Knowledge dynamics and technological change: Trajectories, networks and policies

Dissertation

zur Erlangung des akademischen Grades
doctor rerum politicarum
(Dr. rer. pol.)

vorgelegt dem Rat der Wirtschaftswissenschaftlichen Fakultät
der Friedrich-Schiller-Universität Jena
am 05.07.2017

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Datum der Verteidigung: 22. November 2017

Thesis overview

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Deutsche Zusammenfassung

Die vorliegende Dissertationsschrift leistet einen Beitrag zum Verständnis von technologischem Wandel und der Entstehung neuen Wissens. Neues Wissen und die Übertragung in neue Technologien oder die Verbesserung von bestehenden ist ein wesentlicher Treiber wirtschaftlicher Entwicklung. Das bisherige Verständnis über technologischen Wandel und die Rolle, die Wissensgenerierung und -austausch in diesem Prozess einnimmt, ist jedoch nicht hinreichend ausgeprägt. Bei technologischem Wandel und der Entstehung neuem Wissens wirken dynamische Prozesse und Mechanismen auf der Mikro-Ebene, die nicht-linear, akkumulativ und unter Unsicherheit ablaufen. Dabei sind heterogene Akteure und ihre Interaktionen im Innovationsprozess von zentraler Bedeutung. Akteure verfügen über unterschiedliches Wissen, welches sie in die Generierung neuen Wissens einbringen und untereinander austauschen. Daraus entstehen neue Erkenntnisse und Lösungsansätze die technologischen Wandel fördern und dadurch zu wirtschaftlichem Wachstum führen können.

Die bisherige Forschung hat die inhärenten Dynamiken der Wissensgenerierung und des Wissensaustausches nicht hinreichend berücksichtig. Technologien entwickeln sich über die Zeit weiter, wodurch sich die Bedarfe an Wissen, welches technologische Weiterentwicklung ermöglicht, ändern. Das Aufzeigen und Verstehen dieser Wissensdynamiken im Innovationsprozess ist der erste bedeutende Beitrag dieser Dissertationsschrift. Weiterhin befasst sich diese Dissertationsschrift mit den Interaktionen der Akteure im Wissensgenerierungsprozess. Die Akteure im Innovationsprozess formen Netzwerke des Wissensaustausches, welche zentral für innovative Aktivitäten sind. Vorherige Forschung hat gezeigt, dass sich die Struktur dieser Netzwerke positiv auf Innovationsaktivitäten auswirken kann. Einen weiteren bedeutenden Beitrag leistet diese Dissertationsschrift mit der Analyse der Beziehungen von Netzwerken des Wissensaustausches über verschiedene Aggregationsebenen und wie diese Ebenen einander beeinflussen. Weiterhin sind diese Netzwerke dynamisch und verändern sich in Größe und Struktur. Wie diese Dynamiken induziert werden, insbesondere durch politische Intervention, ist noch nicht hinreichend erforscht und hierzu möchte diese Dissertationsschrift ebenfalls einen Beitrag leisten. Ein tieferes Verständnis der Prozesse und Mechanismen der Wissensgenerierung und des -austausches ist notwendig, insbesondere für politische Entscheidungsträger, um bestehende Versagenstatbestände zu beheben oder lenkend in den Innovationsprozess einzugreifen.

Zur exemplarischen Untersuchung der Prozesse und Mechanismen der Wissensgenerierung und des Wissensaustausches werden zwei Technologien aus der Gruppe der erneuerbaren Energien betrachtet: Photovoltaik (PV) und Windkraft. Beide sind durch multiple Markt- und Systemversagen erheblichen Nachteilen während ihrer technologischen Entwicklung ausgesetzt. Zudem haben beide Technologien das Potential, Klimaveränderungen entgegenzuwirken, da sie elektrische Energie ohne den Ausstoß klimapotenter Treibhausgase erzeugen können. Vor diesem Hintergrund sind verschiedene Politikmaßnahmen implementiert worden, die sich grob in Demand Pull (nachfragefördernd), Technology Push (technologiefördernd) und Systemisch (Förderung der Rahmenbedingungen und der Kooperation), kategorisieren lassen. Diese Instrumente sind Teil eines Politikmixes, in dem sie gemeinsam Innovations- und Kooperationsaktivität beeinflussen. Für die einzelnen Instrumente gibt es mannigfaltige empirische Evidenz, dass sie die

Generierung neuen Wissens unterstützen. Nicht hinreichend untersucht ist jedoch, wie diese Instrumente einzeln und in Kombination auf den Wissensaustausch und die dafür notwendigen Netzwerke und Netzwerkstrukturen wirken.

Zur Betrachtung der Wissensgenerierung und des Austausches werden Patent und Publikationsdaten herangezogen. Insbesondere die Nutzung von Patentdaten ist mit erheblichen Problemen behaftet. Diese Dissertationsschrift nimmt sich ebenfalls dieser Probleme an und zeigt auf, dass der Umgang mit Patentdaten erheblicher Sorgfalt bedarf. Forschende sollten die Eigenarten dieser Daten verstärkt berücksichtigen, um technologische Veränderungen entsprechend analysieren und fundierte Politikempfehlungen ableiten zu können.

Kapitel zwei dieser Dissertationsschrift greift das Problem der technologischen Abgrenzung von Patentdaten auf. Für PV wird in diesem Kapitel eine Abfrageroutine entwickelt, die den Korpus der relevanten Patentdaten dieser Technologie umfasst und in technologische Teilbereiche unterteilt. Diese Teilbereiche, sogenannte Sub-Trajektorien, erlauben eine genauere Betrachtung der Innovationsaktivitäten in dieser Technologie. Diese Sub-Trajektorien, in PV sind das die verschiedenen Zelltechnologien, entstehen innerhalb der Trajektorie und stehen im technologischen Wettbewerb zueinander. Sie weisen verschiedene Charakteristika auf, die für eine Verbesserung der Leistungsfähigkeit oder Kostenreduktion relevant sind. Eine Analyse der Technologie auf dieser Mikro-Ebene ermöglicht ein genaueres Verständnis des Innovationsprozesses und der technologischen Weiterentwicklung.

Die Abfrageroutine besteht aus einer Kombination von Patentklassifikationen und technologiespezifischen Schlüsselwörtern. Die Abfrage wird dabei mit zwei etablierten Routinen verglichen, die häufig Anwendung finden, aber keine Unterteilung in Sub-Trajektorien erlauben. Die vorgestellte Routine erzielt dabei strukturell gleichwertige Abfrageergebnisse, ist jedoch restriktiver. Deskriptive Betrachtungen der Ergebnisse zeigen, dass die Sub-Trajektorien sich unterschiedlich entwickeln und insbesondere die aktuell marktdominierende Zelltechnologie die geringste patentierte Inventionsaktivität aufzeigt. Zudem zeigen sich geografische Unterschiede. So fokussieren sich beispielsweise asiatische Länder eher auf neuere Zelltechnologien. Diese Unterschiede in den Innovationsaktivitäten in den Sub-Trajektorien werden im dritten Kapitel vertiefend aufgegriffen.

Das dritte Kapitel befasst sich mit der Generierung von neuem Wissen und den dahinterstehenden Dynamiken. Ausgehend davon, dass neues Wissen durch die Rekombination von bisherigem Wissen entsteht, wird in diesem Kapitel untersucht, wie sich der Einfluss der Wissensrekombination auf die Weiterentwicklung einer Technologie über ihren Lebenszyklus hinweg verändert. Bisherige Studien haben sich aus einer statischen Sicht mit der Wissensrekombination befasst und verschiedene Mechanismen und Regelmäßigkeiten identifiziert. Allerdings gibt es erste Erkenntnisse, dass verschiedene Arten von Wissen für die Weiterentwicklung einer Technologie relevant sind. Diese bisherigen Erkenntnisse werden in diesem Kapitel mit dem Technologielebenszyklusmodell von Anderson und Tushman (1990) verbunden. Dabei wird das Wissen, welches in eine Technologie eingebracht wird, in verschiedene Arten unterteilt, von denen zu erwarten ist, dass sie in unterschiedlichen Phasen besonders relevant sind.

Zur Analyse der Rekombination von Wissen wird auf Patentanmeldungen für PV und Windkraft deutscher Erfinder zurückgegriffen. Erfinder dieser Patente sind die Akteure der Wissensrekombination und ihre Charakteristika, in dieser Analyse ihre vorherigen inventiven Aktivitäten, repräsentieren unterschiedliche Arten von Wissen. Dabei werden Erfinder in vier Arten unterteilt, Erfinder ohne vorheriges Wissen, Erfinder, die sich auf eine Technologie spezialisiert haben, Erfinder, die aus technologisch verwandten Bereichen kommen und Erfinder, die vorher in Technologien aktiv waren, die keinen technologischen Bezug zur betrachteten Technologie haben. Davon ausgehend, dass verschiedene Arten von Erfindern unterschiedlich zur technologischen

Weiterentwicklung beitragen, wird empirisch getestet, in welchen Phasen des Technologielebenszyklus welche Arten von Erfindern besonders relevant sind.

Es zeigt sich, dass verschiedene Arten von Erfindern und ihr Wissen eine wichtige Rolle entlang des Technologielebenszyklusses spielen. Zwar gibt es Unterschiede zwischen den Technologien, insgesamt bestätigt sich jedoch die Erweiterung des Anderson und Tushman (1990) Modells. Dabei ist in der Entstehungsphase einer Technologie Wissen, welches von außen eingebracht wird, besonders relevant. Im weiteren Verlauf der Technologieentwicklung hingegen, erscheint Wissen von spezialisierten Erfindern, oder Erfinder, die zum ersten Mal innovativ tätig werden, von besonderer Bedeutung zu sein. Diese Erkenntnisse tragen einerseits dazu bei, technologische Entwicklungen besser zu verstehen, andererseits können sie von politischen Entscheidungsträgern genutzt werden, um Fördermaßnahmen gezielt an den Entwicklungsstand einer Technologie anzupassen, etwa durch Förderung heterogener Akteursgruppen bei jungen Technologien.

Die folgenden Kapitel befassen sich explizit mit den Fördermöglichkeiten dieser Technologien. Im vierten Kapitel wird untersucht, wie die verschiedenen Arten von Instrumenten Inventorennetzwerke beeinflussen. Dazu werden dieselben Patentdaten wie in Kapitel drei verwendet, allerdings wird aus Ko-Patentierungen der Erfinder das darunterliegende Erfindernetzwerk rekonstruiert. In diesen Erfindernetzwerken findet Wissensaustausch zwischen verschiedenen Akteuren statt, welcher förderlich für inventive und innovative Aktivitäten ist. Insbesondere die Struktur dieser Beziehungen kann sich förderlich auswirken, wenn Wissen zwischen den Akteuren diffundieren kann. Allerdings gibt es erhebliche Markt- und Systemversagen bei der Weiterentwicklung dieser Technologien und dem dafür notwendigen Wissensaustausch. Einerseits die klassischen Marktversagenstatbestände der positiven Spillover aus der Innovationstätigkeit, die nicht appropriierbar sind, und den negativen externen Effekten konkurrierender Technologien, die nicht entsprechend eingepreist werden. Andererseits gibt es beim Wissensaustausch und dem gemeinsamen Lernen Probleme der Komplementarität, der Reziprozität und der Intermediation. Diese Systemversagenstatbestände werden insbesondere durch Systemische Instrumente adressiert, welche die Rahmenbedingungen und Anreize zum Wissensaustausch verbessern. Wie allerdings diese Instrumente auf Netzwerke und Netzwerkstrukturen wirken, ist bisher nicht näher betrachtet worden.

Mittels empirischer Verfahren wird die Wirkungsweise der verschiedenen Förderinstrumente, Demand Pull, Technology Push und Systemische Instrumente, auf die Größe und Struktur der Erfindernetzwerke untersucht. Es zeigt sich, dass hier ebenfalls technologische Unterschiede bestehen. Bei Windkraft haben Technology Push und Systemische Instrumente einen Einfluss auf die Größe des Netzwerkes, wohingegen für PV nur Technology Push Instrumente die Größe beeinflussen. Nachfragefördernde Instrumente sind hingegen in beiden Technologien relevant für die Größe des Erfindernetzwerkes. Gleiches gilt für die Struktur der Netzwerke. Weiterhin zeigen Systemische Instrumente bei Windkraft ebenfalls einen Effekt auf die Netzwerkstruktur. Technology Push Instrumente haben hingegen in beiden Technologien keinen Effekt auf die Struktur der Netzwerke. Diese Instrumente wirken jedoch nicht nur eigenständig, sondern sind Teil eines Politikmixes, in dem diese Instrumente zusammenwirken. Das Zusammenwirken von Technology Push und Demand Pull Instrumente hat einen positiven Einfluss auf die Größe der Netzwerke. Systemische und Demand Pull Instrumente wirken zusammen positiv auf die Struktur der Netzwerke. Dieses positive Zusammenwirken deutet auf die Konsistenz des Politikmixes hin.

Das fünfte Kapitel befasst sich ebenfalls mit der Wirkung von Politikmaßnahmen auf Netzwerke. In diesem Kapitel verlagert sich der analytische Fokus von der Mikro- auf die Makroebene. Dabei steht die Frage im Zentrum, wie ein Land seine Einbettung in ein internationales Forschungsnetzwerk beeinflussen kann. Es wird davon ausgegangen, dass durch Ko-Publikationen Wissensaustausch stattfindet und dieser auf der Makroebene aggregiert werden kann. Daraus entsteht ein globales Netzwerk, in dem kooperierende Forscher Verbindungen zwischen verschiedenen Ländern darstellen. Die Position eines Landes in diesem Netzwerk erlaubt es dem Land an globalen Wissensflüssen zu partizipieren und diese in eigene Forschungs- und Entwicklungsbemühungen aufzunehmen. Es wird angenommen, dass ein Land aktiv in diesen Prozess eingreifen und durch gezielte Politikintervention versuchen kann, die eigene Position zu verbessern. Weiterhin kann die in einem Land vorherrschende Forschungsstruktur, also die Kooperation zwischen den im Land befindlichen Forschungseinrichtungen, ein Umfeld schaffen, welches internationale Kooperationen begünstigt.

Zur Untersuchung der Faktoren die eine internationale Einbettung beeinflussen können, werden Publikationsdaten für PV herangezogen. Aus diesen Daten wird das globale Kooperationsnetzwerk der Forschenden rekonstruiert und die Einbettung der einzelnen Länder in dieses bestimmt. Diese Einbettung wird durch zwei Gruppen von Einflussfaktoren erklärt. Einerseits durch Politikmaßnahmen und andererseits durch die Struktur des nationalen Forschungssystems. Mit der ersten Gruppe von Faktoren wird die zentrale Frage des vierten Kapitels, wie Politikmaßnahmen, insbesondere Technology Push und Demand Pull Instrumente, Netzwerke beeinflussen, wieder aufgegriffen. Mit der zweiten Gruppe von Einflussfaktoren wird untersucht, wie die Ausgestaltung des nationalen Forschungssystems, welches nicht zufällig entsteht, sondern etwa durch Systemische Instrumente gesteuert, eine bestimmte Struktur annimmt, die internationale Einbettung beeinflussen kann. Methodisch wird dabei untersucht, wie die verschiedenen Aggregationsebenen, die Mesoebene und die Makroebene, miteinander in Beziehung stehen. Untersuchungen wie verschiedene Aggregationsebenen sich gegenseitig beeinflussen, sind in der ökonomischen Forschung erst am Anfang.

