disparity* which measures the dissimilarity of the species or categories (Stirling 2007, Rafols and Meyer 2010).

Analytically, the so-called Rao-Sterling diversity index is traditionally calculated as the sum of the joint probabilities or frequencies of cooccurence of two units *i* and *j* multiplied with their individual dissimilarity. In our case, we consider the frequency (share) of citations of an article in category i by an article in category j and multiply this value by the distance between these two categories. The cognitive distance between these categories is just the inverse of the similarity derived from the citation matrix as explained in the section above. The diversity per article (*Divers*) is thus just the article-specific sum of these terms for all citing categories. The value of this variable increases with higher diversity and decreases with lower degrees of diversity. This variable corrects for the effect that cognitively similar categories are more likely to exhibit a higher citation frequency, since the frequency of citations are weighted by the categories' dissimilarity. In consequence, very likely combinations get a lower weight and very unlikely, because very dissimilar, citations get a higher weight. Thus, articles are more diverse that connect comparably more distant categories. The inclusion of distances between categories into the analytics of interdisciplinarity is one of the major arguments that has been brought forward in favor of the superiority of the diversity measure as compared to the more traditional measures of interdisciplinarity (Leydesdorff and Rafols 2011).

$$Divers = \sum_{ij\ (i \neq j)} p_i * p_j * (1 - s_{ij})$$

Moreover, a profound analysis of the multi-faceted concept of interdisciplinarity requires the combined analysis of multiple, complementary indicators (Porter and Rafols 2009, Rafols et al. 2012). For this reason and to compare our results and check for the robustness of our results against measurement error, we also calculate all other traditional interdisciplinarity measures that have been developed and discussed so far.

First, to separately examine how many disciplines are addressed by the project results, we also include the single indicator for variety of the categories *n* that cite the article *i*. The larger the number of categories spanned, the more interdisciplinary an article is.

$$Variety_i = n_i$$

Second, we are also interested in the *balance* of the distributed citations over categories. In other words, whether publications address only a core of special fields or are rather equally cited by multiple disciplines. Therefore we include a widely utilized measure for calculating diversity on the basis of the evenness of the distribution of observations over categories which is also proposed by Thomson Reuters itself. The Shannon entropy or evenness is a measure of concentration which expresses the uncertainty for a vector of values to predict a value that is randomly chosen from this vector. The higher the concentration and the less equal the distribution of frequencies over categories, the less uncertain is the prediction of the outcome of this random draw. Or alternatively, the more equal the frequencies of the values in the vector, the higher is the uncertainty to predict the value from a random draw from this vector. In other words, the Shannon entropy can be used as a proxy for interdisciplinarity on the basis of the Web of Science categories, indicating that the more categories and the more equal distributed the citations are, the more interdisciplinary this article is. The Shannon diversity is calculated as the sum of the relative shares of citations p_i of an article by articles in category *i* multiplied with its logarithm. This term is normalized by the maximum value it would take in case of a uniform distribution ($log(n)$) to make it comparable across different articles (Leydesdorff and Rafols 2011, Shannon 1948, Stirling 2007).

$$ShannonNorm: = -(\sum_{i}^{n} p_i \, log \, (p_i))/log(n)$$

For the sake of comparability, we also take into account the herfindahl index (*Herfind*) as a further measure of *balance.* We also take the inverse (1-Herfind) so that the modified herfindahl index decreases with the concentration of citations over categories and increases the more the citations are uniformly distributed over categories (which equates maximum entropy) (Leydesdorff and Rafols 2012, Stirling 2007).

Furthermore, the aspect of *disparity* is analyzed separately in our variable *Novel*, because the knowledge integration between rather unrelated fields corresponds to a greater extent of interdisciplinarity (Porter el a. 2008).

Finally, we also include the relative share of forward citations from divergent disciplines (*ShareInterdiscCit*) which was proposed by Porter and Chubin (1985) as it is the most abundantly applied metric for the analysis of interdisciplinarity.

Independent Variables

Funding. Our main variable of interest *PublicFund* is a dummy variable that captures whether an article has received acknowledgeable, additional funding and takes the value one, when there has been support to the project by at least one external public funding source and zero otherwise. This very general information is complemented by further qualitative information such as the number of funding sources or the regional reach of funding and the nature of the funding source.

First, we differentiate between the type of funding, which is whether the project is funded by a private source or a public source. Therefore, we include a dummy for private funds (*PrivateFund*, yes=1) and public funds (*PublicFund*, yes=1). Contractual research financially supported by companies might be focused more on solutions to narrow and applied problems and is therefore less interdisciplinary and less influential.

Moreover, the extent of funding might also influence the spread of the application of project results, as projects with a higher budget are more likely to produce broader ideas and in turn are applied more widely and across more disciplines. We approximate the extent of funding by several indices, as we do not have the exact amount of money donated to the projects. On the one hand, we approximate this by the number of funding sources that an article acknowledges. We control for the number of funding sources indicated in the acknowledgements (*NrFundSource*) assuming that a higher number of funding sources is correlated with a higher financial budget. Rigby (2013) found that the number of funding sources has a significant effect on the scientific impact of a paper.

Furthermore, we also take into consideration the regional level of public funding. That is to say we analyze whether the public funds are from an EU-program, a national funding program or a regional funding program. An increase in geographic reach (from regional to EU) is associated with an increase in budget, coordination, bureaucratic hurdle, and a stronger peer review process. Moreover, the EU-programs in recent years have also put a special focus on supporting interdisciplinary research (Bruce et al. 2004). Therefore, we also want to control for EU-funded projects, as these might have a higher likelihood to produce interdisciplinary outputs as well as higher outputs in general. We further include dummy variables for the two important national research funding authorities to control for any source-specific effects: the BMBF (Federal Ministry for Education and Research) and the DFG (German Research Association). The variable *PublicFund* is an aggregate measure of this set of separate indicators. As robustness checks we exchanged the *PublicFund* variable in the regression models by its single components but we did not find any significant differences.[31]

In the same vain we also want to account for further funding sources that explicitly aim at funding interdisciplinary research and therefore are more likely to produce results with higher cross disciplinary impact. We therefore include a dummy (*IDCentreFund*) for funds provided by interdisciplinary organizations (Max Planck Institutes and Interdisciplinary centers).

Controls. Our main variables of interest are the degree of interdisciplinarity, the novelty and the impact of the research project as outcome variables and the financial support that the project received as input variable. To isolate the effect of funding on the outcome variables, we want to control for as many influential factors as possible that might also influence the outcome variables and/or the funding variable. Furthermore, to compare publications from funded and non-funded projects, we need to include as many variables as possible that explain the receipt of funding to obtain credible matching results.

To separate the effects of interdisciplinary characteristics that might have been the reason for the selection as recipient of public funds rather than the result of funding, we control for input-related interdisciplinarity. In addition, the authors' background in interdisciplinary research might be an important determinant for the quality and application of later project results. Researchers being active in interdisciplinary research groups might have higher chances to be authors of more interdisciplinary publications. Information that is available to us is the authors' past experience in interdisciplinary research and the authors' affiliation to a research organization that is focused on conducting interdisciplinary research. First, the cumulative experience of the author team in past interdisciplinary research is calculated as the sum of different categories of the past publications of each author (*VarietyTeam*). The larger this value is, the broader is the interdisciplinary past experience of the team and the larger is the variety of their combined knowledge. Second, we include a dummy variable that indicates if at least one author is affiliated to a Max-Planck-Institute (*MPInst*), which aims at generating basic and interdisciplinary research, and another dummy variable which takes the value one if at least one of the authors is working in an interdisciplinary research center (*IDOrga*).

Furthermore, besides the funding, the team diversity might also be a crucial factor for receiving public funds and for the production of novel, interdisciplinary and influential outcome (Rigby 2013, Ebadi and Schiffauerova 2015). To capture the diversity of a team, we take into account the team size (*TeamSize*) as measured by the number of coauthors. We assume that all researchers that substantially contributed to the scientific progress are indicated as authors. All other researchers that may have provided support might be listed in the acknowledgment and are therefore not included in the team size variables. A higher number of authors imply a larger and possibly more diverse pool of knowledge brought into the collaboration and therefore a higher likelihood of being cited. Also the larger teams exhibit higher citation counts due to possibly larger network effects (Lee et al. 2015). Furthermore, we complement the raw team size by more qualitative information on the team composition. The team-related variables are constructed based on author publications. The respective author publications were gathered via name matching from the set of all articles in the field of Medical Devices that were published since the beginning of the data collection in 1972. We aggregated the information of each authors' past publication activity by taking the maximum value in all author values. To detect the expertise of the team members, we calculated the maximum number of articles that an author from the team had published in the past (*MaxNrPub*).

To not only control for the quantity of past publications, we also include the maximum number of citations that an article published by one of the authors in the team in the past has received as an indication for research quality and reputation of the author (*MaxCitTeam*). Re-

[31] The results are therefore not separately reported in this chapter but can be accessed upon request.

searcher's past experience has proven to be decisive in generating novel combinations (Verhoeven 2015). Moreover, we also include the maximum age of the career of an author in the team (measured as the time span since the first article was published - *AgeFirstPub*) as an alternative measure for the scientific experience of the researcher. Furthermore, we also include dummies for international collaborations (*InternatCollab*) and collaborations that took place between authors of the same institute (*InstSame*).

With respect to the nature of the problems that the research is trying to solve, we differentiate between basic and applied research. We utilize the information about the linkages of the authors to the private sector, either through the affiliation of the authors to a company (*IndustryPublicOrga*, *PureIndustryOrga*) or the receipt of private funds (*PrivateFund*). We assume that research with industry involvement tends to deal with rather applied problems while researcher teams that are purely associated to the university have a more basic research focus. The variable *Basic* captures just the inverse, aggregate information of these three separate informations.

Furthermore, the amount of citations that an article received is also dependent on the journal it is published in (Leydesdorff and Bormann 2015). Hence, we also control for journal-specific factors. For instance, whether articles are cited by other articles from different disciplines might be simply influenced by the interdisciplinary character of the journal that they are published in. Therefore, we control for the number of Web of Science classes (*NrWoSClass*) that a journal was assigned to. Moreover, articles published in renowned journals have a higher probability of being cited (Leydesdorff and Bornmann 2015, Bosquet and Combes 2012). Thus, we include the impact factor (*ImpactFact*) of the respective journal. By including the dummy variable *IDCateg,* we also control whether the journal is assigned to a category that is explicitly inter-, multi- or transdisciplinary (e.g. "Multidisciplinary applications"). Alternatively, we incorporate pure journal dummies to control for any other unobserved journal peculiarities (e.g. journal policies etc.). To control for any specific development over time we include year fixed effects.

Further confounding factors that drive citation counts of publications and that we want to control for is the article length as measured by the page count (*Page*) and the knowledge inflows as captured by the number of cited references in *CitedRefer* (Rigby 2013). Larger articles potentially contain multiple ideas and therefore receive higher citation counts (Bosquet and Combes 2013).

5.3.3 Estimation strategy

Estimated models

Ever since, the quantification of the effects of public intervention on particular outcomes has posed challenges on econometric analyses. To allow for a sound inference on the effect of a treatment variable (funding for instance) on an outcome variable, the researcher has to ascertain that the differences in the outcome variables between treated and untreated groups are only attributable to the receipt of the treatment and not contingent on other confounding factors (Aerts et al. 2006). In our specific case, we want to eliminate all influences that might explain the degree of novelty (*Novel*), interdisciplinarity (e.g. *Divers*) and impact (e.g. *RelCit*) of the funded projects apart from the funding treatment (*PublicFund*) itself. To analyze the relation between the receipt of public funding and the respective outcome variable, we compare the outcomes of publicly funded and non-funded projects. However, the receipt of public funds as indicated via the funding acknowledgements might itself be a strong predictor for the quality of the research projects (Rigby 2013) and the funded projects might have also outperformed non-funded projects in case of no funding only because of their individual characteristics (may it be better laboratory equipment, better education, better research environment, an experienced researcher in the team, etc.). In this case, the observed quality differences can only be ascribed to the different characteristics both groups had already before the receipt of the funding. By definition, the choice of public agents to pick recipient for financial support is not random and obviously is guided by the qualification of the applicants.

For this reason, our analytical procedure to estimate the effect of public financial support on the novelty, interdisciplinarity and impact of research projects comprises two general steps. First, we apply approved matching methods to reduce the heterogeneity in the distribution of main characteristics between the funded and the non-funded group and to exclude all systematic determinants that might equally cause a non-random selection into the treatment (being selected to receive public funds) and influence the outcome variables (Aerts et al. 2006, Ho et al. 2007, Heinrich et al. 2010, Caliendo and Kopeinig 2008). In the first step, the selection into the treatment $PublicFund_i$ for observation i is modeled contingent on pre-treatment characteristics and a homogenous sample is matched. The x_{ik} represents author team specific variables and the c_{ik} other confounding factors. Since $PublicFund_i$ is a binary treatment variable, we apply a logistic regression model to estimate the probability of being selected for public support. In technical terms, we estimate the logarithmic odds of success (the ratio between the conditional probability of receiving public funds and not receiving public funds) (Wooldridge 2002).

Step 1) $$log\left[\frac{P(PublicFund_i=1|X)}{1-P(PublicFund_i=1|X)}\right] = \alpha + \sum_{k=1}^{n}\beta_k x_{ik} + \sum_{k=1}^{n}\gamma_k c_{ik} + \varepsilon_i$$

After the matching procedure has been implemented, we ran our final estimations on the matched sample to explain outcome by public support. $Outcome_i$ symbolizes our three outcome variables $RelCit_i$, $Divers_i$[32] and $Novel_i$.

Step 2) $$log(Outcome_i) = \alpha + \beta PublicFund_i + \sum_{k=1}^{n}\gamma_k c_{ik} + \varepsilon_i$$

As the output measures are highly correlated ($RelCit_i$ and $Divers_i$), which is not suprising as the likelihood of being cited by a broader range of disciplines increases with the number of citations, we only parallelly include the output measures as dependent variables into the model and do not explain the one by the other. We do, however, take into account non-citation based control variables of interdisciplinarity (*IDOrga, IDCentreFund, VarietyTeam*) to analyze the relation between interdisciplinarity of a research project and impact of a publication.

Since most of the outcome variables are measured on a continuous scale, we estimate the model parameters by means of weighted least squares techniques. The weights are generated during the matching process when one control unit is matched to multiple treated units (see section on "*Matching Results*"). Though, since they are based on citation counts to articles, their distribution is highly right-skewed (Thelwall and Wilson 2014). To let the distribution converge to normality, we apply a logarithmic transformation on the values[33] (Rigby 2013, Leydesdorff and Bornmann 2015, Benoit 2011). Furthermore, for count data (*Variety*) we apply negative binomial regressions and for binary specifications of the continuous outcome variables (*CitBin, AboveAvrg*) we also apply logistic regression models.

The intuition of matching techniques

Theoretically, the average effect size of a treatment T ($PublicFund_i$) on the outcome variables Y can be calculated by comparing the means of the outcome of the treated units in case of a treatment (Y_1) and the counterfactual state of outcome (Y_0) that would have been observed for

[32] Including also the other alternative measures *ShannonNorm* and *Variety*.

[33] Since the logarithm function is not defined for values of zero, we add a constant (1) to every value before taking the logarithm.

the treated unit if it would not have received the treatment. In other words, this average treatment effect on the treated unit is calculated as the mean difference in the outcome in the state with and without treatment (Heinrich et al. 2010):

$$ATT = E(Y_1|T = 1) - E(Y_0 \mid T = 1)$$

In fact, the hypothetical counterfactual state of the outcome in case that the treatment would not have been received is not observable. To compute the ATT the unobservable counterfactual outcome has to be imputed. This can be done by considering the observable outcome values of a similar control group that has not received the treatment $(Y_0 \mid T = 0)$ (Ho et al. 2007), so that

$$E(Y_0 \mid T = 1) = E(Y_0 \mid T = 0).$$

The difference in the means of the outcome of the treated and the untreated group is then

$$\Delta = E(Y_1|T = 1) - E(Y_0 \mid T = 0).$$

Complementing this expression by an additional term yields (Heinrich et al. 2010):

$$\Delta = \underbrace{E(Y_1|T = 1) - E(Y_0 \mid T = 1)}_{\text{ATT}} + \underbrace{E(Y_0 \mid T = 1) - E(Y_0 \mid T = 0)}_{\text{Selection Bias}}$$

The first part of the equation depicts the average treatment effect on the treated unit. The second part represents the difference in the mean outcomes between the treated and the untreated group in case of no treatment which corresponds to the selection bias. In order to accurately estimate the ATT from the difference between the mean outcomes of the treated and the untreated group, the selection bias has to become zero. The selection bias is zero when the assignment to the treatment happened completely random and there is no systematic difference in any aspect between the treated and the untreated group apart from the receipt of the treatment. In other words, if the assignment into the treatment is contingent on the covariates of the treated units, the treated and the control group exhibit significant differences and the term $E(Y_0 \mid T = 1) - E(Y_0 \mid T = 0)$ exceeds zero and the difference in the mean outcomes between the treated and the untreated population is not appropriate to estimate the ATT accurately. Thus, the counterfactual outcome of the treated unit can only be replaced by the outcome in the control group when the assignment to the treatment T and the outcome variables Y_1, Y_0 are independent of the covariates X of the treated and the untreated units. This is called the *conditional independence assumption* (CIA) or technically (Rosenbaum and Rubin (1983)):

$$Y_1, Y_0 \perp T|X$$

In experimental settings, the random choice of participants into treatment warrants that the receipt of the treatment is independent of the characteristics of the participants. Consequently, endogeneity caused by omitted variables that are correlated with the explanatory variables, particularly the treatment, and captured in the error term, does not occur (Ho et al. 2010).

However, in non-experimental observational studies this core assumption is hardly met. The analysis of the effects of public funding is a classical example for selection effects (Aerts et al. 2006). Research projects that are chosen to receive public financial support might differ significantly in their quality as compared to non-funded projects. To warrant the effectiveness of the investment, funding agencies might select the most promising research projects which already have a high impact potential. Likewise, more experienced researchers might possess the knowledge and routine to write successful funding proposals and therefore be more likely to be selected by funding agencies. With respect to our specific research question, the selection problem arises with the increased focus on interdisciplinary cooperation as the preferred target for public support. It entails the risk that the interdisciplinary character of the research team has led to the selection into the funding. If funding agencies prefer interdisciplinary teams over disciplinary teams, then the interdisciplinary application of the research results is just the consequence of the interdisciplinary work rather than the result of the treatment.

Quasi-experimental methods such as matching methods offer a sophisticated approach to respond to the selection problem and structure the data in a way that a quasi-randomization of the selection process can be simulated (Ho et al. 2007, Caliendo and Kopeinig 2008, Czarnitzki and Lopes-Bento 2014, Rosenbaum and Rubin 1983). Basically, the distribution of covariates in the treated and the control group is equalized to fulfill the *conditional independence assumption*. A unit in the treated group is matched with at least one unit in the control group that has similar characteristics and therefore equal chances to receive the funding and equal chances to produce an interdisciplinary output. The similarity between treated and nontreated units can be either measured by directly comparing the covariates (exact matching, mahalanobis matching) or condensing the multiple values of differences into a one-dimensional measure (propensity score matching, caliper matching). Propensity score matching, as originally developed by Rosenbaum and Rubin (1983), has emerged as the dominant approach in evaluation studies owing to its convenience and the intuitive approach even though its application on observational data faces some severe shortcomings (Ho et al. 2007, King and Nielsen 2016). The basic idea behind this technique is that by means of a binary logistic or probit regression the probability to receive the treatment is estimated conditional on the covariates for the treated and the untreated units in the sample. Based on these conditional probabilities, i.e. the propensity scores, control units are matched to treated units according to their similarity in these scores. In consequence, the units in the sample should exhibit equal probabilities to receive the treatment independent of their initial characteristics.