Die Ergebnisse zeigen, dass die Einbettung eines Landes in ein globales Wissensnetzwerk durch Politikmaßnahmen beeinflusst werden kann. Insbesondere Demand Pull Instrumente fördern, wie schon im vorherigen Kapitel gezeigt, eine Steigerung der Kooperationsbeziehungen und dadurch internationale Einbettung. Interessant ist hier, dass öffentliche Beschaffung, in dieser Analyse die Anzahl von Satelliten die ein Land besitzt, einen erheblichen Einfluss hat. Andere Instrumente, etwa Technology Push Instrumente, zeigen hingegen unbestimmte Effekte. Weiterhin hat die Struktur des nationalen Forschungssystems einen erheblichen Einfluss. So führt ein zusammenhängendes nationales Forschungssystem zu einer höheren Einbettung. Hingegen ist ein auf einen oder wenige Akteure zentralisiertes Forschungssystem unzuträglich für die internationale Einbettung. Diese Ergebnisse zeigen, dass der Aufbau und die Funktionalität des Forschungssystems von Bedeutung für den Austausch von Wissen sind und verstärkt in den Fokus der ökonomischen Forschung und der politischen Gestaltung rücken sollten.

Das letzte Kapitel dieser Dissertationsschrift greift wieder methodische Probleme bei der Nutzung von Patentdaten auf. Bei der Nutzung von Patentdaten für ökonomische Analysen bestehen erhebliche Freiheitsgrade bei der Auswahl und Abgrenzung der Patentdaten. Diese Freiheitsgrade betreffen einerseits die Abfrage der Patentdaten aus entsprechenden Datenbanken, andererseits die Unterteilung von Patenten in verschiedene Wertigkeiten. Diverse Studien haben gezeigt, dass nur ein sehr geringer Teil der angemeldeten Patente großen technologischen bzw. ökonomischen Wert haben. Diese Qualitätsdimension der Patente eröffnet weitere Flexibilität bei der Auswahl von Patentdaten. Dabei gibt es verschiedene Wege zur Berücksichtigung der Patentqualität. In dieser Analyse wird die Patentqualität über den Anmeldeprozess der Patente bestimmt. Zur systematischen Untersuchung wie die Flexibilität bei der Patentauswahl ökonomische Untersuchungen beeinflussen kann, werden die Studien von Johnstone u. a. (2010) und Peters u. a. (2012) repliziert. Diese Studien wurden ausgewählt, da sie Maßgebend für die Analyse von Politikeffekten bei erneuerbaren Energien im Allgemeinen und Solartechnologien im Speziellen sind. Mit Hilfe der Replikationen mit verschiedenen Patentabgrenzungen wird untersucht, inwieweit eine systematische oder unbeabsichtigte Ausnutzung der Flexibilität der Patentabfrage Einfluss auf die Messung von Politikeffekten und daraus abgeleitete Politikempfehlungen haben kann.

In der Literatur konnten 51 verschiedene Patentabfragen für Solartechnologien identifiziert werden. Diese lassen sich für sechs verschiedene Patentqualitätsdimensionen abfragen. Daraus ergeben sich 306 verschiedenen Patentausprägungen, die alle die inventive Aktivität in Solartechnologien messen sollen. Diese 306 verschiedenen Patentausprägungen werden in einem ersten Schritt deskriptiv verglichen. Zur Analyse wie diese verschiedenen Patentausprägungen ökonomische Effekte beeinflussen, werden die beiden vorher genannten Studien herangezogen. Diese Studien bestimmen, welchen Effekt verschiedene Politikmaßnahmen auf die Patentanzahl in einem Land haben. Beide Studien werden mit den 306 verschiedenen Patentausprägungen neu geschätzt und die Koeffizienten der einzelnen Politikvariablen untersucht. Dafür wird das sog. Extreme-Bounds Verfahren, welches aus der Wachstumsliteratur stammt, herangezogen, um zu untersuchen, welche Bandbreite der Politikeffekte vorliegt und wie Robust diese Effekte sind. Weiterhin erfolgt eine visuelle Analyse mittels sog. Vibrationsgrafiken, welche die Koeffizienten gegen ihr Signifikanzniveau darstellen. Abschließend kommen Meta-Regressionsverfahren zum Einsatz, um zu bestimmen, welche Parameter der Patentabfrage Einfluss auf die Größe der Politikeffekte haben.

Die deskriptive Betrachtung zeigt erhebliche Unterschiede im Umfang und in der Übereinstimmung der Patentabfragen. Unterschiede zwischen verschiedenen Anmeldeländern sind nur zwischen den verschiedenen Patentqualitätsdimensionen gegeben. Die Extreme-Bounds Analysen zeigen, dass die Flexibilität in den Patentabfragen zu erheblicher Unsicherheit bei den Effektgrößen führt. Für die meisten Politikmaßnahmen lassen sich positiv wie negativ signifikante Effekte finden. Zudem besteht erhebliche Unterschiede zwischen den verschiedenen Patentqualitätsdimensionen. Insbesondere erteilte Patente haben sehr starke und in einigen Fällen diametrale Effekte im Vergleich zu anderen Patentqualitätsdimensionen. Die Unsicherheit über Größe und Richtung der Effekte lässt sich durch eine Auswahl von Qualitativ höherwertigen Abfragen reduzieren. Insbesondere der Ausschluss von extremen Patentanzahlen führt zu einer deutlichen Reduzierung der Bandbreite der Ergebnisse. Für diese restringierte Auswahl zeigen sich für die Demand Pull und Technology Push Instrumente in beiden Studien robuste Ergebnisse hinsichtlich der Richtung der Effekte. Weiterhin zeigen die Meta-Regressionen, dass alle Eigenschaften der Patentabfrage einen Einfluss haben, dieser aber nicht über alle Politikinstrumente und über die beiden Studien hinweg einheitlich sind. Insgesamt kann festgehalten werden, dass die Flexibilität bei der Auswahl von Patentdaten erheblichen Einfluss auf ökonometrische Analysen hat und diese gezielt ausgenutzt werden könnten. Daher sollten Studien basierend auf Patentdaten ein höheres Maß an Sorgfalt bei der Auswahl der Patentdaten walten lassen sowie umfassende Sensitivitätsanalysen durchführen, die insbesondere verschiedene Patentqualitätsdimensionen berücksichtigen.

Zusammenfassend liefert diese Dissertationsschrift tiefergehende Einblicke in die Dynamiken und Mechanismen technologischer Entwicklung. Am Beispiel zwei erneuerbarer Energietechnologien wird aufgezeigt, wie sich die Wissensgenerierung über die Zeit verändert, wie Politikmaßnahmen auf Netzwerke des Wissensaustausches wirken und welche Probleme bei der Analyse solcher Zusammenhänge mittels Patentdaten bestehen. Diese Ergebnisse tragen maßgeblich zur ökonomischen Theoriebildung bei und lassen sich in konkrete politische Handlungsempfehlungen überführen, insbesondere zur Weiterentwicklung umweltfreundlicher Technologien, zur Vermeidung des Klimawandels und für nachhaltiges Wachstum.

Chapter 1

Introduction

1.1 Knowledge dynamics and technological change

Mankind is inseparably connected to innovation and change. Since the invention of prehistoric stone tools humans proceed with inventive and innovative activities to increase their welfare. Thereby humans intervene in the environment to exploit and utilize natural resources and their exploitative activity increases over time. However, such interferences in the environment have adverse consequences, which can be cataclysmic for mankind. The largest exploitation of the environment started with the industrial revolution and the extensive use of fossil fuels. While this brought about large economic prosperity, at the same time several side effects emerged, especially pollutions and in result climate change. Climate change is most likely the biggest threat to mankind in the 21st century (Stern, 2007; IPCC, 2014). Preventing it is a global and interdisciplinary challenge, in which all scientific disciplines need to contribute (Kates et al., 2001).

From an economic point of view, the problem of climate change is the global public good nature of the atmosphere. The atmosphere belongs to everyone and polluting it is without consequences, or in economic terms, pollutants are not forced to internalize their negative externalities. This results in an excessive level of pollution, which needs to be reduced to mitigate climate change. Standard economics proposes regulatory interventions to ensure allocative efficiency of the market and argues that such an externality can be internalized and the problem can be solved by a pricing mechanism (Pigou, 1920; Baumol and Oates, 1988). Others argue that reducing consumption and the respective economic activity and abstaining from further growth is necessary (Paech, 2005, 2012). A third approach is found in evolutionary economics, which builds on mankind's creative and scientific capabilities to induce environmentally friendly innovations and transformative change (Nelson and Winter, 1982; Kemp and Soete, 1992; Erdmann, 1993; Freeman, 1994; van den Bergh, 2007; Cecere et al., 2014). Environmentally friendly technologies can substitute environmentally harmful technologies and mitigate climate change. Thereby these technologies provide the opportunity for green, sustainable growth, which is no longer based on the exploitation of non-renewable resources (OECD, 2011; Jänicke, 2012).

I follow in this thesis the evolutionary thinking in economics and strive to understand how environmentally friendly technologies develop in particular and aim to contribute to the long-lasting research endeavors to understand the processes and mechanisms of technological change in general. Inventive and innovative activities are dynamic and interactive processes of knowledge creation and accumulation (Kline and Rosenberg, 1986) in which novelty is created by recombining knowledge from a diverse set of actors (Kogut and Zander, 1992; Fleming, 2001; Savino et al., 2017). However, scientists have been struggling to understand the innovation process and technical change and how it brings about economic change and growth. Some call these processes the "*measure of our ignorance*" (Abramovitz, 1956, p. 11), a black box, or declare it exogenous to economic analysis. Scholars in the field of evolutionary economics, going back to the early works of Joseph Alois Schumpeter (Schumpeter, 1912), try to understand these processes, open the black box and integrate technological change in economic theory (Rosenberg, 1982; Nelson and Winter, 1982; Dosi et al., 1988).

This thesis opens the black bock of technological change with a particular focus on renewable energy technologies. Since the energy sector is the largest emitter of climate potent gases and locked into the use of fossil fuels (Unruh, 2000, 2002; Stern, 2007), unlocking the energy sector and decarbonizing it by a transition towards renewable energies is required to mitigate climate change. Renewable energies do not only mitigate climate change, but also solve other problems, such as resource scarcity (Höök and Tang, 2013; Capellán-Párez et al., 2014), provide access to energy in developing countries which supports eradicating poverty (Casillas and Kammen, 2010; Yadoo and Cruickshank, 2012), and are an essential means to achieve the sustainable development goals (United Nations, 2015). Furthermore, their industrial base contributes to economic growth and employment (Mazzucato, 2013; REN21, 2016). These favorable characteristics make their technological development and economic application especially relevant and policy support has been widely implemented to support development and diffusion of these technologies.

The two promising technologies, solar energy technologies, in particular photovoltaics (PV), and wind power, are in the focus of my analysis. The energy of both, the sun and the wind, have been utilized for centuries, but only in the 20th century technologies to create electric energy out of these natural forces have been invented. Especially after the oil crises, both technological principles caught the attention of policy makers, since they were considered as possible substitutes for fossil fuels. However, their cost/performance ratio was very high, which made the implementation of large-scale support schemes necessary to reduce it. Since then, they show great dynamics in their technological development. Nowadays, the technologies are cost competitive with conventional energy sources in most regions and account for the highest share in newly installed electricity generation capacity (REN21, 2016). The decrease in their cost/performance ratio goes along with an exponential increase in knowledge generation in the last decades and increased knowledge exchange on different levels.

While their performance increases and knowledge dynamics are a global phenomenon, especially Germany is a forerunner in the development and adoption of both technologies. Figure 1.1 depicts key innovation indicators of policy support, knowledge generation, and adoption of PV and wind power for Germany. Governmental support of R&D in these technologies started in Germany in 1974, as a reaction to the first oil crisis (Lauber and Mez, 2004) and in 1991 Germany was among the first countries which implemented a demand inducing feed-in tariff (Jacobsson and Lauber, 2006). While there where large R&D spendings after the oil crises, inventive output was low. But especially during the last 20 years, knowledge generation in terms of publications and patents is highly dynamic and technological change is immanent. Furthermore, Germany was among the leading markets for these technologies, especially for PV with a world market share between 30 and 60 percent from 2001 to 2010 (IEA, 2010). These dynamics make these two technologies particularly interesting to study knowledge generation and exchange as well as how policy can intervene in the innovation process in Germany and across countries.

For this purpose, the first research objective of this thesis is to analyze the knowledge dynamics along *technological trajectories*, especially knowledge generation by recombination. The innovation process includes heterogeneous actors and the interactions and knowledge exchanges among them are of particular relevance for inventive and innovative activity. These interactions constitute *knowledge networks* and characteristics of these networks are another important part of knowledge dynamics, which this thesis sheds light on in its second research objective. Furthermore, since the innovation process is error prone, faces high costs, and uncertainty, *policy*

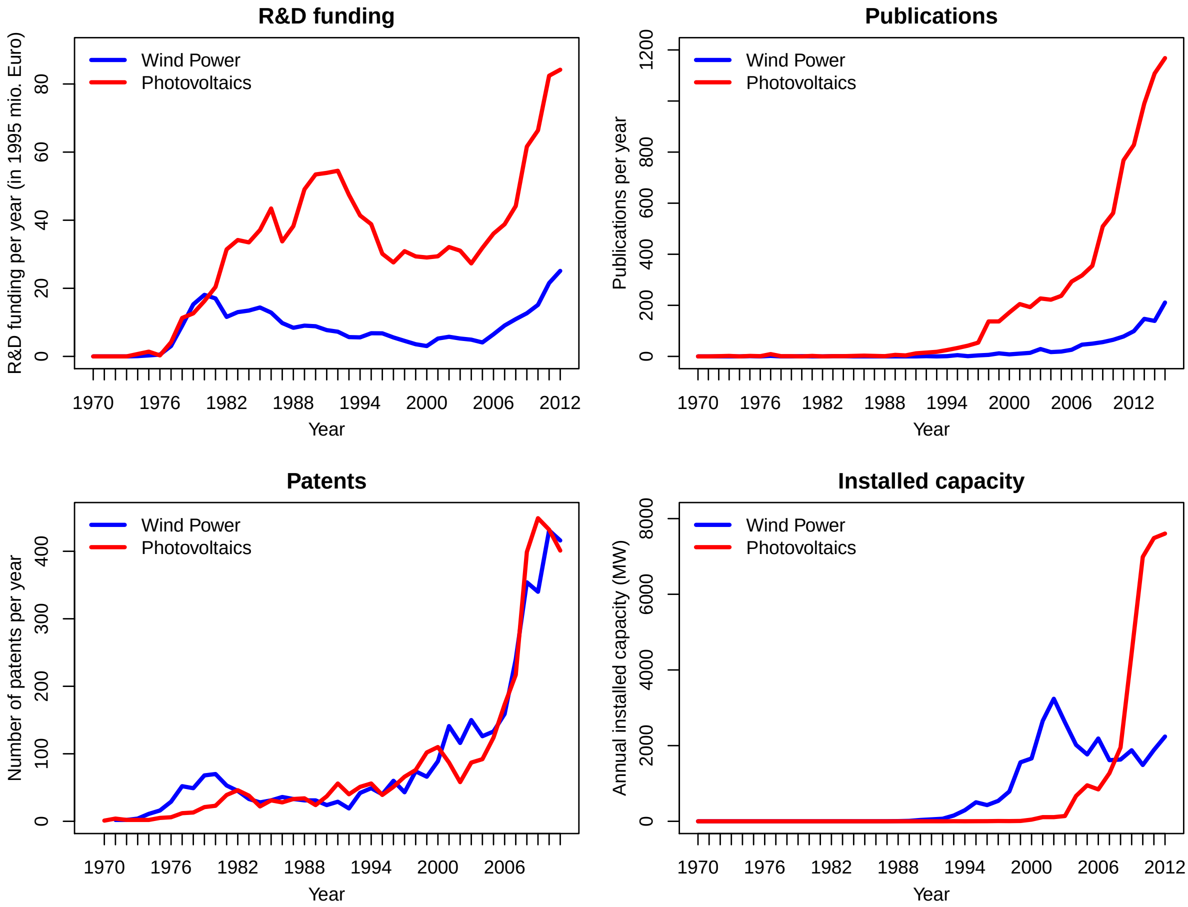


Figure 1.1: Key innovation indicators for wind power and photovoltaics for Germany.