We follow prior studies in employing matching methods, as we value the matching estimator as methodically the most appropriate to our specific data. The limitations of the other alternative analytics to control for selection bias in non-experimental settings, such as the difference-in-difference estimator or the instrumental variable approach (for a comprehensive discussion see Imbens and Wooldridge 2009) outweigh the advantages of matching in our particular framework. The difference-in-difference approach is only applicable on panel data and therefore not useful for our cross-sectional data. For the instrumental variable approach to provide accurate estimations, a careful choice of a valid instrument for the treatment variable is indispensable (Czarnitzki and Lopes-Bento 2014). The quality of this approach is conditioned on finding a variable that is completely exogenous to the public funding variable which is hardly possible in our dataset.

Matching Results

To assess the effect of PublicFund on the three outcome variables, we aim to ascertain that the control group of publications that do not acknowledge a public funding source is equal in their characteristics to the group of publications that do indicate public financial support. To do so, we proceed in seven steps as proposed by Caliendo and Kopeinig (2008) and Heinrich et al. (2010).

Estimation strategy – Overview over analytical steps

(1) Model specification for estimating the similarity between treated and untreated observations in the sample

(2) Match treated and control units based on alternative algorithms and similarity scores (propensity scores, mahalanobis distance) and calibrate parameters of algorithms

(3) Compare the quality of the resulting matched samples (balancing property and sample sizes) and the robustness of results against implementation of different matching algorithms

(4) Choose the superior algorithms and parameters

(5) Check common support and CIA

(6) Run final analyses on the matched sample

(7) Analyze sensitivity of results against the use of different matching algorithms

Researchers with a higher propensity to work in interdisciplinary fields may have a higher likelihood to be preferred as funding target. Therefore, we estimate in the first step the probability of receiving public funds contingent on the observable characteristics of the authors that are not a result of the treatment itself (pre-treatment condition) (Caliendo and Kopeinig 2008, Ho et al. 2007). We are particularly interested in disentangling the effect of researcher pre-treatment experience in interdisciplinarity (*TeamVariety, TeamSize, InstSame, IDOrga, MPInst*) and the effect of additional funds on the interdisciplinarity of the post-treatment outcome. We run several alternative models to identify stepwise those author-specific factors that are decisive for explaining the selection into funding. The variable choice for the probability model should be a balance between theoretical reasoning and evaluation of the relevance of factors as provided by the estimation results (Caliendo and Kopeinig 2008, Ho et al. 2007). We chose the model specification that exhibits the highest explanatory power and where all irrelevant variables are excluded. Table 5.1 contains the result of the model selection process. To obtain the final propensity scores as the basis for the matching procedure, we choose Model 5 since it has the highest goodness of fit (AIC of 7792) while only considering relevant variables. The results of our estimation fit into the expected picture in that prior research success, diversity and collaboration are the main determinants for the receipt of public support. We find that the number of authors, the basic nature of the research, the interdisciplinary background, and having at least one experienced expert in the field within the team is positively correlated with the assignment to funding. This corresponds to the findings of Ebadi and Schiffauerova (2015) who show on the basis of publication data that the collaboration in a large team and with productive researchers increases the probability to receive funds significantly.

An interdisciplinary profile of the authors as measured by being affiliated to interdisciplinary organizations or Max Planck Institutes as well as the knowledge diversity of the team increases the success of receiving public grants. Also reputational effects might play a role as the maximum impact of the publications from the authors in the team (*MaxCitTeam*) shows an equal positive association with funding whereas the age of the first publication seems to have only a weak negative effect. Moreover, funding agencies seem to prefer collaborations that span organizational boundaries as collaboration of authors with the same affiliation (*InstSame*) are less likely to be supported. Likewise and quite surprisingly, international collaborations (*InternatCollab*) exhibit a lower propensity to be funded. In light of the prevalence of national funding among the funded projects, one explanation might be that national funding agencies focus on strengthening the national research infrastructure and try to appropriate the returns from their investment. With respect to the industry involvement in the research process, political support is also less likely for projects with participation of the industry and this irrespective of whether the project was conducted completely by authors affiliated to companies or whether the project was a collaboration between industry and academia. Reasons might be that the industry-science collaboration was a mission-oriented contract research and not in need of additional financial support or the eligibility of the company project was not given because of the applied and specific nature of the potential result.

After having defined the model for the selection process, we apply in the second step miscellaneous matching procedures that are based on either comparing the estimated propensity score that are rendered from the first steps or directly compare the differences in the covariates of the treated and the untreated units. We also vary the parameters of each matching method and compare the results of each change in order to choose the algorithm that performs best according to our quality criteria. The parameters that were subject to modification were the distance measures (one-dimensional propensity score or multi-dimensional covariate matching), the imposition of a fixed radius for the deviation of the matching distance between treated and control unit (fixing the caliper), the replacement of control units, and finally the ratio of control units that are assigned to a treated unit (1:1 matching or 1:N matching). As a baseline, we have tested the straightforward nearest neighbor matching using propensity scores and the mahalanobis distance, with and without replacement, with and without a fixed caliper (varying the caliper size between 0.1 and 0.2) and varying the number of matched control units (1:1, 1:2, and 1:3 matching). In principle, this algorithm matches the control unit to a treated unit which is closest in the respective distance measure (propensity score). A simple nearest neighbour matching would just assign the treated unit to the closest control unit irrespective of the absolute difference in their propensity scores. In this way, also bad matches might enter the sample. To reduce the bias through bad matches, one can set a limit, a caliper, for the maximum difference of the propensity scores (Caliendo and Kopeinig 2008). In consequence, all control units that are outside the caliper are discarded from the sample. To maintain a reasonable sample size, control units with a good match for more than one treated unit can be 'recycled' or replaced. Those re-used control units then get a weight that is proportional to the number of treated units they are matched to. The weights can then be used later in the final regressions to estimate the ATT (Ho et al. 2007). The research also can configure whether only one control unit or multiple units are assigned to each treated observation.

Table 5.1 The propensity of being publicly funded (Model choice for calculating propensity scores)

Logistic Regression							
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Dep.Var.	*PublicFund*						
Constant	-1.408 *** (0.155)	-1.429 *** (0.153)	-1.418 *** (0.129)	-1.616 *** (0.148)	-1.639 *** (0.147)	-1.889 *** (0.142)	-1.761 *** (0.121)
AgeFirstPub	**-0.030 ***** (0.005)	**-0.029 ***** (0.005)	**-0.028 ***** (0.005)	**-0.029 ***** (0.005)	**-0.029 ***** (0.005)	**-0.029 ***** (0.005)	**-0.028 ***** (0.005)
Basic	0.126 (0.081)	0.125 (0.081)		**0.322 ***** (0.069)	**0.320 ***** (0.069)	**0.306 ***** (0.069)	**0.312 ***** (0.069)
IndustryPublicOrga	**-0.471 ***** (0.141)	**-0.470 ***** (0.141)	**-0.570 ***** (0.124)				
InstSame	**-0.515 ***** (0.082)	**-0.512 ***** (0.082)	**-0.417 ***** (0.078)	**-0.546 ***** (0.081)	**-0.543 ***** (0.081)		**-0.548 ***** (0.081)
IDOrga	**0.929 ***** (0.339)	**0.922 ***** (0.339)	**0.943 ***** (0.339)	**0.956 ***** (0.339)	**0.948 ***** (0.339)	**1.036 ***** (0.338)	**0.935 ***** (0.338)
InternatCollab	**-0.212 ***** (0.063)	**-0.211 ***** (0.063)		**-0.202 ***** (0.063)	**-0.201 ***** (0.063)	-0.06 (0.06)	**-0.183 ***** (0.062)
MaxCitTeam$_{log}$	**0.211 ***** (0.026)	**0.219 ***** (0.025)	**0.216 ***** (0.025)	**0.215 ***** (0.026)	**0.223 ***** (0.025)	**0.221 ***** (0.026)	**0.225 ***** (0.026)
MaxNrPub	0.002 (0.002)			0.002 (0.002)		0.002 (0.002)	0.002 (0.002)
MPInst	**1.006 ***** (0.17)	**1.001 ***** (0.17)	**0.974 ***** (0.169)	**1.024 ***** (0.17)	**1.018 ***** (0.17)	**1.062 ***** (0.169)	**1.007 ***** (0.169)
TeamSize	**0.031 ***** (0.009)	**0.030 ***** (0.009)	**0.023 **** (0.009)	**0.030 ***** (0.009)	**0.030 ***** (0.009)	**0.043 ***** (0.009)	**0.030 ***** (0.009)
VarietyTeam	**0.046 ***** (0.009)	**0.048 ***** (0.009)	**0.051 ***** (0.009)	**0.045 ***** (0.009)	**0.048 ***** (0.009)	**0.047 ***** (0.009)	**0.040 ***** (0.009)
PureIndustryOrga	**-1.215 ***** (0.36)	**-1.225 ***** (0.36)	**-1.332 ***** (0.352)				
Year Dummies	Y	Y	Y	Y	Y	Y	N
Obs	6,661	6,661	6,661	6,661	6,661	6,661	6,661
AIC	7,773.327	7,772.406	7,782.843	7,792.891	7,792.180	7,837.643	7,835.435
Deviance	7,735.327	7,736.406	7,750.843	7,758.891	7,760.180	7,805.643	7,813.435

Standard errors in parantheses

Stars indicate significance levels: *** p <0.01 , ** p< 0.05 , * p<0.1

Despite the convenience of the propensity score matching, its applicability is not universal. We have included the mahalanobis distance as an alternative to propensity scores to respond to the strong criticism that has been brought forward against the adequacy of propensity score matching for observational data in the recent years (a comprehensive argumentation can be found in King and Nielsen 2016). The main objections raised concern the so called model dependence of the reliability of the matching results. Dependent on the model chosen in the first instance to estimate the propensity scores, the resulting effect size of the treatment and even the signs of the effect might vary. King and Nielsen (2016) argue that this leaves room for arbitrariness of the researcher to choose the model that yields the desired sign and significance for the effect under study even though the results might be still biased. Therefore other matching methods might be more appropriate and it is proposed to critically evaluate the balancing property of the propensity score matching and to compare it with other matching methods. Hence, we also alternatively implemented optimal matching, genetic matching, exact matching (which is the most conservative one), and full matching. A vivid presentation of these various methods can be found in Ho et al. (2011) as well as Caliendo and Kopeinig (2008). Table 5.8 in the appendix provides an explicit overview over the alternative methods that we implemented and the modification of parameters that we have modified.

After running the various algorithms we assess in the third step the quality of the resulting samples and check if they meet our quality criteria. Our decision rule to choose an optimal algorithm incorporates two aspects: the balancing property and the sample size. The balancing criterion captures whether the matching fulfills its main goal: the reduction of differences in the means of the covariates of the treated and the control group. The minimization of the differences in the mean (the balancing of the distribution of covariates between treated and control) is achieved by only including good matches and the sample quality increases because the potential bias is diminished. However, the quality gains come at the cost of the sample size. More conservative methods are more accurate in eliminating mean differences, but since they discard poor matches, they come with major reduction in sample sizes and associated efficiency losses. The researcher has to find a balance for the tradeoff between bias and efficiency (Caliendo and Kopeinig 2008). We decided to choose the algorithm that minimizes the sum of the absolute mean differences between the funded and the non-funded group (aggregate value for the balancing property) and simultaneously keeps the sample size high (efficiency). Table 5.8 in the appendix compares the performance of the various matching methods on our sample in terms of balancing quality and sample sizes. The exact matching (Method 11) is the simplest but also the most conservative method as it matches only treated and control units that have exactly the same values in every covariate. This explains why the sample size decreases drastically from originally 6661 to 290. Since the other matching methods also yield quite good results in terms of balancing the mean differences but maintain a reasonable sample size, we do only include the exact matching for the sake of checking the sensitivity of our final results (see step 7). When comparing all other methods, the alternative 6, the nearest neighbour matching with a caliper of 0.1 and a ratio of 3 control units per treatment unit and replacement of good matches, appears superior with regards to minimizing the sum of the mean differences (bias) and also keeping an acceptable sample size (acceptable level of efficiency loss). The results of the performance comparison in Table 5.8 also show the inverse relationship between the balancing property and the changes in the sample size.

Afterwards, in a fifth step, we reassessed the performance in terms of balancing of our chosen matching algorithm in more detail and scrutinize whether the main assumptions on conditional independence and common support are met. To analyze in detail the quality of the matching, King and Nielsen (2016) advise against the usage of traditional statistical tests for mean comparisons such as t-tests and rather support the visual inspection of the quality improvement in the sample before and after the matching. Figures 5.1 and 5.2 provide an overview over the distribution of propensity scores and the distribution of the covariates in the treatment and the control group before and after the matching. The corresponding values of the mean differences before and after the matching for the preferential method can be found in the table 5.9 in the appendix. The quality of the matching and the balancing property can be assessed by analyzing two aspects: whether the common support assumption is met and if the researcher can assume that the conditional independence holds. The ATT is only defined for the region of common support and the mean outcome difference between treated and untreated units is only an unbiased estimator if the CIA holds (Caliendo and Kopeinig 2008). The common support assumption basically states that for each combination of covariates of a treated unit a similar control unit can be found. Furthermore, there has to be an overlap of characteristics in the treated and the untreated group (Heinrich et al. 2010). By definition, fixing a caliper already satisfies the common support condition because poor matches outside the caliper (in our case 0.1) are already discarded and an overlap is guaranteed (Caliendo and Kopeinig 2008). However, to still test for the common support assumption, one can compare the propensity scores of the treated and the untreated group to review whether both groups have an equal distribution of propensity scores (Caliendo and Kopeinig 2008). The propensity scores for the matched treatment units and the matched control units as well as the discarded units that lie outside the bounds of the radius are plotted in figure 5.1 (left-hand side). It becomes obvious that the matching performs very well as the propensity scores are equally distributed in the treated group as well in the control group. The improvement in the balance of propensity scores through the matching becomes evident when considering the cluster of low propensity scores in the unmatched control units. This means, that a lot of control units were discarded, which had low chances of receiving the treatment contingent on their characteristics. A second proof that common support was achieved provides Figure 5.1 (right-hand side). It compares the individual density of the propensity scores between the treated and the untreated control group before and after the matching. Obviously, the propensity scores were already quite balanced in the raw sample. However, the propensity scores for untreated observations in the control group were more concentrated at lower values before the matching since the density is larger for smaller values. Thus, the matching procedure has improved the balance in the distributions of propensity scores between the treated and the untreated group. Furthermore, for all values of the propensity scores in the treatment group one finds a similar equivalent in the control group. Hence, the common support condition is met.

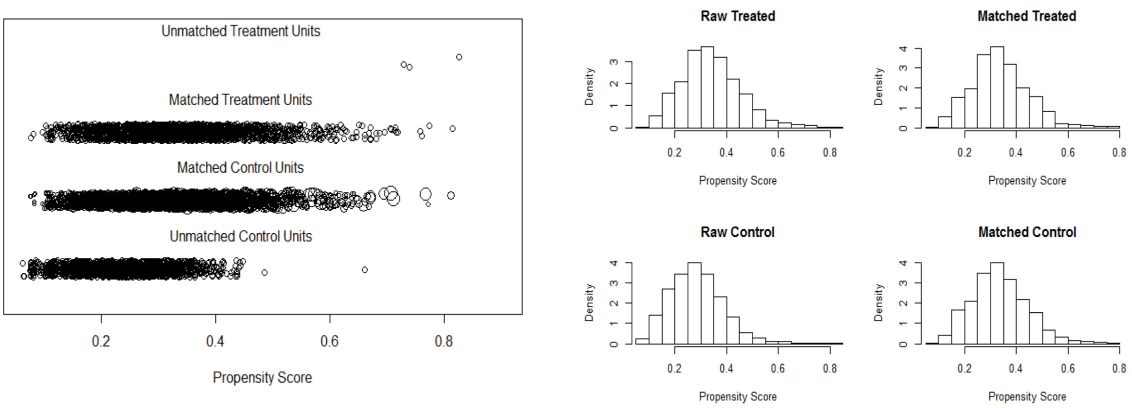

Figure 5.1 Comparison of the propensity scores between treated and control group before and after the matching

So far we have just compared the performance of the matching concerning the balancing of the propensity scores between treated and control units. Though, an in-depth analysis of the balancing property is only reliable when conducted also on the level of the individual covariates. For this reason figure 5.2 (upper left) depicts the standardized mean differences for all covariates and compares pre-matching and post-matching status. It becomes clear that the matching has significantly decreased the heterogeneity in the distribution of covariates in both groups. The related percentage improvements can be found in table 5.9 in the appendix. The same result can be found by the visual inspection of the similarity in the distributions of the single covariates. For this reason, figure 5.2 (upper right and both graphs at the bottom) show the QQ-Plots that compare the quantiles of the distributions of covariates in the treated and the control group. If the quantiles of both distributions resemble, then the points are located on the 45° line. The matching procedure has converged the quantiles of both distributions since the distance to the 45° line has decreased after the sample has been matched. From the inspection of the plots one can infer that the chosen matching method has sufficiently performed to satisfy the common support condition.

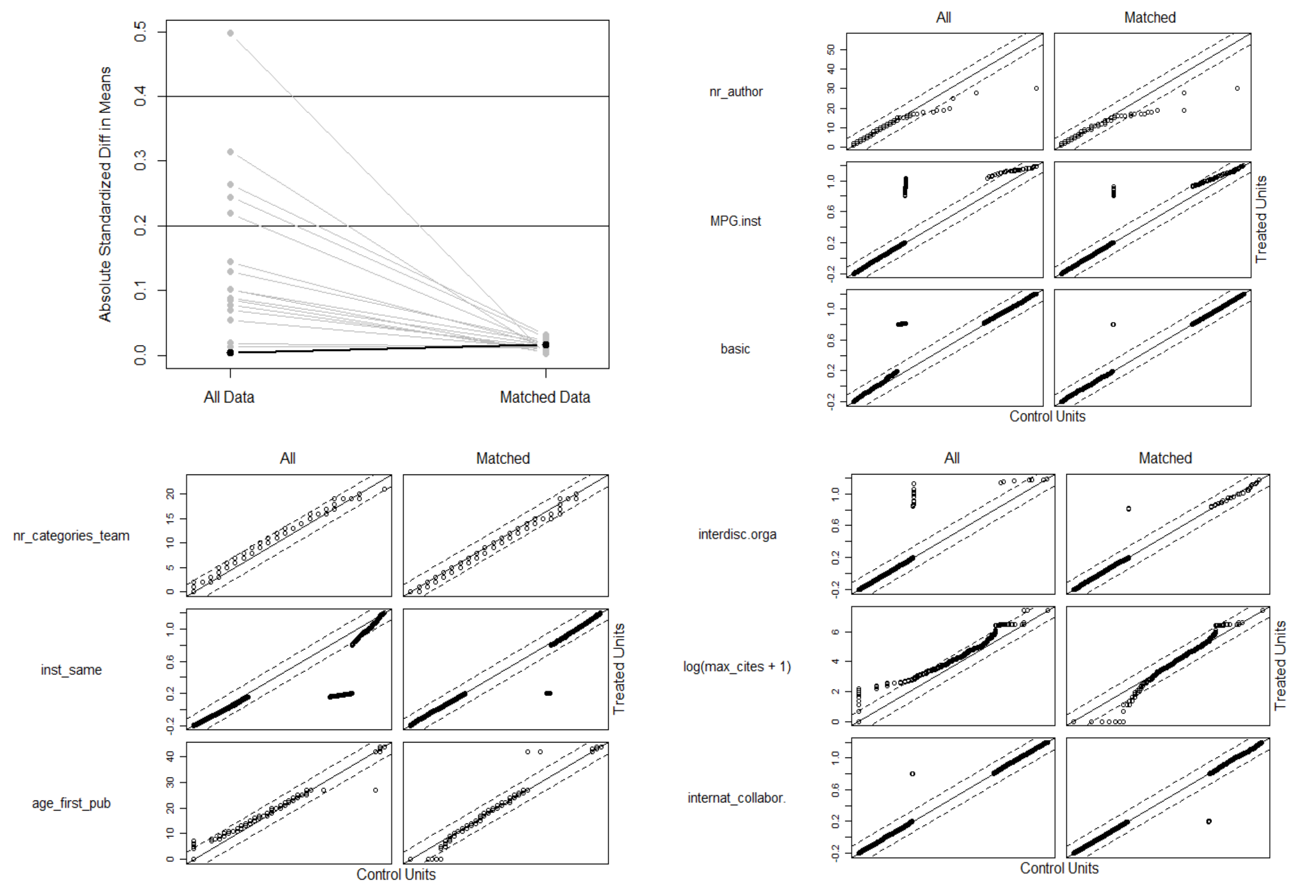

Figure 5.2 Comparison of the mean differences in covariates between treated and control group before and after the matching

In contrast, the satisfaction of the conditional independence assumption is not explicitly testable. To assume that conditional independence is existent, one has to ascertain that the selection model is theoretically founded and all important confounding factors are included in the model. Accordingly, matching procedures put high requirements on the data collection processes (Heinrich et al. 2010). However, to test at least that the matching has achieved the independence of the propensity of being funded from the covariates of the researchers, we re-ran the binary selection model on the matched sample and investigated the results. Table 5.10 in the appendix contains the results of the logit model. As expected, the receipt of public funds is completely unrelated to the covariates after the sample has been matched. It shows, that the matching has succesfully simulated a quasi-random choice into the treatment.

Since the quality diagnostics reveal that both assumptions are fulfilled, we regress in a sixth step the outcome variables of interest, namely *Variety, Divers, ShannonNorm, RelCit, ImpactFact* and *Novel*, on *PublicFund* with the data from our matched sample.

To examine the stability of the estimated effect and to assess the model dependence, we also want to explore how sensitive our final results are against the change of the matching method. We therefore ran in the last step our final analyses on different samples that were matched by different algorithms, including the original raw sample, and compared the results. We estimated the relationship between public funding and interdisciplinarity as measured by the diversity of forward citations. The results are presented in Table 5.11 in the appendix. We compared the estimation output for the original sample, the sample matched by our preferred method (nearest neighbour with caliper on the propensity score), a sample yielded from an exact, a full and a nearest neighbour matching with mahalanobis distance. Even though we find slight differences in the efficiency between the exact and all other matching methods which is according to the expectations (slump in the sample size), the signs of the effect remain constant throughout all models. Moreover, apart from the exact matching, the effect of public funding, holding all other covariates constant, is significant and positive in all estimations. We therefore can state that our final results are not contingent on the choice of the matching method. The following analyses are thus applied onto the sample obtained by our preferred matching method (Method 6).

Table 5.2 presents the sample characteristics of the final matched sample compared to the original sample. The upper table contains the number of publications in each sample and their distribution over the years of observation. The lower table contains the relative shares of publiccations distinguished according to their information in the acknowledgement. After the matching, the share of publications from non-funded projects has decreased while the share of publications from funded projects and from publicly funded projects has increased. Public funding is still the predominant type of funding utilized in our sample.

Table 5.2 Sample characteristics before and after the matching

	2007	2008	2009	2010	2011	2012	2013	**Total**
unmatched	674	717	781	896	856	1,420	1,317	6,661
matched	514	510	569	766	740	1,043	992	5,134

	no funding	funding	public funding	private funding	public and private funding
unmatched	53%	47%	25%	11%	5%
matched	46%	54%	33%	9%	6%

5.4 Results

5.4.1 Descriptives

When looking at summary statistics of the main variables (Table 5.6 in the appendix), it is noticeable that the interdisciplinarity use of publications seems to be generally a frequent phenomenon in our dataset. The median value of categories that cite the publications in our dataset equals 3 and the forward citations are quite balanced over the different classes (mean balance 0.58). Likewise, on average one third (38%, mean of share of interdisciplinary cites 0.38) of the citations, that publications received, was from publications outside their discipline. This reflects the pronounced cross-disciplinary character of the research in the Medical Devices domain which Larivière and Gingras (2010) also found with respect to the relationship between interdisciplinarity and scientific impact. However, the average degree of novelty of the publications in our sample is relatively low (0.34), meaning that the publications are more likely to be cited by publications in related disciplines. With respect to impact, the frequency of articles that were cited at all (this means having non-zero citations) amounts to 70%. However, the median total citations that an article in our sample received was 3 and the articles were mostly cited below their journal average (median relative cites 0.60). This is not surprising, since citations to articles are highly skewed, meaning that the majority of articles gets less citations while few articles count among the highly cited papers (Rigby 2013).

In order to explore further, whether there are potential differences in these outcome variables between funded and non-funded projects, we ran plain t.tests to see whether both groups exhibit significant mean differences in novelty, impact, and interdisciplinarity of their publications. The results are depicted in Table 5.3. The columns two and three indicate the mean values of several outcome measures distinguished after publications that acknowledged public funding and publications that did not. The analysis reveals remarkable differences between funded and non-funded papers for every interdisciplinarity, novelty and impact measure. Articles from publicly funded projects seem to be cited significantly more (in total and relative to their peer articles in the same journal) and they tend to be comparably more often published in journals with higher prestige in terms of impact factor. Moreover, when public funds were involved, the publications achieved higher novelty values as well are higher scoring in the interdisciplinarity indicators. These findings provide a first hint for a positive relationship between the receipt of public grants and interdisciplinarity, novelty and impact.

Table 5.3 Comparison of means of interdisciplinarity, novelty and impact measures between funded and non-funded publications (matched sample)

	Mean			
Variable	**public fund**	**no public-fund**	**p.value**	**t.statistics**
Divers	0.553	0.426	0.000	14.142
Variety	6.949	4.506	0.000	13.287
ShannonNorm	0.711	0.543	0.000	14.035
ShareInterdiscCit	0.475	0.353	0.000	11.226
Herfind	0.594	0.432	0.000	15.953
Novel	0.410	0.325	0.000	10.687
CitTot	9.002	7.198	0.005	2.828
RelCit	1.492	1.268	0.037	2.084
ImpactFact	3.129	2.139	0.000	17.999

We are further interested to see, beyond the mean differences, whether the overall distributions of the several outcome proxies also diverge. Therefore they are visualized in Figure 5.3 separately for publications from funded and non-funded projects. The results from the t-tests are supported by the distribution graphs. Concerning the diversity, one can see that the distribution of citations across disciplines to papers that acknowledge public funding is more diverse as compared to their non-funded equivalents. In case of funded projects, the area under the density curve is much larger for higher values and much smaller for smaller values as compared to publications from the control group. For variety (number of citing categories) and the share of interdisciplinary forward citations, we find equal results in that citations to funded publications are more widespread across multiple disciplines. With respect to the values of the Shannon evenness, we find that publications from publicly funded projects are much more polarized as compared to the control group, because the values of their density curve clearly exceed the curve of the control group at the extreme values of the Shannon index, while less medium values are observable. This means that articles from funded projects are either very narrowly cited within one discipline and therefore the citations are very concentrated onto one category or they are equally often cited by multiple categories without a proper specialization. In this case, the Shannon evenness would reach the maximum value of one.

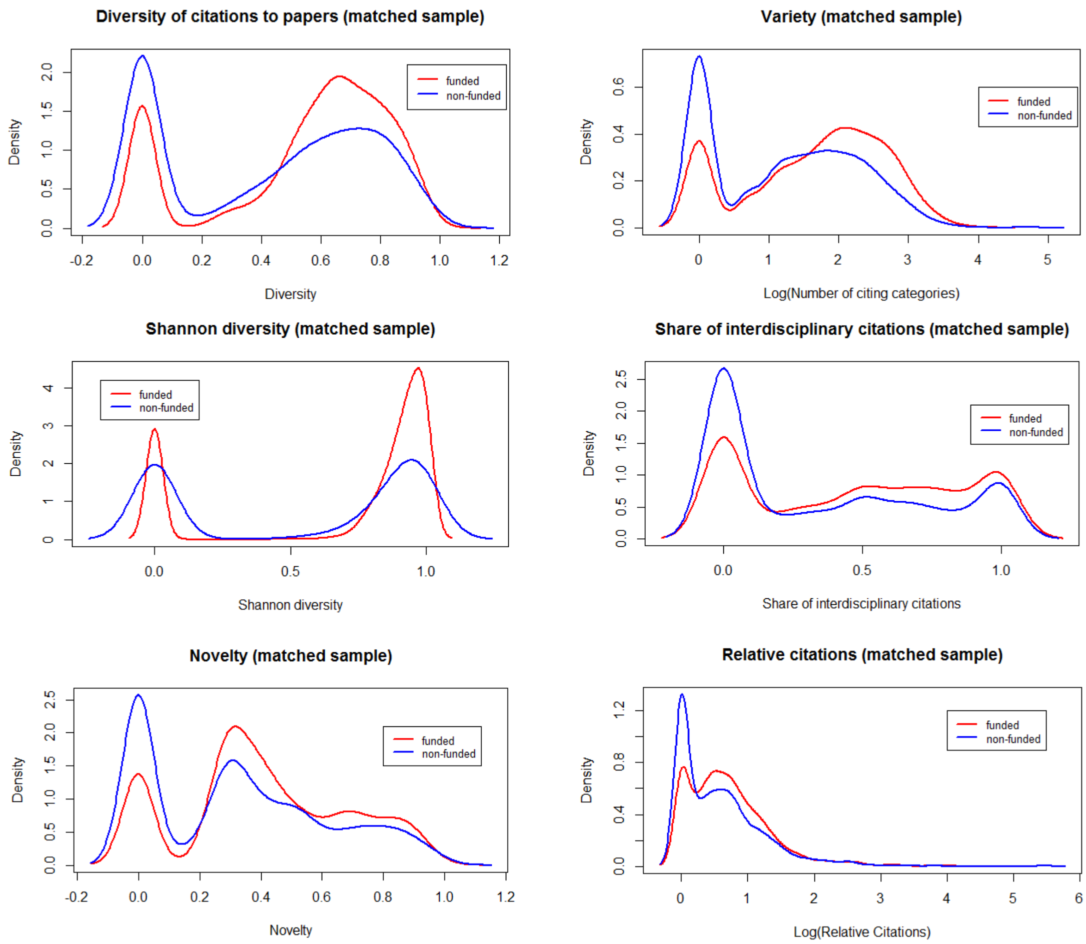

Figure 5.3 Comparison of interdisciplinarity, novelty and impact of articles from funded and non-funded projects

5.4.2 Estimation results

Public Funding, interdisciplinarity and novelty

To gain further insights and to confirm this first hint, we regressed several aspects of interdisciplinarity (Variety, Balance, Diversity) and novelty on the funding variables and included further relevant control variables. Table 5.4 shows the corresponding results of the estimations for the first model. With regards to interdisciplinarity, we find an overall significant positive relationship between the receipt of public funding and the interdisciplinary application of research outcomes. This result is robust to the variation in the measurement of the concept of interdisciplinarity (Diversity, Share of interdisciplinary cites, Balance, Variety), to changes in the estimation method (WLS on log transformed variety or negative binomial on raw variety variable) as well as to the inclusion of time and journal fixed effects. Specifically, we find that public funding increases the mean diversity index by 2,5% (coefficient from the full Model 4 0.025), the mean share of interdisciplinarity citations in all citations that the publication received by 6,1% (coefficient 0.059), the mean balance of citations over diverse categories by 5,9% (coefficient 0.057), and the mean breadth of categories that are citing the publication under review by 27,4% (coefficient from Model 8 0.242). Since we applied a logarithmic transformation, the percent increase in the mean of original variable can only be derived by taking $e^{\beta_{PublicFund}}$ (Benoit 2011). This implies that publicly funded projects are more likely to produce research results that are relevant to a greater variety of disciplines and overarches cognitive boundaries which supports our first hypothesis (H1). Furthermore, this effect holds equally for private additional funds and a higher number of funding sources, even though the results are less robust in this case. This supports the assumption that interdisciplinary endeavors are more resource intensive and therefore in need of additional funds beyond the core funding.

When controlling for other factors that also might determine how interdisciplinary forward citations are, we find that the degree of articles published in an interdisciplinary journal (interdisc category) or whose authors are affiliated to institutes that are dedicated explicitly to interdisciplinary research (interdisc orga) tend to receive more diverse and interdisciplinary forward citations. The latter finding points to a rather complementary relationship between explicit project funding and implicit core funding for interdisciplinary projects (Rigby 2011). Both are likely to generate interdisciplinary knowledge which finds a broad application.

In contrast, the receipt of grants from an interdisciplinary agency has no effect while the breadth of the common knowledge (nr_categories_team) of the author team seems to be even counterproductive. However, the team size itself has a slightly positive effect. This reveals that large teams are needed to create more interdisciplinary outcomes, the variety of the team expertise should not be too large though. The same result can be found for the number of categories of the journal in which the cited article was published in. The number of categories served Morillo et al. (2003) as an indicator for interdisciplinarity. Surprisingly, we find that the number of categories of the cited article is not a good predictor of later interdisciplinary forward citations. Howbeit, the effect disappears when journal dummies are introduced.

Furthermore, research results seem to be more interdisciplinary when the team members are affiliated to organizations located in different countries (international collaboration). In general, cultural diversity seems to foster interdisciplinarity. For researcher teams from the same institute we do not find a stable effect.

Regarding the research experience of an author, we find no conclusive evidence for a relation between the maximum number of publications of the team members and maximum age of the researcher (as indicated by the maximum lapse of time since any of the team members published its first article). However, we do find that the maximum number of citations that an article from an author in the team received promotes the level of interdisciplinary application. In other words, it is not the mere quantity of publications that counts, but the quality of these publications that seems to push the production of interdisciplinary research results. Hence, having at least one expert in the team increases the chances to be cited across diverse disciplines.

When we distinguish applied and basic research by controlling for industry involvement in the research we find that industry-academia publications or pure industry publications are less likely to be cited by an interdisciplinary audience. Publications from authors that are affiliated to a company tend to be also less novel in terms of establishing citation linkages to unconnected disciplines. This is plausible as interdisciplinary research takes place in the realms of basic research rather than applied research, as it is perceived too risky to be conducted upon own financial resources. Accordingly, research that is undertaken by companies tends to be mostly oriented towards very specific problem solutions and less exploratory. We did not explicitly incorporate the indicator for basic research as it is partially an aggregate of the industry involvement variables. Yet, the dummy variable indicating whether any of the authors is affiliated to a Max-Planck-Institute also captures research that is characterized by interdisciplinary basic approaches[34]. Indeed, we find that publications with at least one researcher from an MPI have higher chances to address a more diverse and interdisciplinary audience. This result also supports the idea that both institutional funding as well as project funding has an impact on interdisciplinarity and are rather complementary in fostering interdisciplinarity.

Lastly, the article length is also positively associated with interdisciplinary citations. More exploratory interdisciplinary research might generate multiple ideas which have to be packed into more publication pages (Bosquet and Combes 2013). Broader ideas that are radical and new to the scientific community need to be introduced more comprehensively and need more space to be presented convincingly compared to already existing and established ideas. Alternatively, longer articles might contain a multitude of ideas that have a broader application spectrum (Bosquet and Combes 2013).

With regards to the recombination of unrelated knowledge, the results from the correlation table (Table 5.7 in the appendix) indicate, that novelty and interdisciplinarity (number of citing categories[35]) concur. The novelty value increases with the number of categories that are citing the article. For this reason, the novelty value of the publications is determined by similar factors as the degree of interdisciplinarity. Publicly funded projects tend to bring forth more publications that combine distant disciplines as compared to non-funded controls. The mean novelty value for publications acknowledging public funds is 4,2 % higher (coefficient 0.041). Hence, our findings also support our second hypothesis (H2). Applied research as measured by company involvement is less novel while authors from interdisciplinary organizations and MPI generate articles with higher novelty values. A larger number of authors and an international team are beneficial for interdisciplinary outcomes. Equally, articles with higher novelty potential fill also more pages.

In sum, our findings suggest that the codified outcome of publicly funded projects is more novel and interdisciplinary as compared to their counterparts. However, other additional private funds and the number of the funding sources increase the degree of novel combinations and application across disciplines. One possible interpretation is that grants either serve as a risk premium or enable resource-intensive interdisciplinary research. Diversity in the team with respect to the number of authors and the international collaboration seem to foster interdisciplinarity and the generation of novel ideas.

[34] In Germany, four main research foundations receive public institutional funds. One of them is the Max-Planck-Society with its institutes which focus on interdisciplinary basic research. 95% of their core funding is provided by the government. (https://www.mpg.de/, https://www.bmbf.de/de/max-planck-gesellschaft-834.html)

[35] By construction, novelty is a constituent component of the diversity measure. Therefore, they are highly correlated.