Figure note: Data sources for R&D funding, patents and installed capacity see Chapter 4, for photovoltaic publication data see Chapter 5 and publication data for wind power was collected based on the suggestions by Popp (2016b).

intervention is justified and widely implemented. How policy can influence knowledge generation and especially the underlying network of knowledge exchange is the third research objective of this thesis. Even though this thesis will not be able to uncover all mechanisms and processes, it may contribute to understanding knowledge dynamics and technological change in general which can be integrated in economic theorizing, but also allows to support environmentally friendly technologies further and accelerate their technological development to mitigate climate change and foster green growth.

In the following, the three building blocks of knowledge dynamics and technological change — trajectories, networks and policies – and the corresponding research objectives of this thesis are discussed on more detail.

1.1.1 Trajectories

Technological change takes place along technological trajectories, which provide solutions for particular problems (Dosi, 1982). In a trajectory, knowledge and competences accumulate which provide the means to solve a problem (Dosi and Nelson, 2010, 2013). The knowledge in a trajectory builds the knowledge base of a technology along which the technology evolves. However, the knowledge base itself shows certain dynamics and evolves over time (Malerba and Orsenigo, 1996, 2000). This forms a dynamic process in which new knowledge is added to the knowledge base of a trajectory which can help to provide better solutions to a problem and brings about technological change. These patterns are an essential part of the micro-foundation of economic change and translate to the macro level, where they create growth, induce radical changes, and new paradigms to emerge (Weitzman, 1998; Perez, 2010).

The knowledge accumulation in the trajectory is usually incremental in nature and improves techno-economic characteristics of the artifact or process over time (Dosi, 1982; Dosi and Nelson, 2013),even though in some cases variation of different solutions can emerge inside a trajectory and provide new techno-economic opportunities (Durand, 1992). New knowledge is usually generated by the recombination of existing knowledge (Nelson and Winter, 1982; Olsson, 2000; Fleming, 2001; Arts and Veugelers, 2015). Recombination can take place with knowledge internal to the trajectory, but especially the in-flow of knowledge from sources external to a trajectory is crucial for its evolution in terms of initiating, redirecting and refreshing the knowledge accumulation processes (Dosi and Nelson, 2013). The way external knowledge diffuses into a technology, the source it comes from, and the type of actors involved appear to be core determinants of that technology's further development (Grant, 1996; Dosi and Nelson, 2013). While some studies focus on the structure of the knowledge inside a trajectory and show that there are certain dynamics in the evolution of the knowledge base (Yayavaram and Ahuja, 2008; Krafft et al., 2011, 2014a) and shifts between different regimes (Maleki and Rosiello, 2014), a better understanding how the knowledge base evolves and how the respective technologies are shaped is missing. This is of particular importance, since there is a decline in the recombinatorial success (Jones, 2009). Ideas are harder to find and more knowledge and other resources are needed to keep up previous rates of technological change (Bloom et al., 2017).

The first research objective is to uncover dynamics of knowledge generation inside technological trajectories and how new knowledge contributes to technological development.

1.1.2 Networks

Knowledge recombination is a core component of technological change and it is especially successful in teams that are able to combine diverse sets of knowledge (Wuchty et al., 2007; Bercovitz and Feldman, 2011). Empirical evidence shows that collaboration and networking in R&D in general lead to a higher research output than individual R&D activities (e.g. Czarnitzki et al., 2007; Fornahl et al., 2011). Furthermore, theoretical as well as empirical results suggest a positive influence of increased interaction on performance (Cowan and Jonard, 2004; Powell and Grodal, 2005; Fritsch and Graf, 2011; Phelps et al., 2012). Corresponding networks of knowledge transfer and learning are essential in the innovation process and constitute one important driver of technological change (Kline and Rosenberg, 1986; Dosi, 1988; Powell et al., 1996; Ahuja, 2000). Especially the structure of such knowledge networks and the position of actors influences inventive and innovative performance (Schilling and Phelps, 2007). For example, average innovative performance is higher in well-connected networks (Fleming et al., 2007). Also, the speed of information diffusion increases with the connectivity of the network and the probability of knowledge transfer between individuals decreases the longer the paths connecting them (Singh, 2005). This indicates that networks of knowledge exchange are another core component in the innovation process and influence knowledge dynamics.

Even though knowledge exchange takes place among individual actors, these actors are usually part of functional units, such as universities, firms and other organizations. These connections at a level of higher aggregation, the meso level, constitute the research system in which inventive and innovative activities take place (Nelson, 1993; Lundvall, 1992; Carlsson and Stankiewicz, 1991). The structure and functionality of the research system is of particular importance, since they determine knowledge exchange and diffusion (OECD, 1997; Cowan and Jonard, 2004; Schilling and Phelps, 2007; Cantner and Graf, 2011). While there is a broad stream of literature which analyzes knowledge flows in and the structure of such research systems (Phelps et al., 2012), these research systems are not in isolation but are itself part of a network of higher aggregation. At this macro level of aggregation, national research systems form interactions and knowledge exchange becomes a global phenomenon (Adams, 2012). In such a setting, different levels of aggregation interact and structural properties of lower levels of aggregation can translate to outcomes at higher levels (Dopfer et al., 2004). However, our understanding of dependencies in such multi-modal networks is limited (Gupta et al., 2007).

The second research objective aims to add to our understanding of knowledge exchange in networks at different levels of aggregation and their influence on each other.

1.1.3 Policies

While knowledge generation and exchange in knowledge networks are important processes for technological change and economic growth, there are several failures which hamper these processes. These failures affect the innovation process and relate to the costly, complex, and uncertain nature of such activities. These failures can be distinguished in two groups, market failures and system failures.

Market failures result from problems of resource allocation on markets due to, for example, asymmetric information, externalities, or public goods. In these cases, intervention in the market is justified to to improve allocative efficiency. Relevant failures for inventive and innovative activity are, for example, the partly public good nature of knowledge (Nelson, 1989), which reduces the appropriability of new knowledge and actors reduce their inventive activity below the socially optimal level (Arrow, 1962b). However, such spillovers of knowledge from one actor to others increases inventive performance, if they can be absorbed by others (Cohen and Levinthal, 1990; Griliches, 1992). In such cases, market interventions such as subsidizing R&D activities or implementing property rights protection are possible solutions. Another failure, especially relevant for the substitution of polluting technologies with environmentally friendly ones to mitigate climate change, are network effects. Network effects result in path dependencies and possible lock-ins to inferior technologies (David, 1985; Arthur, 1989; Cecere et al., 2014). Even though new or alternative technologies show certain advantages, the market-dominating technologies benefit from economies of scale or increasing returns to adoption. In the case of climate change, this lock-in into fossil fuel technologies is coined carbon lock-in (Unruh, 2000, 2002).

System failures relate to the systemic component of the innovation process and the overall innovation system. These failures are detrimental to the functionality of the innovation process and the overall innovation system (OECD, 1997; Carlsson and Jacobsson, 1997; Cantner and Graf, 2003; Klein-Woolthuis et al., 2005) as well as to the transformation of the system itself (Weber and Rohracher, 2012). Of particular interest for this thesis are failures with respect to the knowledge exchange and cooperation in the innovation process. The intended knowledge transfer between the actors and the underlying network structures can to be affected by failures of complementarity, reciprocity and intermediation (OECD, 1997; Cantner and Graf, 2003). The problem of complementarity relates to the question if the actors and the knowledge they possess fit so that collaboration allows mutual learning (e.g. Cantner and Meder, 2007). Problems of reciprocity exist if the exchange of knowledge is not based on trust and mutual exchange of knowledge (e.g. Cantner et al., 2011). Failures of intermediation occur if actors are not aware of potential cooperation partners (e.g. Cantner et al., 2011). Such failures reduce the intensity of knowledge exchange and cooperation in research systems and eventually reduce inventive and innovative activity.

Environmentally friendly technologies in general and renewable energy technologies in particular face further disadvantages in their development and adoption compared to competing technologies, which exert negative external effects on the environment. This general problem of environmentally friendly technologies was conceptualized by Rennings (2000) and Jaffe et al. (2005) as the so called double externality problem. It refers to the non-appropriability of basic research due to spillovers (Arrow, 1962b) as well as the negative externalities of other technologies, for example CO_2 emitting energy production, which are not internalized accordingly (Pigou, 1920; Baumol and Oates, 1988). However, the double externality problem captures only a part of the obstacles renewable energies face. The externalities related to the network effects and the carbon lock-in, the system failures, and the failures in the transition towards an economic system based on sustainable principles, constitute a situation of multiple externalities. Therefore, these technologies are an interesting case to study how policy intervention can increase knowledge generation and exchange and promote technological change and provide means to mitigate climate change.

Policy instruments that address market and system failures can be classified along the innovation process in technology push, demand pull, and systemic instruments. Technology push instruments intervene at the beginning of the innovation process and directly support inventive activity. Already Bush (1945) addressed the necessity to subsidize R&D activities to increase the knowledge stock by reducing the private costs of R&D. While there has been a long debate about the effectiveness of direct R&D support and its benefits for inventive activity (cf. David et al., 2000; García-Quevedo, 2004), empirical evidence indicates that direct R&D funding increases inventive output in general (e.g Czarnitzki and Hussinger, 2004; Alecke et al., 2012) and especially in environmental friendly technologies (e.g. Johnstone et al., 2010; Peters et al., 2012; Costantini et al., 2015b, 2017). Demand pull instruments intervene at the end of the innovation process and increase market demand. Schmookler (1962, 1966) postulates that markets with high expected profitability provide incentives to engage in inventive and innovative activities. While there were concerns about the nature of the effect (e.g. Mowery and Rosenberg, 1979; Kleinknecht and Verspagen, 1990), recent empirical evidence indicates that market demand induces inventive activity in general (Peters et al., 2012) and especially fosters process innovations (Fontana and Guerzoni, 2008). In the case of environmentally friendly technologies, these policies show also strong effects (e.g. Johnstone et al., 2010; Peters et al., 2012; Costantini et al., 2015b, 2017). To overcome system failures in the innovation process, systemic instruments are implemented (Smits and Kuhlmann, 2004; Chaminade and Edquist, 2006; Wieczorek and Hekkert, 2012). Such instruments include the provision of infrastructure, especially to facilitate learning and knowledge exchange, to enhance cooperation, for example by cluster initiatives, or to foster cooperation between inventive actors (Smits and Kuhlmann, 2004). The aim of such policies is to connect heterogeneous actors, such as firms, universities and research institutes, to create a network of knowledge exchange, encourage learning processes and open up possibilities of resource and capability sharing. Thereby they affect the rate of knowledge exchange and consequently influence the speed of knowledge generation and technological change (e.g Fornahl et al., 2011).

While these different types of instruments interfere in the innovation process and support and facilitate inventive activity, they are in most cases present simultaneously and interact in a policy mix (Flanagan et al., 2011; Rogge and Reichardt, 2016). Such a policy mix consists of multiple components, where the mix of instruments is an important component. The instrument mix needs to be consistent to support inventive activity. The consistency of the instrument mix can be assessed by interaction analysis and can have three degrees of interaction: strong, if the instruments reinforce each other, weak, if the interaction is neutral, and inconsistent if the interaction effect is negative. First empirical evidence shows that there is evidence of strong consistency for the interaction between public procurement and direct subsidies (Guerzoni and Raiteri, 2015). Such a policy mix and its consistency is of particular importance for environmentally friendly technologies, since they face multiple failures along the innovation process.

There is overall empirical evidence that different types of instruments and a consistent policy mix are beneficial for knowledge generation and technological change, especially in environmental friendly technologies. However, there is hardly any empirical evidence how such policies influence knowledge exchange and collaboration in networks. Since there are several system failures which are detrimental to knowledge exchange, supporting the formation of collaboration and providing incentives for knowledge exchange are important in the innovation process. Especially systemic instruments are designed to overcome such failures, but there is scarce empirical evidence on the effect of such instruments on knowledge networks and the overall research system.

The third research objective sheds light on the effect of policy instruments and their mix on knowledge generation and knowledge networks in environmentally friendly technologies.

1.2 Structure of the thesis

This thesis is cumulative and consists of five individual papers which are the core chapters 2-6. Each chapter sheds light on knowledge dynamics and technological change in renewable energies from different perspectives. All papers are empirical, however, Chapter 2 and 6 have a methodological focus on the use of patent data, while Chapters 3, 4 and 5 use patent or publication data to better understand the innovation process and inventive and cooperative activity. Special attention on how policy instruments influence inventive and cooperative activities is devoted to in the last three chapters. Table 1.1 summarizes the key characteristics of the chapters and each chapter is summarized in the following.

1.2.1 Chapter 2

The second chapter, "Identifying technological sub-trajectories in photovoltaic patents" deals with the problem of selecting patent data for economic analysis. The selection of patent data is a non-trivial task and especially for PV there is no consensus on how to select relevant patents. This chapter proposes a replicatable and modular search strategy for PV patents. The search strategy accounts for the sub-trajectories in PV to analyze technological change at the micro level and is used throughout the thesis.