Table 5.4 Funding and Interdisciplinarity

Model	1	2	3	4	5	6	7	8	9
Dep.Var.	*Divers*$_{log}$				*Novel*$_{log}$	*ShareInter-discCit*	*Shan-nonNorm*$_{log}$	*Variety*	
	WLS	**WLS**	**WLS**	**WLS**	**WLS**	**WLS**	**WLS**	**WLS**	**Negbin**
Constant	0.288 ***	0.287 ***	0.460 ***	0.850 *	0.413 ***	0.471 ***	0.369 ***	1.377 ***	1.280 ***
	(0.019)	(0.018)	(0.018)	(0.360)	(0.017)	(0.022)	(0.023)	(0.07)	(0.088)
IndustryPublicOrga	-0.016	-0.02	**-0.020** *	-0.012	-0.006	**-0.048** ***	**-0.031** **	**-0.119** **	**-0.131** **
	(0.014)	(0.014)	(0.012)	(0.011)	(0.011)	(0.015)	(0.016)	(0.047)	(0.06)
InstSame	-0.014	-0.013	-0.011	-0.002	-0.013	**-0.033** ***	0.002	0	-0.042
	(0.01)	(0.01)	(0.008)	(0.008)	(0.008)	(0.01)	(0.011)	(0.032)	(0.043)
IDCateg	**0.101** ***	**0.103** ***	**0.087** ***	**0.715** **	**0.103** ***	**0.055** ***	0.009	0.083	**0.170** **
	(0.016)	(0.016)	(0.014)	(0.360)	(0.013)	(0.018)	(0.018)	(0.055)	(0.07)
IDOrga	**0.066** **	**0.063** *	**0.069** **	**0.057** **	**0.063** **	**0.060** *	**0.092** **	0.147	**0.234** *
	(0.032)	(0.032)	(0.027)	(0.025)	(0.026)	(0.035)	(0.036)	(0.108)	(0.136)
IDCentreFund	0.052	0.054	0.019	-0.006	0.005	0.045	-0.022	**0.258** *	0.155
	(0.041)	(0.041)	(0.035)	(0.031)	(0.033)	(0.044)	(0.045)	(0.136)	(0.162)
InternatCollab	**0.036** ***	**0.038** ***	**0.023** ***	0.004	**0.013** **	0.011	**0.034** ***	**0.148** ***	**0.173** ***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.025)	(0.032)
AgeFirstPub$_{log}$	0.007	0.006	**-0.014** **	-0.005	**-0.010** *	**-0.030** ***	**-0.019** **	**-0.135** ***	**-0.201** ***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.005)	(0.007)	(0.008)	(0.023)	(0.029)
MaxCitTeam$_{log}$	**0.018** ***	**0.018** ***	**0.010** ***	0.004	0.003	**0.016** ***	**0.019** ***	**0.127** ***	**0.177** ***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.012)	(0.015)
MaxNrPub	**-0.001** ***	**-0.001** ***	0	**-0.001** ***	**0.000** *	**0.000** *	0	0	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
MPInst	0.008	0.009	**0.030** **	**0.024** *	**0.025** *	**0.080** ***	0.025	**0.132** **	**0.167** **
	(0.017)	(0.017)	(0.014)	(0.013)	(0.014)	(0.018)	(0.019)	(0.056)	(0.071)
TeamSize	**0.003** ***	**0.003** ***	**0.004** ***	**0.002** ***	**0.003** ***	**0.006** ***	**0.005** ***	**0.021** ***	**0.032** ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
VarietyTeam	**-0.009** ***	**-0.009** ***	**-0.002** **	-0.001	**-0.002** **	-0.001	**-0.003** ***	**-0.008** **	**-0.007** *
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
NrFundSource	0.001	-0.004	**0.009** ***	0.002	**0.007** ***	**0.012** ***	**0.013** ***	**0.050** ***	**0.065** ***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.009)	(0.011)
NRWoSClass	**-0.040** ***	**-0.040** ***	**-0.033** ***	-0.282	**-0.038** ***	**-0.052** ***	**0.019** ***	**0.061** ***	0.014
	(0.005)	(0.005)	(0.004)	(0.177)	(0.004)	(0.006)	(0.006)	(0.017)	(0.022)
Pages	**0.009** ***	**0.009** ***	**0.007** ***	**0.007** ***	**0.004** ***	**0.002** **	**0.011** ***	**0.031** ***	**0.057** ***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
PublicFund	**0.064** ***	**0.071** ***	**0.057** ***	**0.025** ***	**0.041** ***	**0.059** ***	**0.057** ***	**0.242** ***	**0.332** ***
	(0.008)	(0.008)	(0.007)	(0.006)	(0.006)	(0.008)	(0.009)	(0.026)	(0.032)
PureIndustryOrga	**-0.065** *	**-0.065** *	**-0.088** ***	**-0.062** **	**-0.079** ***	**-0.077** **	**-0.111** ***	-0.172	-0.006
	(0.033)	(0.033)	(0.028)	(0.026)	(0.027)	(0.036)	(0.037)	(0.112)	(0.148)
PrivateFund		**0.041** ***							
		(0.01)							
Year dummies	N	N	Y	Y	Y	Y	Y	Y	Y
Source dummies	N	N	N	Y	N	N	N	N	N
z1 Observations	5,134	5,134	5,134	5,134	5,134	5,134	5,134	5,134	5,134
z2 adj.R2	0.121	0.124	0.369	0.480	0.254	0.234	0.336	0.476	
z3 R2	0.118	0.121	0.366	0.493	0.250	0.231	0.333	0.474	
Z4 F-stats	41.521	40.318	129.771	37.750	75.512	67.892	112.278	202.154	
z2 Deviance									5,921.125
z3 AIC									2,5777.682

Standard errors in parantheses
Stars indicate significance levels: *** p <0.01 , ** p< 0.05 , * p<0.1

Public Funding and Impact

In light of these findings, it is necessary to elaborate whether the emission of research funds might not only push forward interdisciplinary endeavors, but also increases the likelihood of producing a breakthrough contribution. Since our interdisciplinarity measures are equally citation-based and therefore strongly correlated with the impact indicators, we do not explicitly include them as explanatory factors in these regression models. However, we can implicitly utilize information about interdisciplinarity from the input-related controls such as interdisciplinary funds (*IDCentreFund*), interdisciplinary journal category (*IDCateg*), number of WoS-categories (*NRWoSClass*), interdisciplinary organization (*IDorga*), and team variety (*VarietyTeam*).

To identify a breakthrough idea, in a first step we examine whether the foundation is laid by the article being accepted to a prestigious journal. Journal prestige is measured by the impact factor. We assume that outstanding ideas are more likely to be published in higher ranked journals (Model 1 and 2). In a second step, we estimated the correlation between the relative contribution of an article (as measured by the relative citations an article received as compared to the average citations the articles from the same journal and published in the same year received) and the receipt of public funds (Model 3 and 4). We were interested whether publicly funded research disembogues in above average cited articles. Third, to avoid any inaccurate estimates by including both publications that were cited and publications that were not cited at all, we use the binary information (RelCiteBin - being cited yes or no) to explore whether public funds determine whether an article is actually cited at all (Model 5 and 6). Last, we were keen to see whether there is a particular difference between above and below average articles and which role public funded research plays (Model 7 and 8). The overall results are presented in table 5.5.

In general, the results concerning the scientific impact of funded projects are less clear as compared to interdisciplinarity. We find partial support for a superiority of funded projects over non-funded ones in terms of performance. Consequently, our third hypothesis (H3) is only partially supported. In terms of relative citation counts, our findings deviate from the results of prior studies which found that funded projects outperform non-funded projects in terms of citation counts (Costas and Leeuwen 2012, Zhao 2010, Allen et al. 2009, Rigby 2013). First, in our study we find that public funding as acknowledged in the publication is only beneficial with regards to the publication in a high impact journal and with respect to receiving at least one citation at all (RelCitesbin). To be precise, holding all other factors constant, the odds of receiving at least one citation is about 60% higher for publications that acknowledge public funding as compared to publication that do not indicate public support (Model 5 odds ratio for public funds equates 1.595[36]). For the journal normalized citation counts and above average citations we do not find any effect. Costas and Leeuwen (2012) as well found that publications with only financial acknowledgements (without acknowledging other researchers' input) are published in more prestigious journals but at the same time have lower field normalized citations as compared to publications without funding acknowledgements.

For additional private funds we find almost the same effect: solely private grants are positively associated with relative citation counts, which we did not for public funds. Even more, the receipt of additional financial support from private sources increases the odds of producing an above average cited publication. This effect disappears when the non-cited publications are excluded from the sample.

[36] The odds ratio is calculated as the ratio between the chances of receiving at least one citation and receiving zero citations $\frac{P(RelCitebin=1)}{1-P(RelCitebin=1)}$.

Funds from an interdisciplinary center increase the chances to position a paper within a high impact journal but do not necessarily lead to more citations. Likewise, the number of funding sources seems to facilitate the publication in a prestigious journal. Contrary to Rigby (2013) who found a positive but weak relation between number of funds in the acknowledgements and relative citation counts, we do not find a link.

With respect to the controls that are related to interdisciplinarity, we find that articles written by authors from interdisciplinary research organizations have a higher citation probability as compared to authors from other affiliations. Journals in our particular data set that are assigned to an explicit interdisciplinary category (IDCateg) have a lower impact than journals that are not characterized by an explicit interdisciplinary content. However, journals with interdisciplinary categories in our matched sample are very scarce (they account for approx. 7% of all publications in the sample)[37]. However, publications that are never cited are less likely to be found in journals with an explicit interdisciplinary category (IDCateg Model 4 and 5). If we instead consider the breadth of categories that a journal is assigned to (NrWoSClass), we find that more influential journals are also assigned to a greater variety of WoSClasses.

In accordance with prior findings (Leydesdorff and Bornmann 2015, Bosquet and Combes 2012), we also find that articles that are published in higher quality journals exhibit a higher probability of being cited (Imp_Fac Model 6).

Regarding team composition, we find that the team size is a crucial factor in explaining citedness of a paper which meets our expectations and conforms to previous work (Bosquet and Combes 2012). This finding holds whatever proxy we use for citation impact. Particularly, we find positive correlations between team size and journal prestige, relative citation counts, the probability of being cited, and the probability to be even cited above the average. Bosquet and Combes (2012) argue that this result is mainly due to network effects of the researchers. The larger the team size, the larger the network to the scientific community (through conferences and other academic exchanges) and the higher the diffusion of knowledge as traced in citations. Another possible explanation is that team size is a proxy for the size of the knowledge pool that the researchers draw upon. A larger knowledge pool increases the potential for knowledge recombination and resulting breakthrough inventions.

Analyzing further team indicators reveals that international collaborations and prior highly cited publications by at least one team member increase the chances for being published in a high quality journal and being cited above average. In contrast, the maximum age of the career of one of the team members shows a slightly negative correlation with the journal prestige. However, when explaining the other citation-based measures the effect disappears.

Furthermore, the cumulative team experience in interdisciplinary research as measured by the breadth of their combined knowledge components (categories of prior publications) shows a slightly negative association between the publication in a prestigious journal, the normalized citation counts, and the probability of being cited at all. Conceivably, the increased communication costs in very diverse teams might outweigh the benefits of a larger pool of knowledge inputs. In fact, Yegros-Yegros et al. (2015) provide evidence for a curvilinear relationship between interdisciplinarity and scientific impact. They find that interdisciplinarity might be harmful for achieving scientific impact when the covered disciplines are too unrelated. Likewise, Lee et al. (2015) and Hollingsworth (2006) find evidence for a moderate level of field variety with respect to the impact of the research.

While we found that company involvement in research rather impedes interdisciplinary outcomes, in some cases industry involvement might be even beneficial for receiving a larger

[37] If this is a result that is only valid for the specific set of the journals in our sample has to be explored further. The journals "Nature" and "Science" are not included in our sample. They are counted among the most influential journals and they are assigned to a multidisciplinary category.

number of citation counts. For instance, articles from industry-academia cooperations have a higher likelihood to be published in high quality journals. Similarily, publications from purely industry affiliated authors are more prone to be cited at all and even to be cited above average. Even though we found that interdisciplinary and novel research is not likely to take place in applied studies, they are not automatically less cited.

Moreover, our results suggest that high-quality journals tend to prefer publishing articles with at least one author being affiliated to a Max-Planck-Institute. Though, they seem to be cited less often and below average cited as compared to publications with authors affiliated to other organizations.

When looking at article characteristics, we find that the page length and the number of cited references are positively related to scientific impact.

Finally, when we only focus on explaining that a paper belongs to a highly cited paper as compared to the journal average without accounting for non-cited papers (Model 8), we find that funding, independently of the number of funding sources or the type of funding source (private, public or interdisciplinary), does not play a role. Rather, the odds of generating a high impact publication increase with the size of the author team, with having an expert in the team that already published a breakthrough article in the past (MaxCites), and when the paper is written solely by authors that are affiliated to an industrial organization. In addition, highly cited papers tend to span more pages.

In sum, we can conclude that supplementary public financial support for specific research projects favors the acceptance of publications in high-quality journals and increases the propensity to be among the papers that are cited at least once. However, the generation of breakthrough ideas is driven by other determinants like teamsize, international diversity, amount of knowledge that is referred to, and the participation of expert researchers.

Table 5.5 Results Model 3 – Funding and scientific impact

	Weighted Least Squares				**Logit**[38]	**Logit**	**Logit**	**Logit**
Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Dep.Var.	$ImpactFact_{log}$	$ImpactFact_{log}$	$RelCites_{log}$	$RelCites_{log}$	$RelCit_{bin}$	$RelCit_{bin}$	$AboveAvrg_{bin}$	$AboveAvrg_{bin}$
Sample	m	m	m	m	m	m	m	only cited[39]
Constant	-0.149 *** (0.045)	-0.003 (0.048)	-0.267 *** (0.053)	-0.097 (0.059)	0.208 *** (0.422)	0.353 ** (0.439)	0.036 *** (0.257)	0.284 *** (0.311)
PublicFund	**0.113 ***** (0.015)	**0.114 ***** (0.015)	0.018 (0.02)	0.015 (0.02)	**1.595 ***** (0.11)	**1.399 ***** (0.119)	1.101 (0.074)	0.933 (0.081)
IDCentreFund	**0.299 ***** (0.079)	**0.285 ***** (0.077)	-0.042 (0.103)	-0.059 (0.102)	2.146 (0.842)	1.138 (0.889)	0.699 (0.38)	0.623 (0.388)
PrivateFund	0.028 (0.019)	0.022 (0.019)	**0.100 ***** (0.025)	**0.091 ***** (0.025)	**1.485 ***** (0.141)	**1.479 ***** (0.149)	**1.250 **** (0.092)	1.132 (0.101)
IDCateg	**-0.110 ***** (0.032)	**-0.107 ***** (0.031)			**1.457 *** (0.219)	**1.793 ***** (0.223)		
NRWoSClass	**0.038 ***** (0.01)	**0.042 ***** (0.01)			1.061 (0.069)	0.964 (0.072)		
IDOrga	0.078 (0.062)	0.084 (0.06)			**3.236 **** (0.53)	**3.193 **** (0.553)	1.157 (0.308)	0.895 (0.319)
MPInst	**0.155 ***** (0.032)	**0.163 ***** (0.031)	**-0.119 ***** (0.043)	**-0.108 **** (0.042)	1.47 (0.247)	0.983 (0.27)	**0.537 ***** (0.171)	**0.430 ***** (0.182)
$TeamSize_{log}$	**0.104 ***** (0.016)	**0.101 ***** (0.016)	**0.140 ***** (0.021)	**0.147 ***** (0.021)	**1.705 ***** (0.114)	**1.497 ***** (0.121)	**1.627 ***** (0.081)	**1.455 ***** (0.092)
$VarietyTeam_{log}$	**-0.079 ***** (0.015)	**-0.066 ***** (0.015)	**-0.089 ***** (0.019)	**-0.041 **** (0.019)	**0.701 ***** (0.106)	**0.762 **** (0.114)	**0.866 **** (0.072)	0.956 (0.081)
InternatCollab	**0.097 ***** (0.014)	**0.087 ***** (0.014)	**0.043 **** (0.018)	**0.037 **** (0.018)	**1.403 ***** (0.1)	**1.219 *** (0.107)	**1.174 **** (0.067)	1.056 (0.074)
IndustryPublicOrga	**0.048 *** (0.027)	**0.052 **** (0.026)	0 (0.036)	-0.007 (0.035)	1.064 (0.189)	0.863 (0.199)	0.896 (0.133)	0.824 (0.146)
PureIndustryOrga	-0.015 (0.066)	-0.016 (0.065)	0.063 (0.085)	0.046 (0.084)	**0.377 **** (0.388)	**0.341 ***** (0.413)	1.391 (0.326)	**2.499 **** (0.452)
$AgeFirstPub_{log}$	**-0.027 *** (0.015)	**-0.042 ***** (0.015)	0.004 (0.019)	-0.027 (0.019)	1.019 (0.105)	1.005 (0.114)	0.919 (0.073)	0.896 (0.082)
$MaxCitesTeam_{log}$	**0.066 ***** (0.007)	**0.068 ***** (0.007)	**0.043 ***** (0.009)	**0.041 ***** (0.009)	**1.203 ***** (0.048)	**1.131 **** (0.052)	**1.149 ***** (0.033)	**1.122 ***** (0.037)
$CitedRefer_{log}$	**0.265 ***** (0.01)	**0.233 ***** (0.01)	**0.160 ***** (0.013)	**0.140 ***** (0.013)	**2.867 ***** (0.078)	**2.175 ***** (0.083)	**1.830 ***** (0.06)	1.121 (0.076)
Pages	-0.002 (0.002)	0 (0.002)	**0.005 **** (0.002)	**0.006 ***** (0.002)	1.008 (0.013)	1.011 (0.013)	**1.019 **** (0.009)	**1.017 *** (0.01)
ImpactFact						**1.620 ***** (0.038)		
NrFundSource	**0.031 ***** (0.006)	**0.036 ***** (0.005)	-0.001 (0.007)	0.005 (0.007)	1.027 (0.04)	0.954 (0.042)	0.996 (0.027)	0.983 (0.029)
Year Dummies	N	Y	N	Y	Y	Y	Y	Y
Obs	4,974	4,974	5,134	5,134	5,134	4,974	5,134	3,719
Adj.R2	0.343	0.376	0.107	0.126				
R2	0.340	0.373	0.105	0.123				
FStats	151.973	129.671	43.856	36.893				
Deviance					3,539.704	3,112.395	6,336.103	5,028.625
AIC					4,213.578	3,685.951	7,347.909	5,814.916

Standard errors in parantheses

Stars indicate significance levels: *** p <0.01 , ** p< 0.05 , * p<0.1

[38] The results for the logit estimation contain the odds ratios.
[39] The sample includes only articles that received at least one citation. The “m” in sample stands for matched sample.

5.5 Conclusion

The aim of this study was to further understand the relation between public funding to R&D, the interdisciplinarity of research projects, the establishment of novel knowledge linkages, and scientific impact. Since there has been an increased policy emphasis on stimulating interdisciplinary research, it was an open question whether interdisciplinarity can indeed be reached when it is promoted. We used publication data to gather information about collaborative research in Medical Devices disciplines, the information in the acknowledgement section about the sources of supplementary funding, and the forward citations to trace the breadth and diversity of the application of the codified research results.

In a first instance, we modeled the selection process into funding by implementing propensity score matching techniques in order to reduce the heterogeneity between funded and non-funded observational units. Basically, we found that collaborative research which focuses on basic topics and is conducted at interdisciplinary organizations is favored by funding agencies.

Second, we analyzed whether actors increasingly use the opportunity of public grants to engage in interdisciplinary research and generate ideas that combine distant fields of knowledge. We indeed find evidence that the results of funded projects display a higher propensity for interdisciplinary application than those of non-funded projects. Also, publicly funded projects are prone to develop ideas which combine novel and disparate streams of knowledge as compared to non-funded projects. Consequently, the allocation of supplementary public research funds might serve as a risk premium and compensate for the higher costs and risks involved and therefore induce interdisciplinary collaboration.

Regarding our research question about the additional payoff of public funds in terms of scientific impact, the results appear to be less conclusive. We find partial support for our hypothesis that publicly funded projects will achieve a larger impact contribution. Our results suggest that the receipt of public funds indeed opens the door to prestigious journals and increases the likelihood of being cited. Contrariwise, additional project funding and the source of the supplementary funds are irrelevant for the origination of breakthrough ideas. Rather, breakthrough ideas develop in environments where international researchers including at least one expert researcher collaborate and combine multiple knowledge inputs.

However, our study faces also some limitations which leave room for improvements and further research. Principally, the main restriction for elaborating on the effect of funding on the desired outcome is the cross-sectional nature of the data. We utilize the temporal order of observed events to reason that the selection into funding preceded the publication and the following citations by other papers in combination with matching methods to simulate the independence of selection into funding of pre-funding covariates. Still, we cannot ascertain that the initial heterogeneity between both groups was completely eliminated. Advanced approaches applying difference-in-difference estimators analyze the evolution of the initial differences between both groups over time and attribute the changes in these difference to the policy treatment (Aerts et al. 2006). These approaches require panel data or at least repeated observations in two points in time (before and after the treatment). In fact, the collection of panel data is only reasonable for other kinds of observational units than publications such as authors, journals or countries. For the purpose of our analysis, the publication was the only adequate unit of analysis owing to the reasons outlined in the methodological section above.

Furthermore, while we were interested in exploring a general link between funding and scientific outcome in terms of interdisciplinarity, impact, and novelty, the mechanisms that mediate this relationship have to be explored further. One way would be to specify more complex models which include interaction terms between covariates and the funding variables to explain later outcomes. Another possibility would be to complement the quantitative analyses by qualitative information from case studies and expert interviews in the fashion of Bruce et al. (2004) and Lyall et al. (2013).

Another possible extension is to separately analyze the outcomes of projects supported by distinct funding sources to expand the knowledge about the impact of different policy instruments. Policy measures have diverging preconditions, aims and frameworks which might be reflected in heterogeneous outcomes. This might also include the consideration of other indices than citation counts that might be affected differently dependent on the design of the policy measure. While we interchanged our main aggregate funding variable with indicator variables for the single policy measure, we did not find significant differences. More elaborate approaches could modify the matching procedure and match upon subgroups separated according to different treatment variables (funding sources). On this basis, the interdependencies of simultaneously received grants from different funding sources, the so called policy mix, could be examined (Flanagan et al. 2011, Rotolo et al. 2014).

Furthermore, since we have found strong evidence for the benefits of collaboration with respect to being selected for funding as well as for producing more radical, novel and interdisciplinary results, we only assumed that these results are driven by the authors' personal networks. Therefore, a promising enhancement would be the inclusion of further information on the personal networks of the researchers like Ebadi and Schiffauerova (2015) did, when they analyzed the beneficial role of the researcher's network to explain the receipt of funds.

From an innovation-oriented policy perspective, we can conclude that projects which benefitted from external public funds strike risky, novel and interdisciplinary paths. Therefor, public support is crucial for strengthening the national science base and to supply the breeding grounds for radical inventions that might culminate in marketable innovations. Thereby, institutional funds and project-specific funds are by no means substitutes. We rather find that they are complementary in supporting interdisciplinarity and novelty. Their interaction has to be explored further. With regards to the evaluation of the transformation from scientific breakthroughs into successful innovations, additional data such as patent data is required to capture technical novelty or data on licensing agreements to detect the market value of the patented invention.

Since our study was restricted to the analysis of publications in the field of Medical Devices, we hardly can provide a sound statement about the generalizability of our findings. The heterogeneity of results from studies analyzing the impact of IDR (Rinia et al. 2001, Lariviere and Gingras 2010, Rafols et al. 2012) constitutes a need for further research that explores field-specific peculiarities or commonalities between disciplines. Potentially, the strength of the link between public funds and interdisciplinarity is contingent on the relevance of external public funds in different fields or the routine and attractiveness of interdisciplinary research in the field. While interdisciplinary research has been found rather rare and unattractive in the field of economics (Rafols et al. 2012), it is found to be important for scientific impact in biomedicals (Lariviere and Gingras 2010).

5.6 Appendix

Table 5.6 Description of variables

Hypothesis	Concept	Code	Description	Obs	Min	Max	Median	Mean	Std. Dev.
H1	Interdisciplinarity	*Variety*	Number of citing categories	6,661	0	106.00	3.00	5.10	6.19
		ShareInterdiscCit	Share of citations from other categories than the own in all citations	6,661	0	1.00	0.33	0.38	0.39
		Divers	Rao-Stirling-Diversity	6,661	0	1.00	0.56	0.45	0.33
		ShannonNorm	Shannon entropy normalized	6,661	0	1.00	0.86	0.58	0.45
		Herfind	Herfindahl-Index of forward citations	6,661	0	0.96	0.63	0.47	0.38
H2	Novelty	*Novel*	Novelty of citation link	6,661	0	1.00	0.32	0.34	0.29
H3	Impact	*RelCit*	Relative citations of an article as compared to the journal mean	6,661	0	234.25	0.60	1.30	3.82
		CitTot	Absolute number of citations received	6,661	0	1566.00	3.00	7.47	23.38
		CitBin	Being cited (yes = 1)	6,661	0	1.00	1.00	0.70	0.46
		AboveAvrg	Being cited above average (yes=1)	6,661	0	1.00	0.00	0.36	0.48
		ImpactFact	Impact factor of the journal in which the article was published in (journal prestige)	6,435	0	8.31	2.07	2.40	1.83
	Fund	*PublicFund*	Does the article acknowledge a supplementary fund from a public source (EU, national, regional, BMBF, DFG)? (yes=1)	6,661	0	1.00	0.00	0.30	0.46
		PrivateFund	Does the article acknowledge a supplementary fund from a private source (company funds)? (yes=1)	6,661	0	1.00	0.00	0.15	0.36
		NrFundSource	Number of funding sources that are acknowledged	6,661	0	19.00	0.00	0.91	1.42
		EU	Are EU funds acknowledged? (yes=1)	6,661	0	1.00	0.00	0.08	0.27
		National	Are national public funds acknowledged? (yes=1)	6,661	0	1.00	0.00	0.21	0.41
		Regional	Are regional public funds acknowledged? (yes=1)	6,661	0	1.00	0.00	0.08	0.26
		BMBF	Are funds from the Federal Ministry of Education and Research (BMBF) acknowledged? (yes=1)	6,661	0	1.00	0.00	0.07	0.25
		DFG	Are funds from the German Research Foundation (DFG) acknowledged? (yes=1)	6,661	0	1.00	0.00	0.14	0.35
		MPG.fund	Are funds from the Max-Planck-Society (MPG) acknowledged? (yes=1)	6,661	0	1.00	0.00	0.00	0.07
		IDCentreFund	Are funds from an interdisciplinary source or center acknowledged? (yes=1)	6,661	0	1.00	0.00	0.00	0.07
		ForeignPublicFund	Are foreign public funds acknowledged? (yes=1)	6,661	0	1.00	0.00	0.13	0.34
	Author variables	*TeamSize*	Number of authors	6,661	1	56.00	6.00	5.96	3.25
		MaxCitTeam	Maximum number of citations that a previous article from the author team received	6,661	0	1632.00	60.00	93.56	138.02
		MaxNrPub	Maximum number of publications that an author from the team published in the past	6,661	0	115.00	8.00	13.31	15.28
		AgeFirstPub	Maximum time span since the first article of any of the authors was published	6,661	0	44.00	20.00	18.30	8.76
		VarietyTeam	Sum of the distinct categories in which all team members have published in the past	6,661	0	23.00	6.00	6.02	4.00
	Controls	*Journal dummy*	Journal dummy	6,661	-	-	-	-	-
		Pages	Page count of the article	6,661	1	69.00	8.00	8.38	4.52
		NRWoSClass	Number of categories of the journal in which the article was published	6,661	1	5.00	2.00	2.04	0.80
		Year dummy	Year dummy	6,661	2007	2013	2011	2010	1.99
		CitedRefer	Number of references cited in the article	6,661	0	635.00	28.00	29.37	21.66
		IDCateg	Is the journal assigned to a multi-, trans- or interdisciplinary category? (yes=1)	6,661	0	1.00	0.00	0.06	0.24
		PureIndustryOrga	Are all authors affiliated to an industrial organisation? (yes=1)	6,661	0	1.00	0.00	0.02	0.14
		IndustryPublicOrga	Are authors affiliated to an industrial organisation as well as to an academic organisation? (yes=1)	6,661	0	1.00	0.00	0.06	0.24
		IDOrga	Are the authors affiliated to an interdisciplinary organisation? (yes=1)	6,661	0	1.00	0.00	0.01	0.07
		InstSame	Are the authors affiliated to the same institute? (yes=1)	6,661	0	1.00	0.00	0.21	0.41
		CitySame	Are the authors affiliated to organisations within the same city? (yes=1)	6,661	0	1.00	0.00	0.26	0.44
		InternatCollab	Are the authors affiliated to organisations from different nations? (yes=1)	6,661	0	1.00	0.00	0.38	0.49
		MPInst	Is at least one of the authors affiliated to a Max-Planck-Research-Institute? (yes=1)	6,661	0	1.00	0.00	0.02	0.15
		Basic	Are the authors affiliated to organisations that focus on basic research (no industry involvement and no private external funding)	6,661	0	1.00	1.00	0.78	0.41

Table 5.7 Comparison of performance matching algorithms

Alternative	Method	sum_mean_diff	sum_mean_qq	sample_size
1	Nearest, 1:1, no rep	0.5918027	1.0088737	3996
2	Nearest, 1:1, with rep	1.1366359	1.8562769	3409
3	nearest, 1:3, no rep	3.4877384	3.6692288	6658
4	nearest, 1:3, with rep	0.4840759	2.0815945	4926
5	nearest, 1:1, no rep, caliper: 0.1	0.3888687	0.8968473	3934
6	nearest,1:3. with rep, caliper:0.1	0.3829244	1.7941637	5134
7	nearest, 1:3, with rep, caliper=0.2	0.3405823	1.9760107	5124
8	optimal,1:1,with rep	1.5681639	2.3938334	3996
9	optimal,1:2,with rep	1.4181536	1.8590885	5994
10	genetic	0.3747511	2.8325247	3591
11	exact	0	0	290
12	full	1.1009470	53.1169900	6658
13	nearest,1:3,with rep, distance=mahalanobis	0.5261011	1.8939570	4862

Table 5.8 Detailed performance measures for chosen matching algorithm (Method 6)

	Mean difference		
	Before Matching	**After Matching**	**Percent Balance Improvement**
distance	0.0562	0.0002	99.6135
TeamSize	0.6412	-0.047	92.6773
MPInst	0.0259	0.0046	82.2431
Basic	0.04	-0.0018	95.6137
IDOrga	0.0071	0.0013	81.1125
MaxCitTeam$_{log}$	0.4575	0.0089	98.0461
InternatCollab	0.0065	-0.0058	9.8297
VarietyTeam	0.994	-0.1121	88.7206
InstSame	-0.0928	-0.0109	88.3016
AgeFirstPub$_{log}$	0.8217	0.1612	80.3783
as.factor(PY)2007	0.0012	0.005	-327.5382
as.factor(PY)2008	-0.0244	0.0012	95.2127
as.factor(PY)2009	-0.0167	0.003	82.0038
as.factor(PY)2010	0.028	-0.0028	89.8461
as.factor(PY)2011	0.0537	-0.0058	89.114
as.factor(PY)2012	-0.0344	-0.0058	83.008
as.factor(PY)2013	-0.0073	0.0053	26.8308

Table 5.9 Checking the conditional independence assumption

Model	Logit
Dep.Var.	PublicFund
Sample	match
Constant	0.669 ***
	(0.156)
TeamSize	0.995
	(0.009)
MPInst	1.131
	(0.151)
Basic	0.984
	(0.074)
IDOrga	1.15
	(0.289)
MaxCitTeam	1.004
	(0.026)
InternatCollab	0.95
	(0.065)
VarietyTeam	0.986
	(0.009)
InstSame	0.891
	(0.088)
AgeFirstPub	1.007
	(0.005)
Year dummies	Y
z1 Observations	5134
z2 Deviance	6852.809
z3 AIC	7749.752

Standard errors in parantheses

Stars indicate significance levels: *** p <0.01 , ** p< 0.05 , * p<0.1

Table 5.10 Sensitivity of results to changes in matching algorithm

Model	**1**	**2**	**3**	**4**	**5**
Dep.Var.	Diversity				
Sample	Original data	Final matched sample (Method 6)	Exact matching	Full matching	Nearest matching with Mahalanobis distance
Constant	0.415 ***	0.437 ***	0.469 ***	0.420 ***	0.427 ***
	(0.014)	(0.016)	(0.069)	(0.016)	(0.017)
AgeFirstPub	**-0.001** **	**-0.001** **	**-0.011** **	-0.001	**-0.001** *
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)
ImpactFact	**0.023** ***	**0.020** ***	**0.019** **	**0.025** ***	**0.019** ***
	(0.001)	(0.002)	(0.008)	(0.001)	(0.002)
IndustryPublicOrga	**-0.025** **	**-0.019** *	-0.112	**-0.020** **	**-0.035** ***
	(0.01)	(0.012)	(0.128)	(0.01)	(0.012)
InstSame	**-0.013** *	-0.008	0.026	**-0.016** **	-0.001
	(0.007)	(0.008)	(0.037)	(0.007)	(0.009)
IDCateg	**0.112** ***	**0.102** ***	**0.122** **	**0.098** ***	**0.110** ***
	(0.013)	(0.014)	(0.054)	(0.012)	(0.014)
IDOrga	0.005	**0.056** **		0.031	**0.066** **
	(0.03)	(0.026)		(0.023)	(0.026)
InternatCollab	**0.021** ***	**0.017** ***	0.032	**0.019** ***	**0.014** **
	(0.005)	(0.006)	(0.033)	(0.005)	(0.006)
MaxCitTeam$_{log}$	**0.004** *	0.003	**0.052** **	-0.002	0.004
	(0.002)	(0.003)	(0.022)	(0.002)	(0.003)
MaxNrPub	0.000	0.000	0.001	0.000	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
MPInst	0.003	0.011		-0.012	0.015
	(0.015)	(0.014)		(0.012)	(0.013)
NR	**0.001** ***	**0.001** ***	0.001	**0.001** ***	**0.001** ***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
TeamSize	**0.003** ***	**0.003** ***	0	**0.002** ***	**0.004** ***
	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)
VarietyTeam	0.000	0.000	-0.007	0.000	-0.001
	(0.001)	(0.001)	(0.008)	(0.001)	(0.001)
NRWoSClass	**-0.040** ***	**-0.038** ***	**-0.034** *	**-0.034** ***	**-0.039** ***
	(0.004)	(0.004)	(0.019)	(0.004)	(0.004)
Pages	**0.004** ***	**0.003** ***	0.005	**0.005** ***	**0.004** ***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
PublicFund	**0.051** ***	**0.054** ***	**0.068** ***	**0.049** ***	**0.040** ***
	(0.005)	(0.006)	(0.026)	(0.006)	(0.006)
PureIndustryOrga	**0.039** **	**-0.068** **	**-0.141** *	-0.03	-0.01
	(0.017)	(0.028)	(0.079)	(0.024)	(0.03)
Year dummies	Y	Y	Y	Y	Y
Obs	6,435	4,974	270	6,435	4,703
FStats	225.599	151.606	12.904	238.858	132.337
Adj.R2	0.447	0.413	0.522	0.461	0.394
R2	0.445	0.411	0.482	0.460	0.391

Standard errors in parantheses

Stars indicate significance levels: *** p <0.01 , ** p< 0.05 , * p<0.1

6. Conclusion

The aim of this PhD thesis was to empirically analyze the evolution of the linkages between innovative agents as the micro-foundations of innovation systems. Particularly, we explore the relationship between two main factors that influence the formation and the efficiency of knowledge exchange in linkages between the agents of the innovation systems: the proximity of collaboration partners (related to their heterogeneity in technological capabilities) and political intervention in designing the configuration of the system.

We apply a mixed model to explain the emergence and stability of linkages between the actors as well as their performance. First, we utilize information from secondary data sources, namely patent data, to identify collaborative linkages and the cumulative competences and technological capabilities as well as publication data to trace the knowledge diffusion in a science driven technological field. Second, we draw on information from primary sources, namely survey data from interviews with actors funded within a specific systemic innovation program.

In the first main part of the thesis we investigate how innovative agents link up with each other and how policy comes into play. Therefore, we analyse this research question by investigating two aspects:

- **How do competencies, technological proximity and innovative linkages coevolve? (Chapter 2)**

First, the second chapter of this thesis dealt with the question of the dynamics of relations and attributes in the innovation system. The main question that derives from this study is about the nature of the prevailing dynamics of the infrastructure for interactive learning, the networks. Do we observe stable patterns of cooperation or are the observed linkages rather volatile? Furthermore, what drives the dynamics in cooperations, heterogeneity or similarity of the actors?

Specifically, the elaboration of the coevolution of several attributes of cognitive proximity, social proximity, and similarity in competencies and continued collaboration constituted the essence of our second chapter. Contributing to the debate on whether networks are rather stable (i.e., with actors always cooperating with the same partners) or volatile (i.e., with actors changing partners regularly), we find evidence for a preference of actors towards parter switching which in turns hints to rather volatile network structures.

Concerning the effect of assimilating knowledge bases through knowledge exchange and prior common experience on link repetition, our results are less conclusive. Neither knowledge transfer nor mutual cooperation experience do show significant effects on (repeated) cooperation. Instead, we find that overlap between the firms' knowledge bases, an uneven distribution of the reciprocal potential for knowledge exchange, general collaboration experience of the partners and similarity in popularity of the collaboration partners are favorable for cooperation. Quite surprisingly we find, that depending on the attribute, firms tend to prefer both: to connect to similar and to diverse partners. Firms preferably connect to similar others with respect to knowledge base and accumulated collaboration experience. In contrast, regarding organizational nature, patenting experience and potential knowledge gain, firms rather choose partners that are dissimilar. We also included a quadratic term for knowledge overlap to account for the tension between novelty potential and mutual understanding, but we did not find support for the hypothesis that potential for innovation and collaboration decreases as the overlap of the knowledge bases increases (Gilsing et al., 2008; Nooteboom, 1998; Wuyts et al., 2005).

Being aware of the limitations of patent data, we propose further possible extensions to our analyses. Mainly, the question on how these dynamics at the micro level feedback into the configuration of the whole innovation system provides a fruitful further research avenue. Recent research on networks has made advances regarding the explicit modeling of endogenous structural mechanisms such as triadic closure and preferential attachment (Broekel et al., 2014). Our analysis could be extended by elaborating the overall network evolution as a result of partner choice at the microlevel, a selection that is itself determined by similarity and diversity aspects. Stochastic actor-oriented models, for instance, allow for the examination of the relationship between the individual partner choice and the overall network dynamics (Balland et al., 2013). In this context, however, it is debatable to what extent firms are aware of and can directly influence the network beyond their ego network (direct connections) (Gilsing et al., 2008).

Building on that, the second aspect that we wanted to elucidate, was:

- **How are innovative linkages influenced by policy on the meso-level? (Chapter 3)**

In the third chapter, we analysed the relation between public funding and the formation of linkages between the actors of selected regional innovation systems. In doing this, we contribute to the rare studies on the evaluation of cluster policies (Martin and Sunley 2003, Brenner and Schlump 2011). As compared to the evaluations of former systemic instruments of innovation policy that were employed in Germany in the recent years, we employ a rather new tool in the context of the assessment of cluster policies: social network analysis (Guliani and Pietrobelli 2011). By means of SNA on the basis of a carefully constructed questionnaire, it was possible to identify effects on the network of strategically important R&D partners within the clusters that are attributable to the policy instrument.

Our results show that the “Leading Edge Cluster Competition” has lead to significant changes in the network structure in the selected innovation systems. We find that the existent network structures were strengthened and the networks got denser, more centralized and more locally oriented. The political support has induced a somewhat inward orientation of the networking activity of the selected actors. More than half of the linkages were either intensified or initiated by the LECC, while the majority of linkages was established or intensified with actors in the same locality. Moreover, the participation in the cluster programme has shifted the focus of networking increasingly on very few central actors. Another important result concerns technology transfer. The majority of the links that were affected by the policy were between firms and universities or research institutes. However, the relative frequency of science-industry linkages did not increase as a result of the funding. We can conclude that the innovation policy under study was quite effective in achieving the self-set goals. However, follow-up analyses are needed to assess whether the changes in the network configuration that were triggered by the policy entail also an improved innovative performance.