The PV system is a technological trajectory (Dosi, 1982), which consists of several sub-trajectories which emerged through micro-radical innovations in the continuum of incremental and radical innovations (Durand, 1992). These sub-trajectories open up new possibilities for the technology to improve its cost/performance ratio and allows to overcome physical boundaries (Sartorius, 2005). Identifying and analyzing these sub-trajectories provides further insights into the dynamics of technological change, since the sub-trajectories are in most cases in competition with each other and influence industry structures (Kapoor and Furr, 2015). While there is a huge variety of selection approaches established in the literature (see Chapter 6 for the implications of such variety), none of these search strategies accounts for the different sub-trajectories present in PV, which is necessary to understand technological change in PV at the micro level.

The proposed search strategy uses patent classifications in combination with keywords. The selection of classifications and keywords for the search strategy follow established procedures

Table 1.1: Thesis overview.

	Chapter 2	**Chapter 3**	**Chapter 4**	**Chapter 5**	**Chapter 6**
Title	Identifying technological sub-trajectories in photovoltaic patents	Knowledge recombination along the technology life cycle	Inventor networks in renewable energies: The influence of the policy mix in Germany	International research networks: Determinants of country embeddedness	Flexibility in the selection of patent counts: Implications for *p*-hacking and policy recommendations
Co-authors			Uwe Cantner, Holger Graf, Johannes Herrmann	Holger Graf	Stephan B. Bruns
Theoretical foundation	Technological trajectories	Knowledge recombination, technology life cycle	Innovation policy, knowledge networks	Innovation policy, knowledge networks	Innovation policy, economics with patent data
Knowledge dimension	Generation	Generation	Exchange	Exchange	Generation
Policy dimension			Demand pull, technology push, systemic, policy mix	Demand pull, technology push, systemic, policy mix	Demand pull, technology push
Technology	Photovoltaics	Photovoltaics and wind power	Photovoltaics and wind power	Photovoltaics	Solar energy technologies
Data	Patent data	Patent data	Patent data, policy data	Publication data, policy data	Patent data, policy data
Observation period	1970-2011	1970-2006	1980-2011	1980-2015	1978-2005
Country coverage	International	Germany	Germany	International	International
Data structure	Panel	Cross-section over time	Time series	Panel	Panel
Methodology	Descriptive	Negative-binomial regression, rolling-window regression	Social network analysis, OLS-regression	Social network analysis, OLS-regression	Replication, sensitivity analysis, extreme-bounds analysis, meta-regression
Own contribution			Significant contributions to the design of the study, data collection, theoretical and empirical elaborations, and interpretation of results	Significant contributions to the design of the study, data collection, theoretical and empirical elaborations, and interpretation of results	Significant contributions to the design of the study, data collection, theoretical and empirical elaborations, and interpretation of results
Status	In preparation for submission	Under review in Industrial and Corporate Change and available as working paper: Kalthaus (2016)	Published in Research Policy and referred to as Cantner et al. (2016)	After revisions resubmitted to Research Policy and available as working paper: Graf and Kalthaus (2016)	In preparation for submission

(Porter et al., 2008; Costantini et al., 2015a). The patents which can be selected with this strategy are compared against two benchmark search strategies. The proposed search strategy performs similarly to established search strategies and structural differences are not present. However, the search strategy seems to be more restrictive, excluding potentially unrelated patents from the selection.

Since this chapter is methodological in nature and aims to derive the search strategy, it provides only descriptive insights in the development of PV sub-trajectories. The descriptive analysis of the sub-trajectories shows that there are different dynamics between sub-trajectories and that the market-dominating technology shows hardly any patented inventive activity. There are also differences between countries, which points towards specialization into sub-trajectories. Especially Asian countries are frequently patenting in emerging cell technologies. These descriptive results indicate that patenting activity in PV shows dynamics within the trajectory which influence technological progress, but would be missed at the aggregate level without a separation into sub-trajectories.

Patent data selected based on this search strategy is used in Chapter 3 and 4. Furthermore, it is used along other search strategies in Chapter 6 to understand how flexibility in the selection of patent counts influences policy effects. The search strategy is also used in Herrmann and Töpfer (2017) and Herrmann (2017). The chapter is single-authored and in preparation for submission.

1.2.2 Chapter 3

The third chapter, "Knowledge recombination along the technology life cycle" aims to understand how recombination of different kinds of knowledge influences the knowledge bases of PV and wind power along their technology life cycles. Since technological change is a dynamic process which is intimately related to the technology's knowledge base, understanding how knowledge recombination influences the knowledge base from a dynamic point of view provides further insights on the evolution of technologies.

Anderson and Tushman (1990) propose a cyclical model of a technological life cycle. The model distinguishes four phases, an era of ferment, the emergence of a dominant design, an era of incremental change, and a discontinuity, which restarts the cycle. I extend this model to account for the technology's knowledge base and proposes different kinds of knowledge, which are relevant in the life cycle phases. Integrating the mechanisms of knowledge recombination in the technology life cycle model allows to understand the dynamic nature of technical change in more detail. While there is first empirical evidence that different kinds of knowledge matter along the technological development (Krafft et al., 2011, 2014a), no theoretical foundation is provided explaining how different knowledge influences technological progress over time nor are empirical results available so far. While knowledge recombination has been studied for several decades and stylized facts emerged (Savino et al., 2017), studies on the dynamics of recombination have been absent so far.

Knowledge recombination is analyzed at the inventor level, which has recently moved in the focus of research (Gruber et al., 2013; Boh et al., 2014; Conti et al., 2014). Since inventors are the actors which recombine knowledge, their capabilities and previous knowledge is relevant for their recombinatorial success. Inventors are categorized in four groups according to their previous inventive activity: New Inventors have no previous inventive history. Specialized inventors have been active in the same technology. Related inventors gained experience in related technological fields. Unrelated inventors have previous experience in fields which are not related to wind power or PV. These inventors and their different inventive history and assumingly different knowledge and capabilities provide different contribution to the technology's knowledge base, which also might differ in the life cycle phases of the technologies.

To test the success of knowledge recombination by different types of inventors, patents filed by German inventors are used for the period 1970 - 2006. Recombinatorial success and contribution to the knowledge base is measured by the patent's forward citation. Forward citations indicate how many other inventions build on the patent and can be an indicator for the contribution of the invention to the knowledge base. The development of the technologies is separated in different life cycle phases according to their development. There are three phases for wind power and two phases for PV. In the case of PV, the different sub-trajectories which are identified in patent data in Chapter 2 are considered as well. Negative binomial regressions are run for each of these different life cycle phases. Furthermore, rolling-window regressions are proposed as a new approach to capture dynamics.

The results show that different sources of knowledge matter for technological evolution in general but differently in the phases of the technology life cycle, mostly in line with the proposed extension of the Anderson and Tushman (1990) model. Overall, there is a shift over time of relevance from inventors which have been active in fields outside the technology to inventors which are specialized in the technology. These results contribute to a deeper understanding of the evolution of a technology's knowledge base and which dynamics take place along the technology life cycle. In previous studies, it is assumed that the mechanisms of knowledge recombination are static and do not depend on the maturity of the technology. Furthermore, the understanding that recombination differs in different stages of a technology is crucial for policy makers to implement relevant policies and support the right actors as well as for management to pursue the right R&D strategy.

The chapter is single-authored and won ex aequo the Best Student Paper Award at the 16th International Joseph A. Schumpeter Society Conference in Montréal. Currently it is under review in Industrial and Corporate Change.

1.2.3 Chapter 4

The fourth chapter "Inventor networks in renewable energies: The influence of the policy mix in Germany" focuses again on inventors, but particularly on their co-inventor network of knowledge exchange. There is vast evidence that networks of knowledge exchange are crucial for inventive and innovative activity (Dosi, 1988; Powell et al., 1996; Ahuja, 2000). This chapter addresses the particular question how size and structure of these networks are influenced by a mix of different policy instruments which support inventive and cooperative activity.

Technological change and gains in efficiency of wind power and PV are to a large extent driven by governmental support. This chapter builds on the conclusive evidence that demand pull and technology push instruments support inventive activity in general and for renewable energies in particular (e.g. Johnstone et al., 2010; Peters et al., 2012; Wangler, 2013; Nesta et al., 2014). However, there is lacking evidence how policy in general and these two kinds of instruments in particular influence knowledge exchange. Besides these two kinds of instruments, there is a third group of instruments, so called systemic instruments. Systemic instruments solve system failures such as failures of complementarity, reciprocity and intermediation in knowledge exchange and mutual learning (OECD, 1997; Cantner and Graf, 2003; Smits and Kuhlmann, 2004). We provide first insights how these instruments influence size and structure of co-inventor networks. Besides the scarce evidence how these different instruments influence networks, these instruments furthermore interact in an instrument mix, which is part of a broader policy mix. Such a policy mix needs to be consistent to support innovative activity effectively (Flanagan et al., 2011; Rogge and Reichardt, 2016). This chapter also provides some insights on the consistency of the policy mix.

As in Chapter 3, German inventors which filed patents in PV or wind power are the objects of analysis. Co-inventor networks are reconstructed based on co-patenting for the period from 1980 until 2011. The effect of demand pull, technology push and systemic instruments is estimated on size and structure of co-inventor networks. With respect to the systemic instruments, which are designed to increase collaboration between inventive actors, we disaggregate R&D subsidies into technology push if they are granted to single organizations and into systemic instruments if they granted research consortia and assume that they foster collaboration, which can be regarded as systemic (Smits and Kuhlmann, 2004). With respect to the policy mix, we operationalize the consistency of the policy mix by interacting different instruments.

This chapter bring together the literature on knowledge networks and innovation policy for the case of environmental innovations. This provides further understanding of the relationship between policy instruments and their effect on co-inventor networks and knowledge exchange in such networks. We can show that the different instruments do not only increase inventive activity, but also alter the underlying network structure. We find that the network size is positively affected by technology push and systemic instruments in wind power, whereas in PV it is only technology push which shows an effect. Demand pull instruments have a strong positive effect in PV and wind power. The influence of systemic instruments on the structure of the networks finds support only in the case of wind power, whereas for PV, the results are inconclusive. Technology push policies do not increase cooperation in wind power at all, while for PV there is an ambiguous effect. Concerning the effect of demand pull instruments on collaboration, we find a strong positive influence in both technologies. With respect to the policy mix, we find that push and pull instruments work hand in hand in increasing network size. Demand pull and systemic instruments together spur cooperation. Both indicate strong consistency of the policy mix.

This chapter is co-authored with Uwe Cantner, Holger Graf and Johannes Herrmann. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations as well as to the interpretation of the results. The chapter is published in Research Policy and in the following chapters referred to as Cantner et al. (2016).

1.2.4 Chapter 5

The fifth chapter "International research networks: Determinants of country embeddedness" focuses again on knowledge exchange in networks, but has a slightly different perspective. While in Chapter 4 the focus was on the micro level of interaction between inventors, this chapter focuses on the macro level of aggregation. At this level, countries are embedded in the global co-authorship network for PV and the position in this network allows access to global knowledge flows.

The generation and diffusion of knowledge is a collective process and an increasingly global phenomenon. Collaboration among scientists and researchers has steadily increased during the last decades and leads to more valuable output than individual research (Wuchty et al., 2007; Adams, 2013). Especially cooperation with distant partners, which allows access to diverse sets of knowledge, has a positive effects on performance (Bathelt et al., 2004; Cantner and Rake, 2014; Herstad et al., 2014). These cooperation pattern form a global network of knowledge exchange, in which a country can be embedded. This embeddedness allows the country access to global knowledge flows and potentially increases research performance.

We analyze the determinants of embeddedness in the global PV knowledge network, reconstructed from co-authorship of scientific publications. We argue that the position of a country in this network is determined by two driving forces: First, by the structure and functionality of its national research system (Nelson, 1993; Lundvall, 1992; Carlsson and Stankiewicz, 1991) and second, by policy intervention to support research and development. With respect to the research system, we focus particularly on the interaction structure as a determinant of knowledge diffusion within the research system (OECD, 1997; Cowan and Jonard, 2004; Schilling and Phelps, 2007; Cantner and Graf, 2011; Herstad et al., 2014). Thereby we enter an emerging research field by relating country level network characteristics – the meso level – to macro level embeddedness (Dopfer et al., 2004; Gupta et al., 2007). Here, the structure of national networks, i.e. the functionality of the research system and its set-up, determines international collaboration and embeddedness. With respect to policy intervention, similarly to Chapter 4, we account for a variety of instruments that constitute the policy mix for renewable energies.

Our results show positive effects of overall cohesion and connectedness of the national research system on international embeddedness. Countries with a decentralized research network are internationally more embedded, indicating that diffusion oriented national research systems are more open towards external knowledge flows. This provides new insights into the functionality of a research system and helps to understand how the design of the research system influences access to global knowledge flows. Thereby we contribute to the stream of research on multi-level networks (Gupta et al., 2007) by making use of the multi-level structure of publication data. With respect to the instruments of the policy mix, we show that the instruments not only increase research activity, but also positively affect international collaboration and embeddedness. In particular, demand side instruments seem to be important for research and collaboration in PV, as has been shown in Chapter 4 and elsewhere for inventive activity (e.g. Johnstone et al., 2010; Peters et al., 2012). Especially public procurement, proxied by the cumulative number of satellites, shows up as a robust predictor of embeddedness. This result fits well with the more general argument that governmental demand can increase research activity (Geroski, 1990; Guerzoni and Raiteri, 2015). Other instruments show ambiguous results and require further inquiry.

This chapter is co-authored with Holger Graf. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations as well as to the interpretation of the results. The chapter is after revisions resubmitted to Research Policy.

1.2.5 Chapter 6

The last chapter "Flexibility in the selection of patent counts: Implications for *p*-hacking and policy recommendations" is again methodological and refers back to the problem of patent selection already discussed in Chapter 2. While using patent data, researchers have great flexibility in the selection of patent counts. Particularly, high variation is present between different selection approaches and especially between different patent quality dimensions. To elaborate if the flexibility in different selection approaches for solar energy technologies has systematic impact on policy effects, Johnstone et al. (2010) and Peters et al. (2012) are replicated and variation in policy effects induced by different patent selection approaches is assessed.

Even though patent counts are frequently used as a measure of inventive and innovative activity, there is little consensus in the literature how relevant patents can be reliably identified. Chapter 2 already discussed that patents can be searched via different means, but there is also flexibility with respect to the patent quality dimension used for analysis. Patent quality refers to the technological and economic value of the invention. This quality or value shows a very skewed distribution and only a small fraction of patents has meaningful content while the majority of patents is technologically or economically irrelevant (e.g. Harhoff et al., 1999, 2003). Several studies account for this by controlling for different patent quality dimensions. However, there is no consensus how to assess patent quality and which quality dimension to consider. Such a great variety of search strategies and quality dimension imposes the question how reliable empirical analysis is with respect to patent data and how policy makers should interpret such results.