To complement our study on the factors that determine the evolution of the network configuration, we lay the focus of our analyses in the second main part of the thesis on the performance of the linkages between innovative agents. The study in this part comprises two distinct but related research questions. First, we fathom the heavily analysed but still highly controversial role of geographical proximity between actors as a precondition for successful R&D cooperation. This issue still exhibits a certain brisance, as the assumed benefical effect of geographical proximity on project outcome is still considered as a justification for the strong focus of regional innovation policies on fostering regional networking. Moreover, geographical proximity is one of the fundamental elements in the concept of the regional innovation system. Given the ambigoutiy of the results of prior studies and the unique information sources that we had at hand, we reassessed the importance of geographical proximity for the success of joint R&D projects and confronted it with new empirical evidence.

- **What are the contextual factors that determine the relevance of geographical proximity for project success in terms of knowledge diffusion and innovation? (Chapter 4)**

While the constituent role of geographical proximity for the formation of research alliances came to the fore on the innovation research agenda, the consequences for subsequent performance of joint research were still underexplored. Similarily to our SNA analysis, we utilized the data from a unique survey conducted with beneficiaries from the LECC. In detail, we analyzed the simultaneous effects of geographical along with technological aspects, social proximity and actor heterogeneity on intermediate outcome in terms of project satisfaction and final project output in terms of cross-fertilization effects and the introduction of a product or process innovation.

We find that geographical proximity of collaboration partners is not a universal precondition for project success. Our findings suggest that the geographical proximity between partners is deemed especially important in exploration contexts when projects aim at the production of radical novelty or experiment with new technologies which confirms the finding of Audretsch and Feldman (1996), who find strong clustering of innovative activities in the early stages of an industry, when knowledge is tacit and specific. Contrariwise, but in line with prior findings, this effect is less pronounced for projects focusing on basic research (Mansfield and Lee 1996, D'Este and Iammarino 2010, Garcia 2013). Further, we find that geographical proximity to collaboration partners seems to be more relevant to firms as compared to research institutes. Satisfaction levels decrease for firms with an increase of the geographic distance to their partners. With regard to final project results, we find that both, geographical proximity and project satisfaction, foster the cross-fertilization of other projects.

The crux of chapter 5 was to further understand the relation between public funding to R&D, the interdisciplinarity of research projects, the establishment of novel knowledge linkages, and scientific impact. Thereby, we expected insights into the role of public support to the knowledge diffusion between knowledge producers and knowledge users.

- **Can policy support to R&D increase the potential for interdisciplinarity, novelty and scientific breakthroughs? (Chapter 5)**

Since there has been a growing awareness of policy makers on the potential of interdisiciplinary research to respond to urgent societal challenges, it was an open question whether interdisciplinarity can selectively be promoted. By using publication data from the field of Medical Devices, we analysed the forward citations to trace the knowledge diffusion of research projects and to establish a link to public support to research.

Our results mainly meet our expectations. First, we found that public agencies preferably select collaborative research with a focus on basic research and including researchers from interdisciplinary organizations.

Second, we find evidence that the results of funded projects display a higher propensity for interdisciplinary application than those of non-funded projects. Also, ideas developed in publicly funded projects are more likely to combine novel and disparate streams of knowledge as compared to non-funded projects.

Third, we only find partial evidence for the link between supplementary public funds and scientific impact. The receipt of public funds indeed opens the door to prestigious journals and increases the likelihood of being cited. However, additional project funding seems to be irrelevant for the generation of breakthrough ideas. Rather, breakthrough ideas develop in environments where international researchers, including at least one expert researcher, collaborate and combine multiple knowledge inputs.

In sum, on the basis of the complementary empirical analyses we can conclude that proximity between actors plays an important role for the development of the connections in the innovation system. Policy plays an essential role in shaping these innovation systems and the linkages therein. On the one hand, policy may provide incentives to overcome systems failure and to motivate actors to collaborate and therewith provide a solid ground for the efficient knowledge diffusion. On the other hand, policy intervention may prompt the distribution of newly generated knowledge into diverse disciplines, increase the interdisciplinary character of the research outcome and foster the generation of novel and risky ideas. Furthermore, the initiation of diverse linkages should be targeted to avoid the redundancy of knowledge and decreased potential for innovations. Moreover, the exclusive support of regional linkages has to be seen skeptical, since technological aspects are more important for the generation of innovations and regional proximity only builds a crucial basis for the success of innovation projects in certain contexts.

Our findings do not only fertilize the research on innovation systems, interactive learning and networking, but also might inspire policy learning processes. While we have shown, that the political stimulation of the linkages in innovation systems might induce considerable consequences for the configuration of the network structure and in addition actuate knowledge diffusion processes, more research is needed on the relationship between the performance of the system and its inherent network structure. While theoretical contributions favor small-world-networks as the most efficient structure in terms of the speed of knowledge diffusion (Cowan and Jonard 2004), the consequences of a change in the distribution of linkages and their attributes (geographical spread for instance) caused by policitcal intervention should be examined further. More centralized networks for instance are more vulnerable, since their dependence on the functioning of single actors is higher as compared to other network structures. The results of Schilling and Phelps (2007) on the structure of industry networks depict the difficulties in evaluating this development towards increased centralization. They find a negative effect of network centralization on future patenting in the short run but positive effects in the long run.

Additonally, the reinforced inward orientation of the search process for collaboration partners that we observed from the LECC experience is not to be judged without some scepticism. Experiences of a Japanese cluster initiative show that local firms have a higher R&D productivity if they collaborate with partners outside the cluster (Nishimura and Okamuro 2011). Moreover, path-dependencies for firms and regions which can lead to spatial lock-in in the long run inhere the mere search for internal collaborations (Sternberg 2000). These concerns have also been brought up in the discussion on local buzz and global pipelines (Bathelt et al. 2004) and have been related to the stage of the cluster in its life-cycle by Brenner and Schlump (2011). They suggest that a network renewal by means of increased number of cluster external linkages is especially important in more mature phases of cluster development. Since the four clusters analysed in this thesis differ considerably with respect to age or maturity of technology, the dimension “stage in a cluster life cycle” requires further scrutiny.

Our findings emphasize the importance of contextual factors mediating the complex relationship between geographical proximity and successful R&D. It leads us to the conclusion, that policy makers should consider the already existing network structure in their decision on how to allocate funds to R&D. An already established structure of strong ties between the actors of the system might result in an ossification of the network that bears the danger of path dependency and lock in, when cooperation is continuously incentivized by innovation policy that does not account for already existing contextual factors. Consequently, not only the connection to the nearest partners should be supported, but it also should be warranted that the “right” actors are chosen. Our results speak against a one-fits-all type of policy which merely strengthens regional linkages, since other important contextual factors might be overlooked and the policy program will not yield the ex-ante expected effects (Crescenzi 2014, Koschatzy 2000). In consideration of the relative importance of other proximity dimensions and contextual factors, policy makers should shift their focus away from this restrictive view and include these factors into their decision. Regional proximity per se might not always be a warrant for successful research, as the benefits of the expertise might outweigh the cost of the collaboration with a distant partner (Garcia et al. 2013). Moreover, geographical proximity can be even detrimental when regional knowledge has been exploited and there is no access to fresh outward knowledge (Bathelt et al. 2004). Extraregional connections might serve as a source for new knowledge to overcome these critical situations. Also geographical distance can be substituted by other forms of proximities between actors (Boschma 2005, Cerscenzi 2014).

Furthermore policy has to find a balance between funding research with new partners for the reason of access to novel knowledge and the exploitation of the benefits of conducting joint R&D with old acquaintances based on established trust and institutions. Therefore, the stage of the technology of projects and the prevailing network structures should be taken into consideration as the growth of regions specialized on old technologies might be hindered by the mere focus on regional networking.

Moreover, given the dynamical feature of the innovation system and the linkages therein, policy programs need to exhibit a certain flexibility in order to correspond to fastly changing system configuratons.

In sum, future innovation policies would benefit from an awareness of the whole network rather than selecting single teams, which also allows for the detection of a potential malfunctioning of the system. Policy makers would utilize the funds for more targeted incentivizing. These new tools to visualize the network linkages could be used for monitoring and as the foundation for distinct policy decisions.

Approriate means for a liquid knowledge exchanges and network management would be the inclusion of intermediaries that manage and establish linkages between the agents, such as technology transfer offices, network or cluster managers, following the model of the LECC, that provide a common platform for all potential actors to meet. The levers for policies that fertile the processes in the innovation system are the combination of heterogenous actors, incentivizing risky and radical research and also stimulating the diffusion of knowledge.

Our research can be extended in various ways. First, as we only consider the separate influence of a specific program, we potentially neglect the interactions with other policy measures. Thus, a fruitful extension to our analysis would be to account for the interdependencies of several policy measures, the so-called policy mix. There has been an increased interest on the combined effect of different policy measures on output (Flanagan 2011).

Second, many network studies, including our own, have either focused (due to data and time constraints) on analyzing funded networks or non-funded ones. The combination of both and the juxtaposition would be enlightning and allow for sound causal inference on the effect of policy intervention. The coevolution of funded linkages with non-funded linkages would be a potential fruitful research avenue. Related to that, the analysis of long-term effects of public support to R&D on the network structure and density provides an interesting path to follow. Also in light of subsequent funding, it would be beneficial to know, whether the dynamics of funded linkages differ significantly from the dynamics of non-funded linkages.

Furthermore, another interesting research avenue is the quest for decreasing returns to connectivity at the system level. Analogously to the concept of overembeddedness of individual actors, there might also be an overconnectivity of the system. Empricial studies on these topics would provide a useful basis for the development of future innovation policy instruments.

Another extension is conceivable with regards to the consequences of certain network configurations (such as centrality, components, path length) on the performance of the system and the interplay with policy intervention. Do the properties of funded and non-funded networks diverge?

Furthermore, the debate on the dynamics of networks could be enriched by the incorporation of industry dynamics into the analysis. How do networks develop along with the industry life cycle? Do volatile networks with relatively uniform distributions of linkages evolve to rigid networks with a strong core-periphery structure and few central, highly connected actors?

References

Abramowitz, M. (1956), Resource and Output Trends in the United States since 1870, The American Economic Review 46(2), 5-23.

Aerts, K., Czarnitzki, D., Fier, A. (2006), Econometric evaluation of public R&D policies: current state of the art, Working Paper, KU Leuven.

Agrawal, A., Kapurc, D., McHaled, J. (2008), How do spatial and social proximity influence knowledge flows? Evidence from patent data, Journal of Urban Economics 64(2), 258-269.

Aharonson, B.S., Baum, J.A.C., Plunket, A. (2008), Inventive and Uninventive Clusters – The Case of Canadian Biotechnology, Research Policy 37(6-7), 1108-1131.

Ahuja, G. (2000), Collaboration networks, structural holes and innovation: a longitudinal study, Administrative Science Quarterly 45, 425-455.

Allen, L., Jones, C., Dolby, K., Lynn, D., Walport, M. (2009), Looking for Landmarks: The Role of Expert Review and Bibliometric Analysis in Evaluating Scientific Publication Outputs, PLoS ONE 4(6), doi:10.1371/journal.pone.0005910.

Allen, R. (1983), Collective invention, Journal of Economic Behavior & Organization 4(1), 1-24.

Andersson, T., Hansson, E., Schwaag Serger, S., Sörvik, J. (2004), The Cluster Policies Whitebook, IKED-International Organisation for Knowledge Economy and Enterprise Development.

Arthur, W.B. (2007), The structure of invention, Research Policy 36, 274-287.

Asheim, B., Gertler, M. (2006), Regional Innovation Systems and the Geographical Foundations of Innovation, In: Fagerberg, J, Mowery, D., .Nelson, R. (Eds.),The Oxford Handbook of Innovation. Oxford University Press, 291-317.

Audretsch, D.B., Feldman, M.P. (1996), R&D Spillovers and the Geography of Innovation and Production, The American Economic Review 86(3), 630-640.

Audretsch, D.B., Feldman, M.P. (1996), R&D Spillovers and the Geography of Innovation and Production, American Economic Review 86(3), 630-40.

Balland P.A., de Vaan, M., Boschma, R. (2013), The dynamics of interfirm networks along the industry life cycle: The case of the global video games industry 1987-2007, Journal of Economic Geography 13, 741-765.

Balland, P.A., Boschma, R., Frenken, K. (2015), Proximity and Innovation: From Statics to Dynamics, Regional Studies, forthcoming.

Baptista, R., Swann, P. (1998), Do firms in clusters innovate more?, Research Policy 27, 525–540.

Barabasi, A.-L., Albert, R. (1999), Emergence of scaling in real networks, Science 286, 509–512.

Bathelt H, Malmberg A, Maskell P. (2004), Clusters and knowledge: local buzz, global pipelines and the process of knowledge creation, Progress in Human Geography 28, 31-56.

Beaudry, C., Allaoui, S. (2012), Impact of public and private research funding on scientific production: The case of nanotechnology, Research Policy 41, 1589-1606.

Beaudry, C., Breschi, S. (2003), Are firms in clusters really more innovative?, Economics of Innovation and New Technology 12(4), 325-342.

Beaudry, C., Schiffauerova, A. (2011), Impacts of Collaboration and Network Indicators on Patent Quality: The Case of Canadian Nanotechnology Innovation, European Management Journal 29, 362-376.

Belderbos, R., Carree, M., Diederen, B., Lokshin, B., Veugelers, R. (2004), Heterogeneity in R&D cooperation strategies, International Journal of Industrial Organization 22(8-9), 1237–1263.

Benner M., Waldfogel, J. (2008), Close to you? Bias and precision in patent-based measures of technological proximity, Research Policy 37, 1556–1567.

Benoit, K. (2011), Linear Regression Models with Logarithmic Transformations, http://www.kenbenoit.net/courses/ME104/logmodels2.pdf.

Bercovitz, J., Feldman, M. (2011), The mechanisms of collaboration in inventive teams: Composition, social networks, and geography, Research Policy 40(10), 81-93.

Bergstrom, C. (2007), Eigenfactor: Measuring the value and prestige of scholarly journals, College & Research Libraries News 68(5), 314-316.

Besancenot, D., Vranceanu, R. (2015), Fear of novelty: a model of scientific discovery with strategic uncertainty, Economic Inquiry 58(2), 1132-1139.

Bishop, P.R., Huck, S.W., Ownley, B.H., Richards, J.K., Skolits, G.J. (2014), Impacts of an interdisciplinary research center on participant publication and collaboration patterns: A case study of the National Institute for Mathematical and Biological Synthesis, Research Evaluation 23, 327-340.

Blackwell, A.F., Wilson, L., Street, A., Boulton, C., Knell, J. (2009), Radical innovation: crossing knowledge boundaries with interdisciplinary teams, Technical Report 760, Cambridge University, Cambridge.

BMBF (2012), http://www.hightech-strategie.de/en/468.php (15.05.2012).

Bordons, M., Zulueta, M.A., Romero, F., Barrigón, S. (1999), Measuring interdisciplinary collaboration within a university: The effects of the multidisciplinary research programme, Scientometrics 46(3), 383-398.

Bornmann, L., Leydesdorff, L. (2015), Does quality and content matter for citedness? A comparison with para-textual factors and over time, Journal of Informetrics 9, 419–429.

Boschma, R., Frenken, K. (2010), The spatial evolution of innovation networks: a proximity perspective. In: Boschma R., Martin, R. (Eds.), Handbook of Evolutionary Economic Geography, Edward Elgar, Cheltenham, UK.

Boschma, R.A. (2005), Proximity and innovation: A critical assessment, Regional Studies 39(1), 61-74.

Bosquet, C., Combes, P.-P. (2013), Are academics who publish more also more cited? Individual determinants of publication and citation records, Scientometrics 97, 831–857.

Boyack, K.W., Börner, K. (2003), Indicator-Assisted Evaluation and Funding of Research: Visualizing the Influence of Grants on the Number and Citation Counts of Research Papers, Journal of the Association for Information Science and Technology, 54(5), 447-461.

Braczyk, H.J., Cooke, P., Heidenreich, M. (1998), Regional Innovation Systems: The Role of Governance in a Globalized World, UCL Press, London.

Brenner, T., Schlump, C. (2011), Policy measures and their effects in the different phases of the cluster life cycle, Regional Studies, 45(10), 1363-1386.

Breschi, S., Malerba, F., Orsenigo, L. (2000), Technological Regimes and Schumpeterian Patterns of Innovation, The Economic Journal 110(463), 388-410.

Breschi, S., Lissoni, F. (2001), Knowledge Spillovers and Local Innovation Systems: A Critical Survey, Industrial and Corporate Change 10(4), 975-1005.

Breschi, S., Lissoni, F., (2003), Mobility and social networks: localised knowledge spillovers revisited, Proceedings of the Workshop on Empirical Economics of Innovation and Patenting, Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim, 14–15 March.Breschi, S., Lissoni, F. (2009), Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows, Journal of Economic Geography 9(4), 439-468.

Breschi, S., Lissoni, F., Malerba, M. (2003), Knowledge relatedness in firm technological diversification, Research Policy 32, 69–87.

Breschi, S., Malerba, F. (1997), Sectoral systems of innovation: technological regimes, Schumpeterian dynamics and spatial boundaries. In: Edquist, C. (Ed.), Systems of innovation, Pinter Publishers/Cassell Academic, London.

Brewer, G.D. (1999), The challenges of interdisciplinarity, Policy Sciences 32(4), 327-337.

Broekel, T. (2012), The co-evolution of proximities - a network level study, Papers in Evolutionary Economic Geography 1217, Utrecht University, Section of Economic Geography, revised Sep 2012.

Broekel, T., Balland P.A., Burger, M., van Oort, F. (2014), Modeling Knowledge Networks in Economic Geography: A Discussion of Four Empirical Strategies, The Annals of Regional Science, forthcoming.

Broekel, T., Boschma, R. (2012), Knowledge networks in the Dutch aviation industry: the proximity paradox, Journal of Economic Geography 12(2), 409-433.

Brown, M.G., Svenson, R.A. (1988), Measuring R&D Productivity, Research Technology Management 41(6), 11-15.

Bruce, A., Lyall, C., Tait, J., Williams, R. (2004), Interdisciplinary integration in Europe: the case of the Fifth Framework programme, Futures 36, 457-470.

Butler, L. (2001), Revisiting bibliometric issues using new empirical data, Research Evaluation 10(1), 59–65.

Caliendo, M., Kopeinig, S. (2008), Some Practical Guidance for the Implementation of Propensity Score Matching, Journal of Economic Surveys 22(1), 31-72.

Cantner, U., Graf, H. (2003), Innovationssysteme und kollektive Innovationsprozesse: Einige theoretische Grundlagen, In U. Cantner, R. Helm & R. Meckl, (Eds.), Strukturen und Strategien in einem Innovationssystem - Das Beispiel Jena, Verlag Wissenschaft & Praxis.

Cantner U., Conti, E., Meder, A. (2010), Networks and innovation: the role of social assets in explaining firms' innovative capacity, European Planning Studies 18, 1937-1956.

Cantner U., Graf H. (2006), The Network of Innovators in Jena: An Application of Social Network Analysis, Research Policy 35, 463-480.

Cantner U., Meder A. (2007), Technological Proximity and the Choice of Cooperation Partners, Journal of Economic Interaction and Coordination 2, 45-65.

Cantner U., Meder, A., Wolf, T., (2011), Intermediation, reciprocity and innovation cooperations of firms, Papers in Regional Science 90(2), 313-330.

Cantner, U. ,Rake, B. (2014), International research networks in pharmaceuticals: Structure and dynamics, Research Policy 43, 333-348.

Cantner, U., Graf, H. (2003), Innovationssysteme und kollektive Innovationsprozesse: Einige theoretische Grundlagen. In: Cantner, U., Helm, R., Meckl, R. (Eds.), Strukturen und Strategien in einem Innovationssystem - Das Beispiel Jena, Verlag Wissenschaft & Praxis, Sternenfels, Deutschland.

Cantner, U., Graf, H. (2011), Innovation Networks: formation, performance and dynamics. In: Antonelli, C. (Ed.), Handbook on the Economic Complexity of Technological Change, Ch. 15, Edward Elgar, Cheltenham UK.

Carayol, N., Thi, T.U.N. (2005), Why do academic scientists engage in interdisciplinary research?, Research Evaluation 14(1), 70-79.

Carlsson, B., Jacobsson, S., (1997), In Search of Useful Public Policies: Key Lessons and Issues for Policy Makers. In: Carlsson, B. (Ed.), Technological Systems and Industrial Dynamics, Kluwer Academic Publishers, Dortrecht.

Carlsson, B., Jacobsson, S., Holmén, M., Rickne, A. (2002), Innovation systems: analytical and methodological issues, Research Policy 31(2), 233-245.

Cassi, L., Morrison, A., Rabellotti, R. (2014), Proximity and scientific collaboration: Evidence from the global wine industry, Papers in Evolutionary Economic Geography (PEEG) 1405, Utrecht University.

Cassi, L., Plunket, A. (2012), Research collaboration in co-inventor networks: combining closure, bridging and proximities, MPRA Paper 39481, University Library of Munich, Germany.

Cassi, L., Plunket, A. (2014), Proximity, network formation and inventive performance: in search of the proximity paradox, The Annals of Regional Science 53(2), 395-422.

Cassiman, B., Veugelers, R. (2002), R&D Cooperation and Spillovers: Some Empirical Evidence from Belgium, The American Economic Review, 92(4), 1169-1184.

Cohen, W., Levinthal, D. (1990), Absorptive capacity: a new perspective on learning and innovation, Administrative Science Quarterly 35(1), 128–152.

Cooke, P. (2001), Regional Innovation Systems, Clusters, and the Knowledge Economy, Industrial and Corporate Change 10 (4), 945-974.

Cooke, P., Morgan, K., (1994), The regional innovation system in Baden-Württemberg, International Journal of Technology Management 9(3-4), 394-429.

Cooke, P., Uranga, M.G., Etxebarria, G. (1997), Regional innovation systems: Institutional and organisational dimensions, Research Policy 26(4-5), 475-491.

Coppin, A. (2013), Finding Science and Engineering Specific Data Set Usage or Funding Acknowledgements, Issues in Science and Technology Librarianship, DOI:10.5062/F4CV4F.

Costas, R., Leeuwen, T.N.V (2012), Approaching the "reward triangle": General analysis of the presence of funding acknowledgments and "peer interactive communication" in scientific publications, Journal of the Association for Information Science and Technology 63(8), 1647-1661.

Cowan, R., Jonard, N. (2004), Network structure and the diffusion of knowledge, Journal of Economic Dynamics and Control, 28(8), 1557-1575.

Cowan, R., van de Paal, G. (2000), Innovation Policy in a Knowledge-Based Economy, Publication no. EUR 17023 of the Commission of the European Communities, Luxembourg.

Cowan, R.; David, P., Foray, D. (2000), The explicit economics of knowledge codification and tacitness, Industrial and Corporate Change 9(2), 211-254.

Crescenzi, R. (2014), The evolving dialogue between Innovation and Economic Geography. From physical distance to non-spatial proximities and 'integrated' frameworks, Papers in Evolutionary Economic Geography (PEEG) 1408, Utrecht University.

Crescenzi, R., Gagliardi, L., Percoco, M. (2013), Social capital and the innovative performance of Italian provinces, Environment and Planning 45, 908-929.

Criscuolo, P., Salter, A., ter Wal, A. (2010), The role of proximity in shaping knowledge sharing in professional services firms. Paper presented at the Summer Conference 2010 on "Opening Up Innovation: Strategy, Organization and Technology" at Imperial College London Business School, June 16 - 18.

Cronin, B., Shaw, D. (1999), Citation, funding acknowledgement and author nationality relationships in four information science journals, Journal of Documentation 55(4), 402–408.

Cronin, B., Shaw, D., La Barre, K. (2004), Visible, less visible, and invisible work: patterns of collaboration in 20th century chemistry, Journal of the American Society for Information Science and Technology 55(2), 160-168.

Cummings, J.N., Kiesler, S. (2005), Collaborative research across disciplinary and organizational boundaries, Social Studies of Science 35(5), 703-722.

Czarnitzki, D., Fier, A. (2003), Publicly Funded R&D Collaborations and Patent Outcome in Germany, ZEW Discussion Papers 03-24, ZEW - Zentrum für Europäische Wirtschaftsforschung / Center for European Economic Research.

Czarnitzki, D., Hall, B.H., Oriani, R. (2006), The market valuation of knowledge assets in US and European firms. In: Bosworth, D., Webster, E. (Eds.), The Management of Intellectual Property, Edward Elgar Publishing Inc..

Czarnitzki, D., Lopes-Bento, C. (2014), Innovation Subsidies: Does the Funding Source Matter for Innovation Intensity and Performance? Empirical Evidence from Germany, Industry and Innovation 21(5), 380-409.

Czarnitzki, D., Toivanen, O. (2013), Innovation Policy and Economic Growth, European Economy - Economic Papers 2008 - 2015 482, Directorate General Economic and Financial Affairs (DG ECFIN), European Commission.

d'Aspremont, C., Jacquemin, A. (1988), Cooperative and Noncooperative R&D in Duopoly with Spillovers, American Economic Review 78(5), 1133-1137.

Dahlander, L., McFarland, D.A. (2013), Ties that last: Tie Formation and Persistence in Research Collaborations over Time, Administrative Science Quarterly 58, 69-110.

Dekker, D., Krackhardt, D. (2007), Sensitivity of MRQAP tests to collinearity and autocorrelation conditions, Psychometrika 72, 563-581.

D'Este, P., Iammarino, S. (2010), The spatial profile of university-business research partnerships, Papers in Regional Science 89(2), 335-350.

Dosi, G, Nelson, R.R. (1994), An Introduction to Evolutionary Theories in Economics, Journal of Evolutionary Economics 4(3), 153-172.

Dosi, G. (1982), Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change, Research Policy 11(3), 147-62.

Dosi, G., Nelson, R.R. (2013), The Evolution of Technologies: An Assessment of the State-of-the-Art, Eurasian Business Review, 3(1), 3-46.

Easterly, W., Levine, R. (2001), It's Not Factor Accumulation: Stylized Facts and Growth Models, The World Bank Economic Review 15(2), 177-219.

Ebadi, A., Schiffauerova, A. (2015), How to Receive More Funding for Your Research? Get Connected to the Right People!, PLoS ONE 10(7), DOI:10.1371/journal.pone.0133061.

Edquist, C. (1997), Systems of innovation: Technologies, institutions and organizations, London, Pinter Publishers.

Edquist, C. (2005), Systems of innovation - perspectives and challenges, In J. Fagerberg, D. Mowery & R. Nelson,(Eds.), The Oxford Handbook of Innovation, Oxford Univerity Press.

Eickelpasch, A., Fritsch, M. (2005), Contests for cooperation - A new approach in German innovation policy, Research Policy 34(8), 1269-1282.

Engel, D., Mitze, T., Patuelli, R., Reinkowski, J. (2012), Does Cluster Policy Trigger R&D Activity? Evidence from German Biotech Contests, European Planning Studies, forthcoming (http://ssrn.com/abstract=2007931).

Fagerberg, J., Srholec, M., Verspagen, B. (2009), Innovation and Economic Development. In: Hall, B., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, North Holland.

Falck, O., Heblich, S., Kipar, S. (2010), Industrial innovation: Direct evidence from a cluster-oriented policy, Regional Science and Urban Economics 40(6), 574-582.

Fedderke, J.W., Goldschmidt, M. (2015), Does massive funding support of researchers work?: Evaluating the impact of the South African research chair funding initiative, Research Policy 44, 467-482.

Feldman, M.P. (1994), The Geography of Innovation, Kluwer Academic Publishers, Dortrecht.

Feller, I. (2006), Multiple actors, multiple settings, multiple criteria: issues in assessing interdisciplinary research, Research Evaluation 15(1), 5-15.

Fidjar, R.D., Huber, F., Rodriguez-Pose, A. (2015), Not too close, not too far. Towards an Empirical Test of the Goldilocks Principle of Non-Geographical Distance in Collaboration Networks for Innovation, Paper presented at DRUID 15, Rome, June 15 – 17.

Flanagan, K., Uyarra, E., Laranja, M. (2011), Reconceptualising the 'policy mix' for innovation, Research Policy 40(5), 702-713.

Fontagné, L., Koenig, P., Mayneris, F., Poncet, S. (2010), Clustering the Winners: the French Policy of Competitiveness Clusters, CEPII Working Papers No. 2010-18, CEPII.

Fornahl, D., Broekel, T., Boschma, R. (2011), What drives patent performance of German biotech firms? The impact of R&D subsidies, knowledge networks and their location, Papers in Regional Science 90(2), 395-418.

Freeman, C. (1987), Technology policy and economic performance: lessons from Japan., Pinter, London.

Freeman, C. (1991), Networks of Innovators: A Synthesis of Research Issues, Research Policy 20, 499-514.

Freeman, C., Soete, L. (1997), The Economics of Industrial Innovation, 3rd edition, MIT Press, Cambridge.

Freeman, L.C. (1979), Centrality in Social Networks: Conceptual clarification, Social Networks 1, 215-239.

Freeman, C. and Lundvall, B.-Å. (1988), Small Countries Facing the Technological Revolution, London: Pinter Publishers.

Frenken, K., van Oort F.G., Verburg, T. (2007), Related variety, unrelated variety and regional economic growth, Regional Studies 41(5), 685-697.

Galliano, D., Magrini, M.B., Triboulet, P. (2014), Marshall's versus Jacobs' Externalities in Firm Innovation Performance: The Case of French Industry, Regional studies, forthcoming.

Garcia, R., Araujo, V.C., Mascarini, S., Santos, E.G., Costa, A. (2013), Geographical proximity and the role of the quality of academic research to the university-industry linkages, presented at the Regional Studies Association European Conference 2013 "Shape and be Shaped: The Future Dynamics of Regional Development", RSA 2013, Tampere, May 5-8.

Geuna, A., Martin, B.R. (2003), University Research Evaluation and Funding: An International Comparison, Minerva 41(4), 277-304.

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., Trow, M. (1994), The New Production of Knowledge - The Dynamics of Science and Research in Contemporary Socities, Sage, London.

Gilsing, V., Nooteboom, B., Vanhaverbeke, W., Duysters, G., van den Oord, A. (2008), Network embeddedness and the exploration of novel technologies: Technological distance, betweenness centrality and density, Research Policy 37, 1717-1731.

Giuliani, E. (2007), The selective nature of knowledge networks in clusters: evidence from the wine industry, Journal of Economic Geography 7(2), 139-168.

Giuliani, E., Pietrobelli, C. (2011), Social Network Analysis – Methodologies for the Evaluation of Cluster Development Programs, Technical Notes No. IDB-TN-317, Inter-American Development Bank.

Goossen, M. (2013), Community-spanning, network-spanning, and scientist innovativeness, DRUID working paper, presented at 35th DRUID Celebration Conference 2013, Barcelona, Spain, June 17-19.

Granovetter, M. (2005), The Impact of Social Structure on Economic Outcomes, Journal of Economic Perspectives 19, 33-50.

Grant, R.M., Baden-Fuller, C. (1995), A Knowledge-Based Theory of Inter-Firm Collaboration, Academy of Management Annual Meeting Proceedings, 17-21.

Griliches, Z. (1990), Patent statistics as economic indicators: a survey, Journal of Economic Literature 28, 1661–1707.

Gulati, R. (1995), Does familiarity breed trust? The implications of repeated ties for contractual choice in alliances, Academy of Management Journal 38, 85–112.

Gulati, R. (1999), Network location and learning: the influence of network resources and firm capabilities on alliance formation, Strategic Management Journal 20, 397–420.

Gulati. R., Gargiulo, M. (1999), Where do interorganizational networks come from?, American Journal of Sociology 104, 1939-1493.

Hagedoorn, J. (2002), Inter-firm R&D partnerships: an overview of major trends and patterns since 1960, Research Policy 31(4), 477-492.

Hagedoorn, J., Frankort H.T.W. (2008), The gloomy side of embeddedness: The effects of over-embeddedness on inter-firm partnership formation, Advances in Strategic Management 25, 503-530.

Hall, B.H. (2007), Measuring the Returns to R&D: The Depreciation Problem, NBER Working Paper 13473.

Hall, B.H., Jaffe, A.B., Trajtenberg, M. (2001), The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools, NBER Working Paper 8498.

Hamel, G. (1991), Competition for competence and interpartner learning within international strategic alliances, Strategic Management Journal 12(51), 83–103.

Hazir; S., Autant-Bernard, C. (2011), Conceptualizing the Role of Geographical Proximity in Project Based R&D Networks: A Literature Survey. ERSA conference papers ersa11p1616, European Regional Science Association.

Heckman, J.J. (1981), Heterogeneity and State Dependence, NBER Chapters. In: Studies in Labor Markets, pages 91-140, National Bureau of Economic Research, Inc.

Heinrich, C., Maffioli, A., Vásquez, G. (2010), A Primer for Applying Propensity-Score Matching, Inter-American Development Bank, Technical Notes No. IDB-TN-161.

Hellerstein, J.K. (1998), Public Funds, Private Funds, and Medical Innovation: How Managed Care Affects Public Funds for Clinical Research, The American Economic Review 88(2), 112-116.

Ho, D.E., Imai, K., King, G., Stuart, E. (2007), Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference, Political Analysis 15(3), 199-236.

Ho, D.E., Imai, K., King, G., Stuart, E. (2011), MatchIt: Nonparametric Preprocessing for Parametric Causal Inference, Journal of Statistical Software 42(8), 1-28.

Hollingsworth, J.R. (2006), A path-dependent perspective on institutional and organizational factors shaping major scientific discoveries. In:Hage, J., Meeus, M. (Eds.), Innovation, Science, and Institutional Change. Oxford University Press, Oxford, 423-442.

Horlick-Jones, T., Sime, J. (2004), Living on the border: knowledge, risk and transdisciplinarity, Futures 36, 441-456.

Huutoniemi, K., Klein, J.T., Bruun, H., Hukkinen, J. (2010), Analyzing interdisciplinarity: Typology and indicators, Research Policy 39, 79-88.

Imbens, G.W.,. Wooldridge, J.M. (2008), Recent Developments in the Econometrics of Program Evaluation, Journal of Economic Literature 47, 5-86.

Jaffe A.B., Trajtenberg M., Henderson R. (1993), Geographic localisation of knowledge spillovers as evidenced by patent citations, Quarterly Journal of Economics 10, 577-598.

Jaffe, A. (1986), Technological opportunity and spillovers of R&D: evidence from firms' patents, profits, and market value, American Economic Review 76, 985–1001.

Katz, J.S. (1994), Geographical proximity and scientific collaboration, Scientometrics 31(1), 31-43.

Katz, J.S., Martin, B.R. (1997), What is research collaboration?, Research Policy 26(1), 1-18.

Kennedy, P. (2009), A Guide to Econometrics, Blackwell Publishing.

Khanna, T., Gulati, R., Nohria, N. (1998), The dynamics of learning alliances: Competition, cooperation and relative scope, Strategic Management Journal 19, 193-210.

King, G., Nielsen, R. (2016), Why Propensity Scores Should Not Be Used for Matching, Working Paper.

Kline, S.J., Rosenberg, N. (1986), An overview of innovation. In: Landau, R., Rosenberg, N. (Eds), The Positive Sum Strategy: Harnessing Technology for Economic Growth, National Academy Press, Washington DC.

Kogut B., Shan, W., Walker, G. (1992), The Make or Cooperate Decision in the Context of an Industry Network. In: Nohria, N., Eccles, R. (Eds.), Networks and Organizations, Cambridge, 348-365.

Koschatzky, K. (2000), The Regionalisation of Innovation Policy in Germany – Theoretical Foundations and Recent Experience. Working Papers Firms and Region No. R1/2000. Fraunhofer Institute for Systems and Innovation Research.

Larivière, V., Gingras, Y. (2010), On the Relationship Between Interdisciplinarity and Scientific Impact, Journal of the Association for Information Science and Technology 61(1), 126–131.

Laudel, G., Origgi, G. (2006), Introduction to a special issue on the assessment of interdisciplinary research, Research Evaluation 15(1), 2-4.

Lecocq, C., Leten, B., Kusters, J., Van Looy, (2009), Do Firms benefit from being present in Technology Clusters? Evidence from a Panel of Biopharmaceutical Firms, Open Access Publications from Katholieke Universiteit Leuven, Katholieke Universiteit Leuven.

Lee, Y.-N., Walsh, J.P., Wang, J. (2015), Creativity in scientific teams:Unpacking novelty and impact, Research Policy 44, 684–697.

Lepori, B., van den Besselaar, P., Dinges, M., van der Meulen, B., Potì, B., Reale, E., Slipersaeter, S., Theves, J. (2007), Indicators for comparative analysis of public project funding: concepts, implementation and evaluation, Research Evaluation 16(4), 243-255.

Lewison, G., Dawson, G. (1998), The effect of funding on the outputs of biomedical research, Scientometrics 41(1), 17-27.

Lewison, G., Devey, M.E. (1999), Bibliometric methods for the evaluation of arthritis research, Rheumatology 38(1), 13-20.

Lewison, G., Lipworth, S., de Francisco, A. (2002), Input indicators from output measures: a bibliometric approach to the estimation of malaria research funding, Research Evaluation 11(3), 155-163.

Leydesdorff, L., Rafols, I. (2011), Indicators of the interdisciplinarity of journals: Diversity, centrality, and citations, Journal of Informetrics 5(1), 87-100.

Leydesdorff, L., Rafols, I. (2012), Interactive overlays: A new method for generating global journal maps from Web-of-Science data, Journal of Informetrics 6(2), 318-332.

Lhuillery, S., Pfister, E. (2009), R&D cooperation and failures in innovation projects: Empirical evidence from French CIS data, Research Policy 38(1), 45-57.

Linder, R. (2010), Innovationspolitik bei Querschnittstechnologien – Das Beispiel Medizintechnik, TAB-Brief Nr. 37, Schwerpunkt: Innovationen im Gesundheitssystem.

Lundvall, B. A. (1992), National Systems of Innovation: Towards a theory of innovation and interactive learning, London: Pinter.

Lundvall, B.-Å, Johnson, B. (1994), The learning economy, Journal of Industry Studies 1(2), 23-42.

Lundvall, B.-Å. (1988), Innovation as an Interactive Process – From User-Producer Interaction to the National System of Innovation, In: Dosi, G., Freeman, C., Nelson, R., Silverberg, G., Soete, L. (Eds.), Technical Change and Economic Theory, Pinter Publishers, London.