We identified 51 different selection approaches for solar energy technologies which intend to measure inventive activity in these technologies. We use the research design of Johnstone et al. (2010) and Peters et al. (2012) to show how flexibility in the selection of patent counts results in uncertainty about the sizes and even signs of estimated policy effects. We replicate the empirical setup from these two studies and reestimate their econometric models with the 51 different search strategies proposed in the literature and for six different patent quality dimensions each. To assess the variation in the estimated policy effects, we rely on three methods from different streams of literature. First, we use the concept of extreme-bounds analysis proposed by Leamer (1983) and prominently applied in the growth literature and elsewhere (Levine and Renelt, 1992; Sala-i Martin, 1997; Wang, 2010). While extreme-bounds analysis is usually applied to estimate the extreme-bounds of some key explaining variables when the set of control variables is varied, we use extreme-bounds analysis to characterize the set of estimates that can be obtained due to the flexibility in the selection of patent counts, which is the dependent variable in the analyses. Furthermore, we use vibration plots applied in natural sciences (Patel et al., 2015) to visualize the estimates and infer on patterns across search strategy, technology and patent quality. These plots also show how intentional search for significant estimates is possible. Finally, we use meta regression techniques to assess determinants of coefficient size (Stanley and Jarrell, 1989).

We find that flexibility in the selection of patent counts results in a wide range of estimates for the effects of policies on patent counts. The uncertainty regarding signs and sizes of these policy effects is substantial. For almost all policy effects both positive and negative estimates that are statistically significant can be obtained. With respect to the quality dimension of patents, we show that especially granted patents show very large and in many cases deviating effects. Using three different quality subsets reduces the uncertainty, which nevertheless remains substantial. The different search strategies influence effect sizes, but there is no consistent pattern. However, the larger the number of patents selected, the lower the estimated policy effect, indicating that policy effects are targeted.

Overall, we show that flexibility in the selection of patent counts has several implications for the use of patent data and calls for a careful interpretation of results obtained with patent data, providing empirical evidence for the warnings made by Griliches (1990). We demonstrate the potential for conscious and unconscious p-hacking by estimating policy effects on varying patent counts obtained by different patent selection approaches. Thereby we show how uncertainty in the estimated policy effects translates into uncertainty for policy makers in how to evaluate the effectiveness of policy instruments.

The chapter is co-authored with Stephan B. Bruns. I contributed significantly to the design of the study, the data collection, the theoretical and empirical elaborations, and to the interpretation of the results. The chapter is in preparation for submission.

Chapter 2

Identifying technological sub-trajectories in photovoltaic patents

2.1 Introduction

Technological progress unfolds along a technological trajectory by accumulation of knowledge and competences (Dosi, 1982). While the technological trajectory summarizes the means to solve a specific problem, inside a trajectory sub-trajectories can be present. Such a sub-trajectories provide the same solution, but via different means or with different performance characteristics (Durand, 1992). Sub-trajectories emerge in the continuum of incremental and radical innovations and provide opportunities for substantial improvements along the trajectory. Competition between different sub-trajectories can take place and technological lock-in into inferior outcomes can emerge, hampering overall technological progress (Arthur, 1989; Cowan and Hulten, 1996). Furthermore, sub-trajectories can open up new potential for improvements or widen the application space of a trajectory (Kash and Rycoft, 2000; Funk, 2003). This makes sub-trajectories a relevant object to analyze technological change.

The understanding of drivers and mechanism of progress on this micro level of the sub-trajectory provides further insides on technological progress in general and helps to forecast future potentials and developments of specific technologies. At this micro level, dynamics can take place, such the emergence of new sub-trajectories or shifts in the dominating sub-trajectory, which shapes the development of the overall trajectory (Durand, 1992). Revealing these dynamics can provide valuable insights in the innovation process and drivers of technological change. However, analyses on the sub-trajectory level are scarce and usually descriptives. Patent data can be used to empirically assess technological progress along sub-trajectories and provide a better understanding of knowledge creation and accumulation. For this end, this chapter proposes a patent search strategy for photovoltaic (PV) patents, which separates the trajectory in its sub-trajectories. While there are many search strategies to select PV patents (see Chapter 6), non of these distinguishes between the different sub-trajectories. PV is a particular good example

Acknowledgments: This chapter benefited from discussions with Uwe Cantner, Josefin Diekhof, Katja Ewert, Fritz Falk, Holger Graf, Johannes Herrmann, Thomas Kalthaus, Abdolreza Momeni, Carsten Ronning, Susanne Walter and Christian Weber.

to study technological change on the sub-trajectory level, since it is highly dynamic and several sub-trajectories emerged over time, which allow overcoming physical boundaries. Since PV helps to mitigate climate change, understanding the dynamics in the technological development can help to accelerate this process and decrease its cost/performance ration further.

The aim of this chapter is to develop a replicable and modular patent search strategy for PV patents, which allows to distinguish and analyze sub-trajectories. Even though patent data is a problematic indicator for inventive and innovative activity (Griliches, 1990) and only a fraction of inventions is patented (Cohen et al., 2000), it allows to infer on patterns of inventive activity and technological progress. The proposed search strategy is based on keywords and classification derived using established procedures (Porter et al., 2008; Costantini et al., 2015a). Based on extensive review of the technical literature, the proposed search strategy distinguishes the overall PV system into three different cell sub-trajectories and two generic components. A corresponding list of keywords and classes is derived from the literature and validated by leading experts. The patents which are selected based on the proposed search strategy are compared against two benchmark search strategies and the search strategy is comparable in its scope and coverage, but allows for the more detailed analysis of inventive activity in sub-trajectories.

Descriptive results show that there are differences in the inventive activity between sub-trajectories. Surprisingly, the market-dominating silicon wafer cell sub-trajectory shows the least patented inventive activity, while there are changes in intensity between other sub-trajectories over time. Geographical differences between countries are present. Asian countries, for example, focus their inventive activity on the emerging cell sub-trajectory, while the USA focuses on the established thin-film sub-trajectory and inventive activity in Germany focuses on the module component.

The descriptive results presented in this paper show substantial differences in the dynamics of the sub-trajectories. The proposed search strategy can be used to analyze how these differences translates to other economic dimensions. For example, the sub-trajectories can influence industrial dynamics, as shown by Kapoor and Furr (2015) for entry in the PV industry. Their findings could be extended by accounting for inventive activities in these sub-trajectories or how it influences firm survival. With respect to the technological development, Momeni and Rost (2016) and Park et al. (2015) show that different sub-trajectories emerge over time, but they do not provide an overall assessment of the technological development, which is possible with the proposed search strategy. Furthermore, the knowledge dynamics along each sub-trajectory can be analyzed in more detail, as proposed for example by Jamali et al. (2016) or Lacerda and van den Bergh (2016) to uncover how knowledge is integrated or shared between the sub-trajectories.

A better understanding of technological development on the sub-trajectory level has several implications for economic research and policy. Using sub-trajectories helps to break up the dichotomy of radical and incremental innovation, since there are substantial changes in a trajectory, which need to be considered if technological progress is studied. Here, patent data can be used to uncover such changes over time. This is especially relevant if sub-trajectories reach their physical boundaries and active search for alternatives is required. In such a case governmental intervention is required to support such search processes. Furthermore, technology neutral policies can hinder progress, if sub-trajectories with high potential, but initially higher cost/performance ratio are locked-out from the market, a lock-in into an inferior solution might occur and have detrimental effects on overall progress of the trajectory. Also, the emergence of new sub-trajectories needs to be monitored to forge ahead in international competition by supporting upcoming solutions early on.

The chapter proceeds with a theoretical discussion of the definition and usage of sub-trajectories in Section 2.2. In Section 2.3 the sub-trajectories and components of the PV system are discussed. The patent search strategy is derived in Section 2.4 and analyzed in detail in Section 2.5. Section 2.6 concludes.

2.2 Technological progress along sub-trajectories

A technology can be characterized by the dynamic accumulation of knowledge and competences to solve a specific problem (Dosi and Nelson, 2010, 2013). Thereby variation among possible solutions can exist which constitute a technological paradigm, or as Dosi (1982, p. 152) defines it: "*... we shall define a "technological paradigm" as "model" and a "pattern" of solution of selected technological problems, based on selected principles derived from natural sciences and on selected material technologies*". Such a technological paradigm sets boundaries and provides orientation for research and inventive activity to solve a particular problem. These activities foster technological process which unfolds along a technological trajectory, which provide the solution for the problem. This progress is incremental and improves techno-economic characteristics of the artifact or process over time via accumulation of knowledge (Dosi, 1982; Dosi and Nelson, 2013). Since multiple technological trajectories can be present in a paradigm, competition between these can take place (Arthur, 1989). Such a selective competition can result in a dominant design which defines the paradigm (Abernathy and Utterback, 1978; Murmann and Frenken, 2006).

While there can be multiple trajectories present in a paradigm, also the technological trajectory can consist of multiple sub-trajectories, which provide the same solution for a problem, but have different techno-economic characteristics. Such sub-trajectories are introduced along the trajectory by "*micro-radical innovations*" (Durand, 1992, p. 363), in "*transition patterns*" (Kash and Rycoft, 2000, p. 822) or by "*proactive development of technical alternatives*" (van de Poel, 2003, p. 59), which do not alter the trajectory itself, but opens up variation inside through new solutions to the same problem, with potential to improve the technology further. Thereby the technological trajectory envelopes the sub-trajectories and represents the frontier of technological performance (Durand, 1992). As depicted in Figure 2.1, the trajectory is the envelope curve (solid line) consistent of four sub-trajectories which each improve over time and possibly outperform one another by decreasing costs and/or increasing performance. However, usually emerging sub-trajectories have higher costs and/or lower performance than existing ones, but higher learning rates might be possible, especially if the technological potential of existing sub-trajectories is exhausted. It is not likely that each sub-trajectory provides the best characteristics and selection between them takes place, therefore certain sub-trajectories fail or do not improve as fast as other sub-trajectories (Cowan, 1990; Durand, 1992). Furthermore, the emergence of sub-trajectories is necessary if the established one reaches its full potential, for example if physical boundaries restrict further improvement (Sahal, 1985; Kash and Rycoft, 2000). Besides changes in the cost/performance ratio, these sub-trajectories can increase the application space or change trade-offs in the product design and can help to establish a dominant design (Funk, 2003).

Analyzing technological progress on the sub-trajectory level helps to understand mechanisms and drivers in more detail, since patterns at the sub-trajectory level might be indistinguishable on the trajectory level or unfold only for key components, but exert substantial improvements. The development of sub-trajectories and their influence on the overall trajectory have been studied for many technologies, but not always explicitly considered as such. Durand (1992) uses several examples, such as insulin production, public switching in telecommunication, dynamic random access memory, and semiconductors to illustrate that sub-trajectories emerge frequently and influence the development of the respective trajectory. Their emergence can furthermore rejuvenate a technology if it reaches its technical or physical limits (Sahal, 1985). An

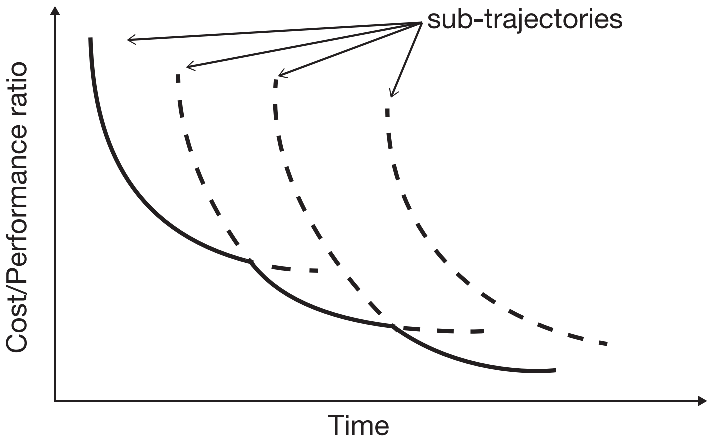


Figure 2.1: Sub-trajectories in a trajectory.
Source: Adapted from Durand (1992).

example are aircrafts, where moving form propeller to jet engines overcomes aerodynamic limits (Constant, 1980). Rennings et al. (2013) illustrates the case in which artificial limits are imposed on a trajectory by tightening emission regulations in coal-fired power plants. In this case, sub-trajectories opened up possibilities to further improve performance but at the same time complying with environmental regulations. In a similar vein, Oltra and Jean (2009) integrate environmental performance into the assessment of sub-trajectories and show for car engines that this additional performance measure influences the prospects of a sub-trajectory. Competition between different sub-trajectories can have detrimental effects on technological progress, if a lock-in in a inferior sub-trajectory emerges, as shown by Cowan (1990) for nuclear reactor and Cowan and Hulten (1996) for car engines. However, the opposite effect was shown by Funk (2003) for the mobile internet, where the emergence of sub-trajectories increases competition which lead to product innovations and overall expands the application space and broadens the trajectory.

The emergence of sub-trajectories also influences industry dynamics as shown for the flat panel display trajectory by Mathews (2005). In the flat panel display trajectory several new 'generations' with respect to the production process were introduced over time and changes in the industry composition are attributed to it, especially entry. Similar effects were found for the aircraft industry. Bonaccorsi and Giuri (2003) emphasize that different sub-trajectories exist for different types of customers and firms specialize and learn from the heterogeneity of sub-trajectories and thereby influence industry composition. Also Durand (1992) stresses this point and concludes that the emergence of sub-trajectories and the increases in technological performance increases competition and that firms can 'surf the waves of change'.

Sub-trajectories are also present in the photovoltaics trajectory. In PV, different cell generations emerged over time and are in competition with each other. Menanteau (2000) showed that path-dependency and learning from related knowledge increased efficiency. Due to exhausting technological potential, a lock-in occurred and new sub-trajectories need to overcome this situation. Sartorius (2005) points out that this lock-in into an inferior PV sub-trajectory can be overcome if policy support would not be technology neutral but favor the emerging sub-trajectories that show favorable characteristics and support their progress. Otherwise accumulation of knowledge would increase the lock-in situation while competition between the sub-trajectories would foster progress. The competition between the different sub-trajectories affects also entry decisions in the PV industry. Kapoor and Furr (2015) show that the technology choice is important for entry.

Since sub-trajectories are important for technological change in general and particularly in PV, in the following the PV system and its sub-trajectories are discussed from a technical and economic point of view to derive a patent search strategy to analyze inventive activity in more detail.

2.3 Sub-trajectories in the photovoltaic system

2.3.1 Technological components of the photovoltaic system

The PV system consists of three components: The PV cell, the PV module and the balance of system components (comp. Figure 2.2). The core component is the PV cell, which converts the sunlight into electricity. The PV cells are encapsulated in a module which connects several cells and protects them from the environment. The modules need to be connected to and managed by grid infrastructure, which are so-called balance of system components (BoS). While the two latter components are generic for every PV system, whereas for the PV cell multiple technological solutions exist. These different cell types are the sub-trajectories of the overall PV trajectory. In the technical literature, they are referred to generations and have distinct technological and economic characteristics (e.g. Green, 2001; Conibeer, 2007; Jayawardena et al., 2013)[1]. Currently, three to four different PV cell generations can be distinguished. The first generation uses crystalline silicon wafer, the second generation uses semiconductor thin-films and the third generation uses novel materials (here, some authors distinguish further and a fourth generation seems to emerge, see Jayawardena et al., 2013). These different generations or sub-trajectories co-exist and research and development is performed in all of them. The different cell generations emerge at different points in time and their improvement is heterogeneous (see also Green et al., 2017). In the following, I briefly discuss the different components of the PV system and the different PV cell sub-trajectories.

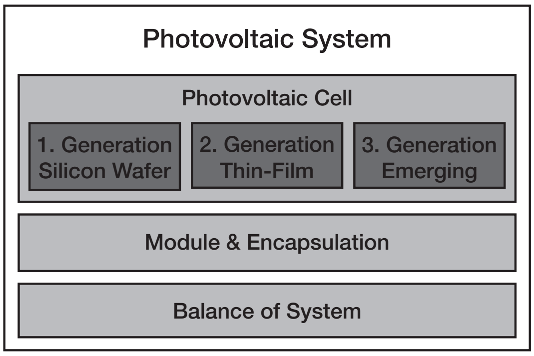


Figure 2.2: Components of the photovoltaic system.

The photovoltaic cell The PV cell is the core component of the PV system. The cell absorbs the sunlight and converts it to electric energy via the photoelectric effect.[2] The capacity to absorb sunlight depends on the material used for the PV cell. Semiconductors, such as silicon, germanium, or gallium-arsenide, have a so-called band gap, which is the distance between the valence band and the conducting band, which have free electrons to conduct a current (Sze

[1] To be in line with the technical literature, in the following the term generation is used to refer to the different sub-trajectories.

[2] For a more detailed discussion of the following physical principles and components of a PV system see Green (1982), Fraas and Partain (2010), Fonash (2010) and others.

and Ng, 2007).[3] The photoelectric effect results from the energy content of the photon and the material's band gap. If the energy content of a photon is high enough to allow an electron to move from the valence band to the conducting band, a current emerges. To convert this current to electricity, the charge needs to be separated and directed to prevent the electron to go back to its initial state. This separation is usually achieved by a so-called n-p-junction if the same material is used or a hetero-junction, if the cell consists of different materials (Sze and Ng, 2007). This junction is usually an electric field created by doping (inserting) different materials in the absorber layer so that a positive and a negative current are present (Fonash, 2010; Fraas and Partain, 2010).

Since the material's band gap is a decisive factor for the conversion of sunlight into electricity, different materials can be considered based on their band gap. However, the so-called Shockley-Queisser-limit restricts the conversion for a single band gap cell. This limit sets the theoretical conversion maximum of sunlight in a material (the limit can be increased if the light is concentrated) and is based on the material's band gap (Shockley and Queisser, 1961). This limit can only be overcome if multiple layers of different materials are combined to absorb different energy contents of photons. This combination of different materials is however restricted eventually by a thermodynamic limit, which restricts the overall energy conversion (Vos and Pauwels, 1981).

Three different cell generations can be distinguished so far. They can be described based on their conversion efficiency, related to the material used, and their costs. Figure 2.3 depicts the three different cell generations with respect to these two dimensions. The first generation, silicon wafer cells, are expensive, but also efficient and have reached their physical conversion limit. The second generation, thin-film cells, are much cheaper in general, but not as efficient as the first generation. Only the third cell generation can, especially by combining different materials in multi-junction cells, overcome the Shockley-Queisser limit and at the same time be cost competitive (see also Green, 2001; Conibeer, 2007, for further discussions). In the following, the different cell generations are discussed in detail.

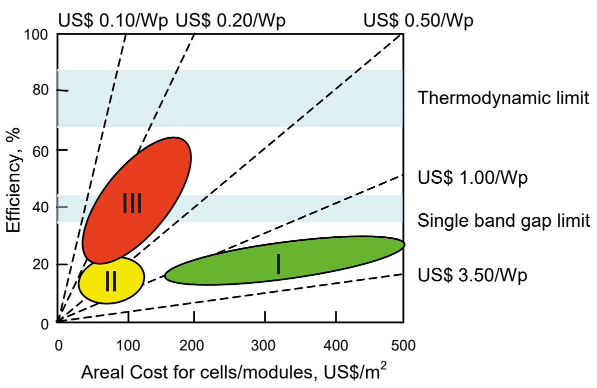


Figure 2.3: Photovoltaic sub-trajectories and their efficiency and physical limits.

Figure note: Source: Conibeer (2007). The ellipses for the cost/efficiency range are indicative, only for the first generation (green ellipsis) the area is quite accurate, while for the second generation (yellow area) and third generation (red area) they are based on predictions.

[3] Technically speaking, all materials have a band gap, however, conductors (usually metals) have no or a very small band gap, so electrons can easily move between the band, and insulators have a very large band gap, making it very difficult for electrons to move between the bands. For further details on the physical principles, see, for example, Sze and Ng (2007).

1. Generation: Silicon wafer cells The first PV cell generation emerged in the 1950s and uses a silicon wafer to absorb light (Chapin et al., 1954). These cells are simple to produce and knowledge and competences are related to the microelectronic sector (Sze, 1981; Green, 2000). Since silicon has a favorable band gap, its conversion efficiency is high. However, silicon is an indirect semiconductor, which requires that the material needs a certain thickness to absorb and convert the sunlight. Since silicon is a rather expensive material, the costs for silicon wafer cells are high and cost reductions due to thinner wafers have reached its technical boundaries (Fraunhofer ISE, 2016). There exist several approaches to fabricate the cell material, which divides the cells in two groups, mono- or single-crystalline and poly- or multi-crystalline cells. The mono-crystalline silicon cells are cut out of a single silicon crystal, which is most frequently produced by the Czochralski process. Poly-crystalline silicon cells consist of silicon which is cast in ingots from smaller silicon pieces and then cut into cells. A specific technique to produce poly-crystalline silicon is the so called ribbon silicon, which, however, did not reach the competitive efficiency levels (Nakayashiki et al., 2006). In general, the poly-crystalline cells can be produced cheaper, but they have lower conversion efficiency than mono-crystalline cells (Miles et al., 2005).[4]

Overall, silicon wafer cells are characterized by high conversion efficiency and high costs.

2. Generation: Thin-film cells The high cost of the first generation cells lead already in the 1960s to the development of cells, which can be produced cheaper (Fraas and Partain, 2010). For these kinds of cells, direct semiconductor materials are deposited on a (flexible) substrate to absorb sunlight. These thin-film cells widens the application space, since they are lightweight and flexible, which allows integration, e.g. in clothing or other objects. The cell materials can be divided in two kinds, one relying on the use of amorphous silicon films and another uses materials from the so called II-VI-, III-V-, and I-III-VI-groups of the periodic table (Miles et al., 2005; Fraas and Partain, 2010). Amorphous silicon is an alloy of silicon and hydrogen and can be deposed in very thin layers on a substrate (Miles et al., 2005). However, the cells suffer from severe degradation in sunlight, the so called Staebler–Wronski effect. To overcome this effect and to increase the cell efficiency, layers of different absorptive materials are combined to double- or multi-junction cells. Further variations of silicon thin-films use micro- or nano-crystalline silicon which assemble closer to the physical characteristics of mono-/poly-crystalline cells but has the favorable characteristics of a thin-film material.

From the II-VI-group, especially cells which use cadmium-telluride (CdTe) are favorable, since CdTe has a nearly optimal band gap (Miles et al., 2005). CdTe cells are characterized by very low production costs and nowadays high efficiency rate (Fraas and Partain, 2010). Materials from the I-III-VI-group, so called chalcopyrites, are among others copper-indium-diselenide ($CuInSe_2$) and copper-indium-gallium-diselenide ($CuInGeSe_2$), also called CIS and CIGS cells. These cells also have already high efficiency and low costs, but contain still expensive and toxic materials and cells based on copper-zinc-tin-sulfide (CZTS) are a possible replacement.

A particular case are the materials from the III-V-group, which are also semiconducting thin-films, but very expensive.[5] In this group, especially gallium arsenide (GaAs) but also indium-phosphide (InP) and gallium-antimonide (GaSb) are considered for PV cells. These materials are expensive, but have favorable characteristics, especially for space applications. These materials are in most cases combined in multi-junction cells and/or used with a concentrator to focus light

[4] The cells receive also further treatment to increase the absorptive capacity. For example, the single crystal cells are etched to create a surface structure consisting of small pyramids which reflect the light downwards. Also the cells receive anti-reflection coating to reduce losses (see for further treatments Green, 2000).

[5] There is no consensus in the technical literature to which generation these cells should be attributed. Here, they are attributed to the second generation, since they use traditional semiconducting materials.

on the cell (Miles et al., 2005). Their terrestrial application is only marginal due to their high costs (Fraunhofer ISE, 2016).

Overall, thin-film cells for the mass-market are generally characterized by low costs and low efficiency.

3. Generation: Emerging cells While the first and second generation of PV cells reach a state of maturity, several other approaches emerged. These emerging cells usually do not use semiconductors but other materials, which are frequently combined in tandem structures to increase efficiency (Miles et al., 2005; Conibeer, 2007; Brown and Wu, 2009; Jayawardena et al., 2013). Most prominent are dye-sensitized solar cells (DSSC) or organic cells. The DSSC were invented by O'Regan and Grätzel (1991) and utilizes the highly porous structure of titanium-dioxide (TiO_2) which increases the absorptive surface in the cell. Organic or polymer PV cells use a polymer as an absorber and use the physical principles of organic electronics (Nelson, 2011). Recent approaches use perovskite as an inorganic component in an organic cell and provide very promising efficiency rates (Kojima et al., 2009). Furthermore, quantum dot cells which use semiconducting particles of different size to create different band gaps are recently explored (Baskoutas and Terzis, 2006). Also recently, the introduction of different inorganic nanomaterials in polymer cells are considered as having the potential to lead to a fourth cell generation (Jayawardena et al., 2013). Additionally, several materials allow for the production of semi or fully transparent cells, which extends the range of application to e.g. windows or screens (Zhao et al., 2014).

Overall, third generation cells are characterized by (potentially) high efficiency and low costs.

Module production and encapsulation The PV cells need to be connected to each other to form a PV module, which needs encapsulation and further components. Several parts of the module were improved over time to increase efficiency and to reduce costs. Especially the electric contacts on the front and back of the cell, as well as the components for encapsulation were improved substantially. Furthermore, there is great flexibility in where to use a PV module, such as installment on the ground, integration into a building and mounting on a vehicle or spacecraft (Fraas and Partain, 2010).[6] In principle, these parts of the PV system are generic and independent from the cell generation used.

Balance of system components The last part of the PV system connects the PV module to the electricity consumer. Several distinct ways are possible, but usually separated into off- and on-grid applications. The off-grid applications usually use the direct current produced by the PV module to either power specific applications or to store the electricity in a battery. However, the battery itself is not considered, but only the charging component. The on-grid application usually needs an inverter to convert the direct current into an alternating one (Fraas and Partain, 2010). Furthermore, there are several ways to optimize the energy production, for example via tracking systems to follow the sun's movement (Mousazadeh et al., 2009). The BoS components are also generic for the PV system.

Overall the PV system consists of three components, while among the PV cell, three or even more sub-trajectories exist which are in competition among each other. The other two components, the module and encapsulation as well as the BoS components are generic components and are required in every PV system.

6 Some researchers treat this mounting component as an independent part and separate it from the module encapsulation (e.g. Huenteler et al., 2016b).

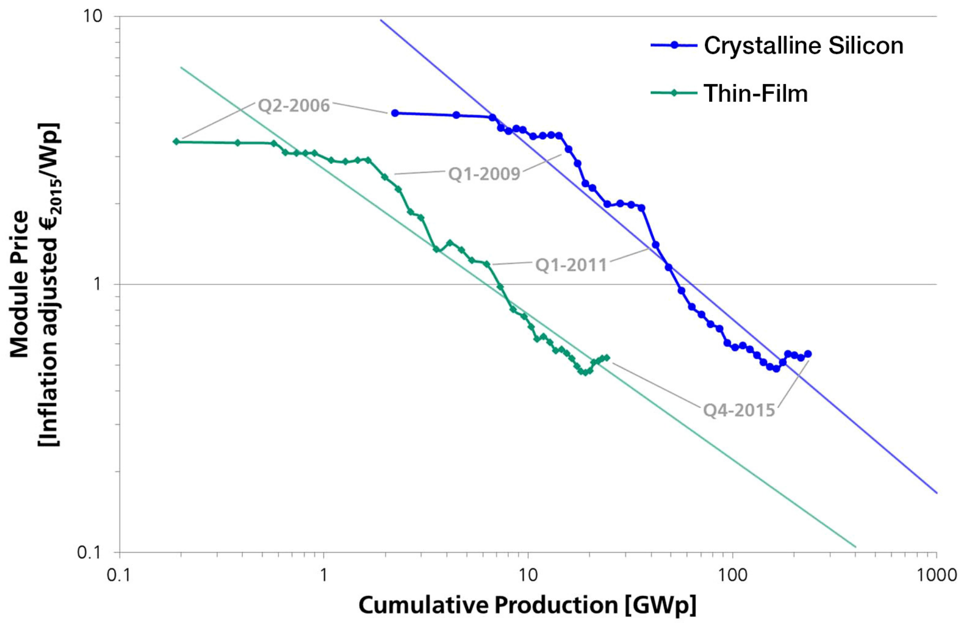


Figure 2.4: Global learning curves for crystalline-silicon wafer and thin-film cells. **Source:** Fraunhofer ISE (2016).

2.3.2 Economic dimension of the photovoltaic system

The PV system and the different sub-trajectories can also be evaluated from an economic point of view. Technological progress in the overall trajectory but also in the different sub-trajectories is remarkable and allowed PV to be cost competitive with other electricity generating technologies. Substantial learning effects and steep learning curves are present in PV (Fraunhofer ISE, 2016) and development follows a generalized Moore's law (Farmer and Lafond, 2016). For example, Fraunhofer ISE (2016) calculates a 23% learning rate for the last 35 years for PV modules. Even though there are several approaches how to estimate learning curves, such as two- or multi-factor learning curves (Yu et al., 2011), all reveal a strong reduction in module costs and also decrease of other factors, such as electricity consumption and emissions during production, took place (Louwen et al., 2016).[7] This strong decrease in module prices is immanent in the different cell generations as well. Figure 2.4 depicts the learning curves for the first and second generation cells. Both module prices decrease over time, however, the second-generation cells reach the same price level with only a tenth of the cumulative production of silicon cells. Other components of the PV system increase in efficiency and decrease in price, too. Fraunhofer ISE (2015) calculates a learning rate of about 19% per year for small scale PV inverters from 1990 until 2013. Cost reductions of different components lead to overall cost reductions for PV systems in general but nowadays the BoS components have a larger share of the PV system costs than the PV modules (Fraunhofer ISE, 2016).