Lundvall, B.A. (2007), Innovation System Research and Policy - Where it came from and where it might go, Paper to be presented at CAS Seminar, Oslo.

Lyall, C., Bruce, A., Marsden, W., Meagher, L. (2013), The role of funding agencies in creating interdisciplinary knowledge, Science and Public Policy 40, 62-71.

Malerba, F. (2002), Sectoral systems of innovation and production, Research Policy 31(2), 247-264.

Malerba, F., Orsenigo, L. (1997), Technological Regimes and Sectoral Patterns of Innovative Activities, Industrial and Corporate Change 6(1), 83-118.

Mansfield, E. (1998), Academic research and industrial innovation: An update of empirical findings, Research Policy 26, 773-776.

Mansfield, E., Lee, .J (1996), The modern university: contributor to industrial innovation and receipt of industrial R&D support, Research Policy 25, 1047–1058.

Mansila, V.B. (2006), Assessing expert interdisciplinary work at the frontier: an empirical exploration, Research Evaluation 15(1), 17-29.

Maraut, S., Dernis, H., Webb, C., Spiezia, V., Guellec, D. (2008), The OECD REGPAT Database: A Presentation, OECD Science, Technology and Industry Working Papers 2008/02, OECD Publishing.

March, J.G. (1991), Exploration and Exploitation in Organizational Learning, Organization Science 2(1), 71–87.

Marshall, A. (1890), Principles of Economics: An Introductory Volume, MacMillan, London.

Martin, P., Thierry, M., Mayneris, F. (2011), Public support to clusters – A firms level study of French "Local Productive Systems", Regional Science and Urban Economics 41, 108-123.

Martin, R., Sunley, P. (2003), Deconstructing clusters: chaotic concept or policy panacea?, Journal of Economic Geography. 3(1), 5–35.

Marx, W., Bornmann, L. (2012), Der Journal Impact Factor: Aussagekraft, Grenzen und Alternativen in der Forschungsevaluation, Beiträge zur Hochschulforschung, 34. Jahrgang, 2/2012.

McKelvey, M. (1997), Coevolution in commercial genetic engineering, Industrial and Corporate Change 6, 503-532.

McPherson M., Smith-Lovin, L., Cook J.M. (2001), Birds of a Feather: Homophily in Social Networks, Annual Review of Sociology 27, 415–44.

Metcalfe, J.S. (1995), Technology Systems and Technology Policy in an Evolutionary Framework, Cambridge Journal of Economics, 19(1), 25-46.

Metcalfe, J.S., James, A., Mina, A. (2005), Emergent innovation systems and the delivery of clinical services: The case of intra-ocular lenses, Research Policy 34(9), 1283-1304.

Mora-Valentin, E., Montoro-Sanchez, A., Guerras-Martin, L.A. (2004), Determining factors in the success of R&D cooperative agreements between firms and research organizations, Research Policy 33, 17-40.

Morillo, F., Bordons, M., Gómez, I. (2003), Interdisciplinarity in science: A tentative typology of disciplines and research areas, Journal of the American Society for Information Science and Technology 54(13), 1237-1249.

Mowery, D.C., Oxley, J.E., Silverman, B.S. (1996), Strategic alliances and inter-firm knowledge transfer, Strategic Management Journal 17, 77–91.

Mowery, D.C., Oxley, J.E., Silverman, B.S. (1998), Technological Overlap and Interfirm Cooperation: Implications for the Resource-Based View of the Firm, Research Policy 27, 507-523.

Nelson, A.J. (2009), Measuring knowledge spillovers: What patents, licenses and publications reveal about innovation diffusion, Research Policy 38, 994-1005.

Nelson, R.R. (1993), National Innovation Systems, Oxford University Press, Oxford.

Nelson, R.R., Winter, S. (1982), An Evolutionary Theory of Economic Change, The Belknap Press of Harvard University Press, Cambridge.

Nishimura, J., Okamuro, H. (2011), R&D productivity and the organization of cluster policy: an empirical evaluation of the Industrial Cluster Project in Japan, Journal of Technology Transfer, 36(2), 117-144.

Nissani, M. (1997), Ten cheers for interdisciplinarity: the case for interdisciplinary knowledge and research, The Social Science Journal 34(2), 201–216.

Nomaler, O., Verspagen, B. (2008), Knowledge Flows, Patent Citations and the Impact of Science on Technology, Economic Systems Research 20, 339-366.

Nooteboom, B. (1998), Cost, quality and learning based governance of buyer-supplier relations. In: Colombo, M.G. (Ed.), The Changing Boundaries of the Firm, Routledge, London, pp. 187-208.

Nooteboom, B. (1999), Innovation and inter-firm linkages: new implications for policy, Research Policy 28, 793–805.

Nooteboom, B. (2005), Learning and Governance in Inter-Firm Relations, Discussion Paper 2005-38, Tilburg University, Center for Economic Research.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., van den Oord, A. (2007), Optimal cognitive distance and absorptive capacity, Research Policy 36, 1016–1034.

OECD (2006), Revised Field of Science and Technology (FOS) Classification in the Frascati Manual, OECD Working Paper, DSTI/EAS/STP/NESTI(2006)19/FINAL, JT03222603.

Oerlemans, L., Meeus, M. (2005), Do organizational and spatial proximity impact on firm performance?, Regional studies 39(1), 89-104.

Paier, M., Scherngell, T. (2008), Determinants of collaboration in European R&D networks: Empirical evidence from a binary choice model perspective, SSRN 1120081.

Penrose, E. (1959), The theory of the growth of the firm, Oxford University Press, Oxford.

Polanyi, M. (1966), The Tacit Dimension, Doubleday Anchor.

Polanyi, M., (1962), Personal knowledge: Toward a post critical philosophy, University of Chicago Press, Chicago.

Porter, A.L., Chubin, D.E. (1985), An indicator of cross-disciplinary research, Scientometrics, 8(3), 161-176.

Porter, A.L., Cohen, A.S., Roessner, J.D., Perreault, M. (2007), Measuring researcher interdisciplinarity, Scientometrics 72(1), 117-147.

Porter, A.L., Garner, J., Crowl, T. (2012), Research Coordination Networks: Evidence of the Relationship between Funded Interdisciplinary Networking and Scholarly Impact, BioScience 62(3), 282-288.

Porter, A.L., Rafols, I. (2009), Is science becoming more interdisciplinary? Measuring and mapping six research fields over time, Scientometrics 81(3), 719-745.

Porter, A.L., Roessner, J.D., Cohen, A.S., Perreault, M. (2006), Interdisciplinary research: meaning, metrics and nurture, Research Evaluation 15(3), 187-195.

Porter, A.L., Roessner, J.D., Heberger, A.E. (2008), How interdisciplinary is a given body of research?, Research Evaluation 17(4), 273-282.

Porter, M. (1990), The Competitive Advantage of Nations, Free Press, New York.

Porter, M. (1998), Clusters and the New Economics of Competition, Harvard Business Review 76(6), 77-90.

Powell, W.W. (1998), Learning From Collaboration: Knowledge and Networks in the Biotechnology and Pharmaceutical Industries, California Management Review 40, 228-40.

Powell, W.W., Grodal, S. (2006), Networks of Innovators. In: Fagerberg, J., Mowery, D., Nelson, R. (Eds.), The Oxford Handbook of Innovation. Oxford University Press, 291-317.

Powell, W.W., Koput, K.W., Smith-Doerr, L. (1996), Interorganizational collaboration and the locus of innovation: networks of learning in biotechnology, Administrative Science Quarterly 41, 116-145.

Rafols, I., Leydesdorff, L., O'Hare, A., Nightingale, P, Stirling, A. (2012), How journal rankings can suppress interdisciplinary research: A comparison between Innovation Studies and Business & Management, Research Policy 41, 1262-1282.

Rafols, I., Meyer, M. (2010), Diversity and network coherence as indicators of interdisciplinarity: case studies in bionanoscience, Scientometrics 82(2), 263-287.

Rigby, J. (2011), Systematic grant and funding body acknowledgment data for publications: New dimensions and new controversies for research policy and evaluation, Research Evaluation 20(5), 365–375.

Rigby, J. (2013), Looking for the impact of peer review: does count of funding acknowledgements really predict research impact?, Scientometrics 94, 57-73.

Rogers, E.M., Bhowmik, D.K. (1970), Homophily-Heterophily: Relational Concepts for Communication Research, Public Opinion Quarterly 34, 523-538.

Romer, P.M. (1990), Endogenous technical change, Journal of Political Economy 98(5), 71-102.

Rosenbaum, P.R., Rubin, D.B. (1983), The central role of the propensity score in observational studies for causal effects, Biometrika 70(1), 41-55.

Rosenberg, N. (1982), Inside the Black Box, Cambridge University Press, Cambridge.

Rosenberg, N. (2004), Innovation and Economic Growth. OECD 2004, p.1-6 www.oecd.org/dataoecd/55/49/3426/7902.pdf

Rothgang, M., Cantner, U., Dehio, J., Engel, D., Fertig, M., Graf, H., Hinzmann, S., Linshalm, E., Ploder, M., Scholz, A.-M., Töpfer, S. (2014), Accompanying evaluation of the funding instrument "Spitzencluster-Wettbewerb" (Leading-Edge Cluster Competition) of the federal ministry of education and research : research project for the federal ministry of education and research ; final report - Summary ; 11/2008 - 4/2014, RWI Materialien; 83.

Rotolo, D., Hopkins, M., Grassano, N. (2014), Do Funding Sources Complement? The Case of the UK Cancer Research, Working Paper.

Schmidt, J.C. (2008), Towards a philosophy of interdisciplinarity: An attempt to provide a classification and clarification, Poiesis & Praxis 5(1), 53-69.

Schmoch, U. (1993), Tracing the knowledge transfer from science to technology as reflected in patent indicators, Scientometrics 26, 193-211.

Schmoch, U., Breiner, S, Cuhls, K., Hinze, S., Münt, G. (1994), Interdisciplinary cooperation of research teams in science-intensive areas of technology. Final report to the Commission of the European Unit (VALUE II, Interface II, HS1). Fraunhofer Institute for Systems and Innovation Research, Karlsruhe.

Schummer, J. (2004), Multidisciplinarity, interdisciplinarity, and patterns of research collaboration in nanoscience and nanotechnology, Scientometrics 59(3), 425-465.

Schumpeter, J.A. (1934), The Theory of Economic Development: An Inquiry into Profits, Capital, Credit,

Schumpeter, J.A. (1942), Capitalism, Socialism and Democracy, London, Unwin.

Shannon, C.E. (1948), A Mathematical Theory of Communication, The Bell System Technical Journal 27, 379-423, 623-656.

Singh, J. (2005), Collaborative Networks as Determinants of Knowledge Diffusion Patterns, Management Science 51(1), 756-770.

Singh, J., Fleming, L. (2010), Lone Inventors as Sources of Breakthroughs: Myth or Reality?, Management Science 56(1), 41-56.

Smith, R. (2002), Making progress with competing interests - Still some way to go, BMJ 325, 1375–1376.

Smits, R., Kuhlmann, S. (2004), The rise of systemic instruments in innovation policy, International Journal of Foresight and Innovation Policy 1(1/2), 4-32.

Solow, R. (1956), A Contribution to the Theory of Economic Growth, Quarterly Journal of Economics 70, 65–94.

Solow, R. (1957), Technical change and the aggregate production function, Review of Economics and Statistics 39(3), 312–320.

Staber, U. (2001), Spatial Proximity and Firm Survival in a Declining Industrial District: The Case of Knitwear Firms in Baden-Württemberg, Regional Studies 35, 329-341.

Staehler, T., Dohse, D., Cooke, P. (2007), Evaluation der Fördermaßnahmen BioRegio und BioProfile, http://www.e-fi.de/fileadmin/Evaluationsstudien/Evaluation_der_Foerdermassnahmen_BioRegio_und_BioProfile.pdf (18.05.2012).

Steele, T.W., Stier, J.C. (2000), The impact of interdisciplinary research in the environmental sciences: A forestry case study, Journal of the American Society for Information Science 51(5), 476-484.

Sternberg, R. (2000), Innovation Networks and Regional Development - Evidence from the European Regional Innovation Survey (ERIS): Theoretical Concepts, Methodological Approach, Empirical Basis and Introduction to the Theme Issue, European Planning Studies 8(4), 389-407.

Stirling, A. (2007), A general framework for analysing diversity in science, technology and society, Journal of The Royal Society Interface 4(15), 707-719.

Strumsky, D., Lobo, J. (2015), Identifying the sources of technological novelty in the process of invention, Research Policy 44, 1445–1461.

Stuart, T.E. (2000), Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry, Strategic Management Journal 21, 791-811.

Teece, D.J. (1992), Competition, cooperation, and innovation: Organizational arrangements for regimes of rapid technological progress, Journal of Economic Behavior and Organization 18(1), 1-25.

Teece, D.J. (1996), Firm organization, industrial structure, and technological innovation, Journal of Economic Behavior & Organization 31(2), 193-224.

ter Wal, A., (2014), The dynamics of the inventor network in German biotechnology: geographic proximity versus triadic closure, Journal of Economic Geography 14, 589-620.

ter Wal, A., Boschma, R. (2009), Applying Social Network Analysis in Economic Geography: Framing Some Key Analytical Issues, Annals of Regional Science 43(3), 739-756.

ter Wal, A.L.J., Boschma, R. (2011), Co-evolution of Firms, Industries and Networks in Space, Regional Studies 45(7), 919-933.

Thelwall, M., Wilson, P. (2014), Regression for citation data: An evaluation of different methods, Journal of Informetrics 8(4), 963–971.

Torre, A., Wallet, F., (2014), Introduction. The role of proximity relations in regional and territorial development processes. In: Torre, A., Wallet, F. (Eds), Regional development and proximity relations, New Horizons in regional Science, Edward Elgar, London, 375-419.

Uzzi, B. (1997), Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness, Administrative Science Quarterly 42, 35-67.

Uzzi, B., Mukherjee, S., Stringer, M., Jones, B. (2013), Atypical combinations and scientific impact, Science 342, 468–472.

Uzzi, B., Spiro, J. (2005), Collaboration and Creativity: The Small World Problem, American Journal of Sociology 111(2), 447-504.

Van Oort, F., de Geus, S., Dogaru,T. (2015), Related variety and regional economic growth in a cross-section of European urban regions, European Planning Studies 23(6), 1110-1127.

van Raan, A.F.J., van Leeuwen, Th.N. (2002), Assessment of the scientific basis of interdisciplinary, applied research - Application of bibliometric methods in Nutrition and Food Research, Research Policy 31, 611-632.

van Rijnsoever, F.J., Hessels, L.K. (2011), Factors associated with disciplinary and interdisciplinary research collaboration, Research Policy 40, 463-472.

Verhoeven, D., Bakker, J., Veugelers, R. (2015), Measuring technological novelty with patent-based indicators, Working Paper, KU Leuven.

Veugelers, R.(1998), Collaboration in R&D: An Assessment of Theoretical and Empirical Findings, De Economist (1998) 146: 419 - 443.

von Hippel, E. (1988), The Sources of Innovation, Oxford University Press, New York.

Wagner, C.S., Roessner, J.D., Bobb, K., Klein, J.T., Boyack, K.W., Keyton, J., Rafols, I., Börner, K. (2011), Approaches to understanding and measuring interdisciplinary scientific research (IDR): A review of the literature, Journal of Informetrics 165, 14-26.

Walker, W., Harremoes, P., Rotmans, J., Van der Sluijs, J., Van Asselt, M., Janssen, P., Krayer von Krauss, M. (2003), Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support, Integrated Assessment 4, 5-17.

Wang, J., Shapira, P. (2011), Funding Acknowledgement Analysis – An Enhanced Tool to Investigate Research Sponsorship Impacts: The Case of Nanotechnology, Scientometrics 87(3), 563-586.

Wang, X., Liu, D., Ding, K., Wang, X. (2012), Science funding and research output: a study on 10 countries, Scientometrics 91, 591-599.

Winter, S.G. (1984), Schumpeterian competition in alternative technological regimes, Journal of Economic Behavior and Organization 5, 287-320.

Wooldridge, J.M. (2002), Econometric Analysis of Cross Section and Panel Data, The MIT Press, Cambridge.

Wuyts, S., Colombo, M. G., Dutta, S., Nooteboom, B. (2005), Empirical tests of optimal cognitive distance, Journal of Economic Behavior & Organization 58, 277-302.

Yang, H., Phelps, C. C., Steensma, K. (2010), Learning from What Others Have Learned from You: The Effects of Knowledge Spillovers on Originating Firms, Academy of Management Journal 53, 371-390.

Yegros-Yegros, A., Rafols, I., D'Este, P. (2015), Does Interdisciplinary Research Lead to Higher Citation Impact? The Different Effect of Proximal and Distal Interdisciplinarity, PLoS ONE 10(8), doi:10.1371/journal.pone.0135095.

Zhao, D. (2010), Characteristics and impact of grant-funded research: A case study of the library and information science field, Scientometrics 84, 293–306.

Overview over contributions to the single chapters in case of co-authorship according to §7 Abs. 2 PromO

Chapter	Authors	Idea	Theory	Data collection	Empirical Analyses	Paper draft	Conception/ Consultation/ Discussion
Chapter 2 The coevolution of innova-tive ties, proximity and competences - Towards a Dynamic Approach of In-novation Cooperation	Susanne Walter, Uwe Cantner, Tina Wolf	leading	leading	leading	proportional	leading	proportional
Chapter 3 Policy induced innovation networks: the case of the German "Leading-Edge Cluster Competition"	Susanne Walter, Holger Graf, Uwe Cantner	minor	leading	proportional	minor	leading	proportional
Chapter 4 The role of geographical proximity for project per-formance – Evidence from the German „Leading - Edge Cluster Competition”	Susanne Walter, Holger Graf, Uwe Cantner	leading	leading	proportional	leading	leading	proportional
Chapter 5 Does public support in-crease interdisciplinarity and innovative outcome? Evidence from publication data	Susanne Walter	leading	leading	leading	leading	leading	leading

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Publications

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- Cantner U., Graf, H., Hinzmann, S. (2013), Policy induced innovation networks: The case of the German "Leading-Edge Cluster Competition", in: Scherngell T. (ed), The Geography of Networks and R&D Collaborations, Springer. Cham et al., 335-353.

- Rothgang, M., Cantner, U., Dehio, J., Engel, D., Fertig, M., Graf, H., Hinzmann, S., Linshalm, E., Ploder, M., Scholz, A.-M. and Töpfer, S. (2014), Begleitende Evaluierung des Förderinstruments "Spitzencluster-Wettbewerb" des BMBF - Abschlussbericht, RWI Materialien RWI.

- Cantner, U., Graf, H., Hinzmann, S. (2015), The role of geographical proximity for project performance – Evidence from the German 'Leading -Edge Cluster Competition', Jena Economic Research Papers, 2015 – 025. (*revision for publication in the Journal of Technology Transfer*)

- Cantner, U., Hinzmann, S., Wolf, T. (2016), The coevolution of innovative ties, technological proximity and competencies – Towards a Dynamic Approach of Innovation Network (in press).

- Hinzmann, S. (2016), Does public support foster Interdisciplinarity and innovative outcome? (mimeo)

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Erklärung gemäß § 4 Abs. 1 PromO

Hiermit erkläre ich,

1. dass mir die geltende Promotionsordnung bekannt ist;

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