The efficiency increases and reduction in costs can be partly attributed to strong political support. Demand as well as supply side policies such as feed-in tariffs, quota systems and R&D subsidies were in place supporting R&D as well as diffusion (Watanabe et al., 2000; Johnstone et al., 2010; Peters et al., 2012; Polzin et al., 2015). However, most of these policies were technology neutral or data about a finer grained support is not available. For Germany, a distinction of R&D funding for the different PV sub-trajectories is available. Figure 2.5 shows the governmental R&D subsidies for different research areas. The first PV generation receives

[7] For further influences on the cost reductions in PV, see, Nemet (2006), Candelise et al. (2013), or Pillai (2015).

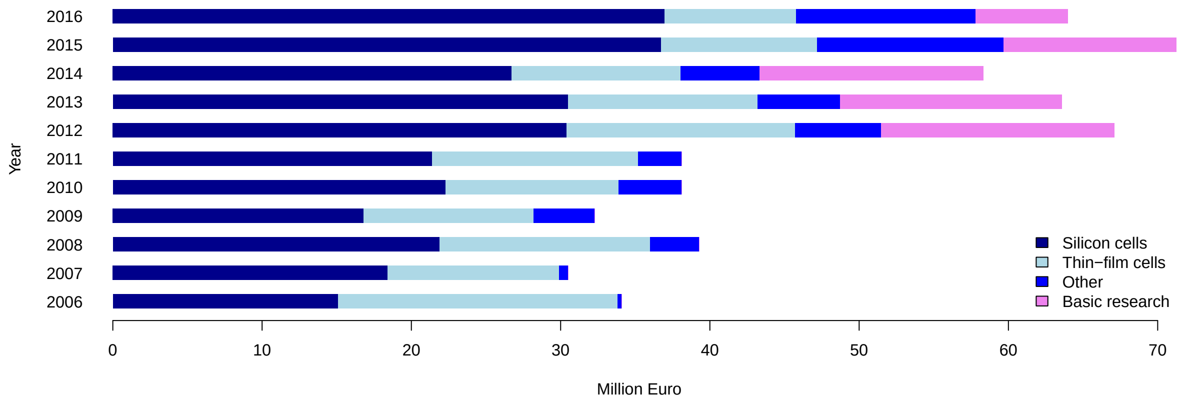


Figure 2.5: German R&D subsidies for photovoltaic sub-trajectories 2006–2016.
Data source: BMWi (2013, 2017).

most funding and over time the funding for thin-film technologies is reduced in absolute and relative terms.

Due to efficiency increases and declining prices, the diffusion of PV increased exponentially in the last decades and nowadays PV contributes substantially to electricity production globally (REN21, 2015). With respect to the different cell generations used, Figure 2.6 displays the production shares of first- and second-generation cells over time. The first generation clearly dominates the market. But among the silicon cells, a shift from mono-crystalline to poly-crystalline takes place. Second generation thin-film cells play a minor role and account nowadays for about 10% of overall cell production. Inside the share of thin-film cell technologies, dynamics take place as well. In the early 2000s, amorphous silicon dominated the thin-film technologies but was replaced by CdTe over time (Fraunhofer ISE, 2016). Third generation cells as well as cells with concentrators are produced only in very small amounts and their market share is yet negligible (Fraunhofer ISE, 2016).

2.4 A patent search strategy for photovoltaic sub-trajectories

The previous section discussed the technological and economic differences between the PV sub-trajectories and components. In the following, a patent search strategy for the PV system and its cell sub-trajectories and generic components is developed to be able to analyze inventive activity in the different sub-trajectories. The development of the search strategy follows established procedures, especially Porter et al. (2008) and Costantini et al. (2015a). First, different patent search methods and their advantages and disadvantages are discussed. Second, the development of the search strategy is elaborated in detail and third, an evaluation and comparison of the proposed search strategy and two benchmark search strategies are presented to validate the proposed one.

2.4.1 Patent search strategies

Patent data is stored in databases, usually managed by the respective patent offices. The selection of patents for economic analysis requires a search strategy to identify relevant patents in databases. A multitude of approaches exist to search for technology specific patents (see Abbas et al., 2014, for an overview). The most common and easy to replicate search strategies

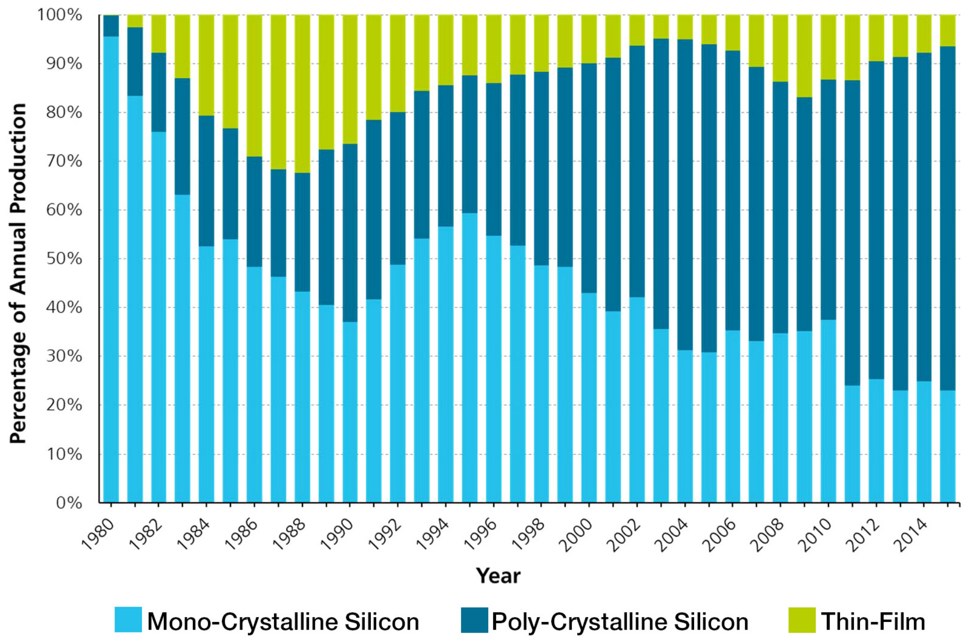


Figure 2.6: Share of annual worldwide photovoltaic cell production.
Source: Fraunhofer ISE (2016).

use either a classification scheme or technology specific keywords as well as the combination of both (Eisenschitz and Crane, 1986; Dirnberger, 2011; Xie and Miyazaki, 2013).[8]

Classification schemes are used by patent offices to support the examination process and to ease their search for prior art (Jaffe and Trajtenberg, 2002). These schemes are structured according to technological principles and are not designed for economic analysis on a product or process level (Vijvers, 1990; Costantini et al., 2015a). One frequently used classification scheme is the International Patent Classification (IPC) managed by the World Intellectual Property Organisation (WIPO).[9] Additionally, recently the Cooperative Patent Classification (CPC) was introduced, which has a specific classification for emerging cross-sectoral technologies such as PV (Veefkind et al., 2012). Using a classification scheme is relatively easy and can derive sufficient results if the desired product or process is exclusively covered by one or multiple classes.[10] However, the use of classification scheme to select patents has potential problems. One major problem emerges if a technological principle is used in several products or processes and using such a class to select patents might include patents which are not related to the product or process under consideration. Furthermore, it is also possible that a product or process combines different technological principles and if a class is not considered, relevant patents are missing.[11]

A keyword search can deliver sufficient results, if a technology can be described by a set of specific keywords. However, several problems exist, since keywords can be used for multiple products or processes not related to the one under consideration. Therefore, keywords need to be selective to avoid including patents which are not related to the relevant product or process. Furthermore, patent documents can be intentionally written to avoid specific keywords

[8] Other possible approaches use, for example, co-occurrences of classifications or keywords on patents, use a pre-defined set of patents to train a search algorithm, or use citations from a specific set to retrieve previous patents (Abbas et al., 2014). However, these approaches are not easily replicable and are sensitive towards the database used.

[9] Further classification schemes are the ones by the United States Patent and Trademark Office (USPTO) or the Japan Patent Office (JPO). See Held et al. (2011) or Wolter (2012) for comparisons.

[10] Such a case are the patents for wind power. The F03D classes cover nearly all relevant patents for wind power.

[11] Other problems relate to the classification system itself, such as changes over time or that patent examiners misclassify a patent or assign too many or too few classes to a patent.

to keep the invention hidden from competitors or not to reveal all details about the invention. Also, language differences or differences in the terminology can affect the number of selected patents (Montecchi et al., 2013).[12] A combination of both, a classification scheme and a set of keywords can mitigate some the above mentioned problems, but is more restrictive than each one individually.

2.4.2 A new patent search strategy for photovoltaics and its sub-trajectories

In the following, I explain how the proposed search strategy is developed using a combination of IPCs and keywords to provide an overall search strategy for PV patents and to distinguish different components and sub-trajectories in the patent data. Similar approaches were proposed earlier, but they do not sufficiently cover the different cell sub-trajectories and PV components.[13] In order to collect the specific keywords and patent classifications for PV, the technical as well as economic literature was reviewed to define the boundaries of the technology. During this process, the three different components and the three different cell sub-trajectories are identified (compare Figure 2.2). Such an in-depth analysis is a crucial part since several other technologies are very close in the technological space. For example, other means exist to convert sunlight into electricity, such as concentrated solar power, which collects heat to run a steam engine and also solar heat collectors are quite similar (see, for a comparison Peters et al., 2011). But these technologies follow different technological principles and are not related to a PV system. Furthermore, the core technological principle of PV is the same as for light emitting diodes, but in the case of PV the light is not emitted, but absorbed.[14] Other technologies and products are also close to PV, such as optical sensors or digital cameras. With respect to the materials used, semiconductors are essential in the microchip industry as well. Even though there are spillovers from adjacent technologies (Sze, 1981; Nemet, 2012), the aim of the search strategy is to understand the development in the different PV sub-trajectories and therefore requires a sharp distinction from adjacent technologies.

Based on the overall understanding of the technology, IPCs and keywords for the different components of the PV system and the different cell sub-trajectories are collected. The keywords and classes are grouped according to the different PV system components and sub-trajectories. Special attention is given to the different materials and processes used in PV cell production to avoid inclusion of non-relevant patents if the material or process is used elsewhere. Patent classifications are selected based on an in-depth review of the IPC system. The scope of the IPCs is intentionally wider (the 8-digit main group level) than in comparable IPC search approaches. Since patents assigned to these classes are searched also by keywords, this allows to capture patents which are misclassified or which are affected by changes in the classification scheme and would be missed out otherwise.

Overall, six different sets of classes and keywords are identified: the three different cell sub-trajectories as well as the module and encapsulation and the balance of system components. For the sub-trajectories, differentiation between the materials is possible, such as mono- and poly-crystalline cells, but since the sub-trajectory is the level of analysis, such more product like

[12] Additionally, patent databases are not always complete and titles, abstracts, or other content can be missing which leaves out potentially relevant patents.

[13] For example, Liu et al. (2011) and Breyer et al. (2013) distinguish different PV-cell materials but do not take into account other components of the PV System. Jang et al. (2013) select patent for different parts of the PV value chain. Jamali et al. (2016) use the recently introduced Cooperative Patent Classification (CPC) to distinguish between different PV generations, but here other components of the PV system are neglected.

[14] A light emitting diode uses a semiconductor and via a n-p-junction light is emitted (see Schubert, 2006, for a technical discussion).

separation is not considered in more detail, but possible.[15] However, there are cases where the patent document does not have enough information to attribute it to any of the sub-trajectories or components. A residual category is introduced for all patents which are related to the PV system in general, but cannot be attributed. There are at least three reasons for a patent not being able to be assigned to the different components. The first could be that the list of keywords miss certain aspects and the respected keywords are not included. Second, the patent is intentionally written to avoid certain keywords to disguise them from competitors. The third reason is incomplete data, since patents can be stored with missing information and have, for example, only a title which could be very simple, such as "photovoltaic cell" and no abstract is present to infer about the actual content of the patent. Since these patents are nevertheless relevant, they are included in this residual category.

The sets of IPCs and keywords for each component and cell sub-trajectory was validated in an iterative process by leading experts in the field covering different parts of the PV system and having a background in academia and practice.[16] The final list of IPCs and keywords is presented in Appendix 2.7.1.[17]

2.4.3 Evaluation and comparison with benchmark search strategies

To evaluate the quality of the proposed search strategy in terms of scope and coverage, the patents which can be selected by the proposed search strategy are compared with two other leading patent selection approaches, the WIPO Green Inventory for PV (GI) and the Cooperative Patent Classification for PV (CPC).[18] For this purpose, patent data is extracted from the Worldwide Patent Statistical Database (PATSTAT) (EPO, 2014).[19] Patents from 1970 until 2011 are selected. Two different patent quality dimensions are considered: priority patent applications, which includes first filings of patent applications and triadic patents, which are applications jointly filed at the USPTO, JPO and the EPO, which are considered to be very valuable patents (Grupp, 1996; Dernis et al., 2001).

There are in total 49,171 priority patents in the proposed search strategy, while there are 129,253 priority patents based on the GI and 57,508 priority patents based on the CPC (comp. Table 2.1). While there is a difference in the magnitude, structural differences in the development over time are not present (comp. Figure 2.7). The proposed selection and the selection based on the CPC have nearly the same development over time. The development of the Green Inventory follows the same pattern, but with a greater magnitude. The results for the higher valued triadic patents is similar in its development. The overall triadic patent count is smaller, with 2,952 from the proposed search strategy, 9,865 for the Green Inventory and 3,577 in the CPC. The development over time is different between priority and triadic patents. Especially the

[15] The list of IPCs and keywords in Table 2.3 contains for each cell sub-trajectory two sets. The silicon wafer cells can be separated in mono- and poly-crystalline cells, the thin-film cells in silicon thin-film and cells using materials from the II-VI-, III-V-, and I-III-VI-groups, and the emerging cells can be separated in organic cells and cells with inorganic materials.

[16] Personal interviews to validate the different keywords and IPCs for the components and sub-trajectories took place in November 2014 in Jena, or via phone or email. Documentation is available on request.

[17] The SQL-code to use the search strategy is available on request.

[18] Both search strategies are widely used in the literature, the WIPO Green Inventory for example in Lei et al. (2013), Martinez et al. (2013), Choi and Anadn (2014), Gallagher (2014), Groba and Cao (2015), and the CPCs for example in Bointner (2014), Stek and van Geenhuizen (2015), Leydesdorff et al. (2015), Diederich and Althammer (2016), Glachant and Dechezleprêtre (2016), Jamali et al. (2016).

[19] Patents are selected by first searching for the respected classes and keywords in all patents in the database and then selected based on the patent's DOCDB patent family the priority patent. This approach allows capturing patents where title or abstract are only available for family members.

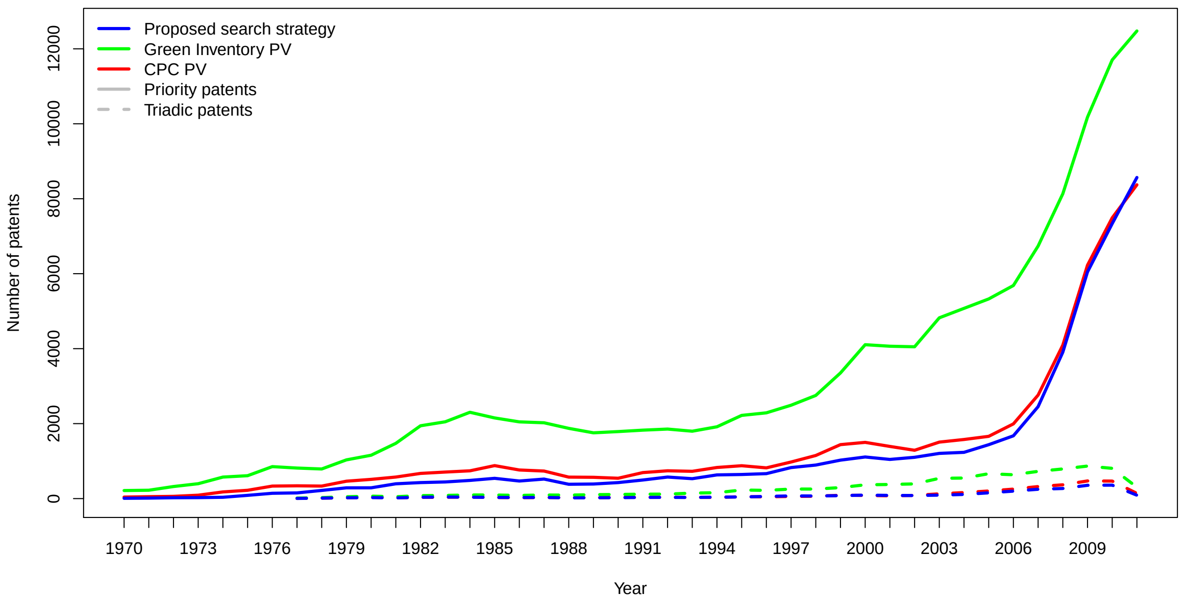


Figure 2.7: Comparison of different patent search strategies for photovoltaics over time.

Table 2.1: Priority patent overlap between different search strategies.

	Absolute overlap				Relative overlap		
	Proposed	GI	CPC		Proposed	GI	CPC
Proposed	**49,171**			Proposed	—	0.839	0.744
GI	41,268	**129,253**		GI	0.319	—	0.410
CPC	36,564	52,963	**57,508**	CPC	0.636	0.921	—

Note: In the right table, the bold diagonal represents the number of patents per search strategy while the lower triangle represent the absolute overlap between two search strategies.

surge of priority patents the last years is not present for triadic patents[20] but there is again no structural difference between the search strategies.

A closer evaluation of the selected patents reveals that the overlap between different search strategies is considerable.[21] About 84% of the patents from the proposed search strategy are included the GI search strategy, while, on the other hand, only 32% of the patents in the GI are also in the proposed selection. However, the GI selects a very large number of patents overall. With respect to the CPC, the proposed selection contains 75% of the patents which can be selected by the CPC, while the CPC contains about 64% of the patents that are selected by the proposed search strategy. A comparison between the GI and the CPC reveals that the CPC is nearly (92%) a complete subset of the GI, but far more restrictive. Overall, there are 35,197 patents which are selected by all three approaches. If the overlap is considered for triadic patents, the share of patents from the proposed search strategy in the GI and CPC search strategies increases marginally (comp. Table 2.4 in the Appendix).

Further differences between the search strategies can be found in their technological coverage. Each patent has one or several classes assigned to it. On average, the patents selected by the proposed search strategy have 2.6 classes per patent, while patents selected by the GI have 3.5 classes and the CPC patents have 3.0 classes per patent. Since all search strategies use a pre-defined set of classes, calculating the share of classes that should be covered and classes that

[20] The decline in the last year stems from the delay in the patent offices procedures.

[21] The overlap between the different search strategies is calculated by $\frac{Patents A \cap Patents B}{Patents A}$. For example, the share of patents from the proposed search strategy that are also in the Green Inventory is: $\frac{49{,}171 \cap 129{,}253}{49{,}171} = \frac{41{,}268}{49{,}171} = 0.839$.

are not covered, gives an idea how widespread the patents are in the technological space. If we assume that the more concentrated the search is on the technological landscape, the better it is to distinct the technology from other technologies. To get an idea how well a search strategy selects the patents, I calculate the share of classes which are not in the pre-defined set over all classes obtained by the respective search strategy. The higher this share, the broader are the patents distributed on the technological landscape. The share of non pre-defined classes is for the proposed search strategy 29%, while it is 67% for the GI and 65% for the CPC. This conveys that the proposed search strategy discriminates better between relevant and irrelevant patents. However, we need to keep in mind that the initial set of relevant classes is larger for the proposed search.

Figure 2.9 in the Appendix depicts a graphical representation of of the technological landscape by the classification co-occurrences of the priority patents. The figure displays in blue the classes (at the group level) which were used to query the patent data and in red are classes which are also on these patents. The classes are connected to each other if they co-occur on the same patent. The size of the nodes represents the number of this co-occurrences per class (in log transformation). The proposed selection has a large fraction of blue nodes in the landscape representing the relevant IPCs. Red nodes are only peripheral and not that large. The landscape derived from the Green Inventory has many more red nodes of considerable size. The CPC landscape however has only one central blue node, which is the Y02E 10 group which covers all PV patents. However, there are also many other classes which co-occur on these patents.

With respect to the country coverage by the different search strategies, Figures 2.10 and 2.11 in Appendix 2.7.2 depict country shares of priority and triadic patents over time.[22] No structural differences between the three search strategies are immanent, indicating that the use of keywords does not bias the selection of patents. Japan has the highest share of priority patents, which is related to their patent regulations in the past, which allowed only one claim per patent, while other patent offices allowed broader patents. This inflation of patents declined after regulation changed in 1988 (Sakakibara and Branstetter, 2001). The second and third countries are the USA and Germany. In recent years, Asian countries, especially South Korea and China, gain remarkable shares as well. With respect to the triadic patents, the USA has the highest share, but it declines over time. Japan is second, followed by Germany. Asian countries have hardly any triadic patents. Especially for China, hardly any triadic patents are filed. de la Tour et al. (2011) attribute this lack of filing patents internationally to the low quality of Chinese patents, since Chinese firm use patents to signal the government that they are inventive rather then to protect their inventions.

Overall, the proposed search strategy does not structurally differ from the two benchmark search strategies in terms of development over time and country coverage. However, the absolute number is much lower compared to the GI, which seems to be broader in its technological coverage. The proposed search strategy as well as the CPC are more focused on the core PV patents. Therefore the proposed search strategy is comparable to the benchmark search strategies, but has the advantage to distinguish the sub-trajectories, which are analyzed in the following.

2.5 Sub-trajectories in photovoltaic patents

Based on the proposed search strategy, it is possible to analyze the development of the different sub-trajectories over time. The disaggregated patent data for the different components and sub-trajectory is given in absolute and relative terms for the priority patents in Figure 2.8 and

[22] A patent is assigned to a country based on the patent office of the priority filing.

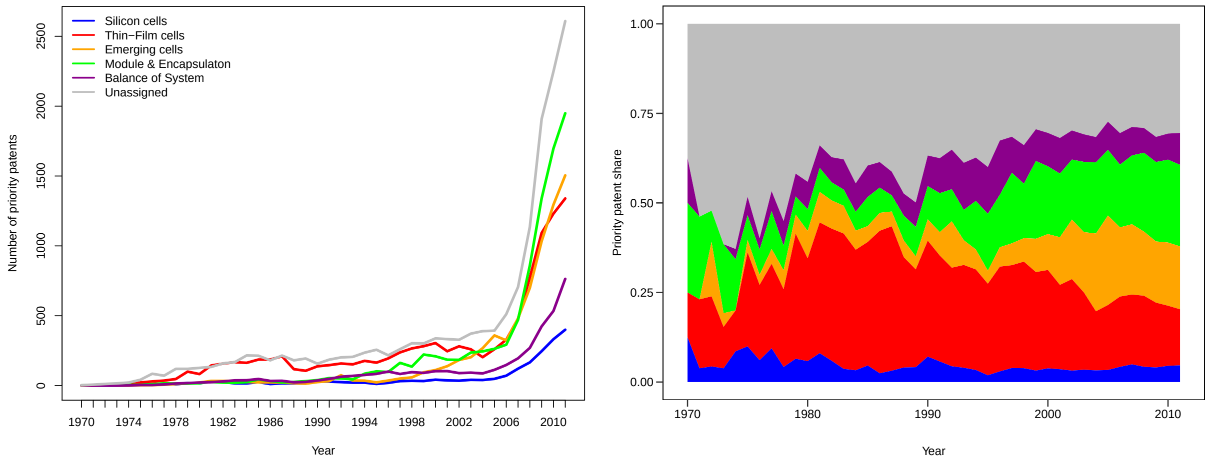


Figure 2.8: Absolute and relative number of priority patents per sub-trajectory.

for triadic patents in Figure 2.12 in Appendix 2.7.3. However, there are hardly any differences between the two patent quality definitions. We observe a steady increase in absolute inventive activity in all sub-trajectories, especially in the last years. With respect to the relative development, it is surprising to see that the share of the silicon cell sub-trajectory is very low and invariant over time. Even though it increases in absolute numbers, its relative share is very small. This is also remarkable since these cells clearly dominate the market and have high learning rates. With respect to the thin-film sub-trajectory, there is an increase in inventive activity in the 1970s and 1980s when the majority of patents where filed for this sub-trajectory. However, from the 1990s onwards, the relative share of thin-film patents declines, but is still about three times as high as for the silicon cell sub-trajectory. The emerging cell sub-trajectory starts to get relevant shares from the 1990s onwards, especially with the introduction of the Grätzel-Cell and follow up inventions. Nowadays they have even a higher share than the thin-film cells, indicating in which direction further inventive activity will unfold.

With respect to the module and encapsulation component, there is also an increase in inventive activity. This increase can be related to the fact that especially the silicon cells have reached their physical boundaries and cost reductions and increases in efficiency can only be achieved if the whole module is improved, for example, by reducing the size of the electronic contacts which reduces the absorptive area of the cells. The share of the Balance of System component does not change over time, even though a steep learning curve is present (Fraunhofer ISE, 2015). Unfortunately, there is a considerable share of patents which cannot be attributed to the different components and sub-trajectories. However, this share declines over time and shifts between the different components can maybe be attributed to the increase in patents which can assigned to sub-trajectories. The overall development trend of sub-trajectories should not be affected by unassigned patents.

If we turn to the different countries and their inventive activity in sub-trajectories (Table 2.2), we can observe several differences between the countries. As indicated earlier, the countries differ in their patenting intensity, but there is also a focus of some countries on specific sub-trajectories. For example, while priority patents for silicon cells account for about 3% in most countries, in China these cells account for nearly 10% of their patenting activity. Another example are thin-film cells, where the US has a quite high share of 27% of these patents in its patenting activity, while, for example, Germany has only half of that amount. However, Germany has a high share of patents for the module and encapsulation. Emerging cells have about twice the share among priority patents in Asian countries compared to the US and Germany, indicating their direction of research. Furthermore, it is noteworthy that there is hardly any differences between the

Table 2.2: Priority patents per country and sub-trajectory from 1970-2011.

	Absolute per sub-trajectory						Relative per sub-trajectory					
	US	DE	JP	KR	CN	RoW	US	DE	JP	KR	CN	RoW
Silicon cells	165	102	660	262	727	183	3%	3%	3%	4%	9%	3%
Thin-film cells	1,434	501	4,833	1,438	1,294	991	27%	14%	24%	21%	16%	19%
Emerging cells	482	271	3,167	1,324	1,495	628	9%	8%	16%	19%	19%	12%
Module	1,019	1,135	3,417	1,355	1,096	1,259	19%	32%	17%	20%	14%	24%
BoS	465	260	1,546	408	886	483	9%	7%	8%	6%	11%	9%
Unassigned	1,831	1,288	6,482	2,150	2,424	1,712	34%	36%	32%	31%	31%	33%
Total	5,396	3,557	20,105	6,936	7,922	5,255	100%	100%	100%	100%	100%	100%

share of unassigned patents across countries, indicating that there seems to be no bias between countries but also not between sub-trajectories.

If we consider the distribution of triadic patents (Table 2.5 in the Appendix), the absolute numbers are greatly reduced, especially for China where less than 1% of all patents are filed in the tree patent offices. The overall distribution of patenting activity inside the countries is similar as for priority patents. However, remarkable is the high share of triadic patents for the module component for Japan, which exceeds the high share of Germany. There are also some changes for China. Even though the total number of triadic patents is very low, half of them are for emerging cells, indicating that China tries to secure their inventive activity in this promising sub-trajectory internationally.

Overall, the proposed search strategy for the different PV sub-trajectories reveals that there are surprising differences in the development. First, the currently prevailing sub-trajectory, silicon wafer cells, shows the smallest share of patents among the whole PV system, despite its market domination and political support. However, this might not be that surprising, since this sub-trajectory reached its physical limits and improvements in efficiency are nearly exhausted or incremental. However, inventive efforts might have switched to the module production, which could reduce costs further for modules using this cells. The development of thin-film cells is more dynamic and increased in relative inventive activity until the 1990 and decreases since then, when the emerging cell technologies achieved a break through with the Gräzel-cell. Nowadays inventive activity is focused on this emerging cell sub-trajectory, since it allows to overcome the physical limits of the other sub-trajectories. There are also geographical differences in inventive activity in the different sub-trajectories. For example the US focuses inventive activity on the thin-film sub-trajectory, while Germany focuses on inventive activity in modules. Asian countries seem to focus on emerging cells.

2.6 Conclusion

The aim of this chapter is to propose a modular and replicable patent search strategy for the photovoltaic system and its sub-trajectories, since existing search strategies are not able to distinguish PV patents on this micro-technological level. For this purpose, the search strategy is developed following established procedures (Porter et al., 2008; Costantini et al., 2015a) and allows to distinguish different components of the pv system, as well as the different cell sub-trajectories. The search strategy provides similar results as the commonly used WIPO Green Inventory and the newly introduced CPC Classification for emerging technologies, but the search strategy allows to analyze the technological development of the different sub-trajectories. The analysis of the development of sub-trajectories provides a better and finer-grained understanding of technological progress in PV. Surprising results are revealed, especially that the prevailing sub-trajectory, silicon wafer cells, has the lowest share of patenting activity, even though it dominates the market. This indicates that inventive activity in this cell sub-trajectory is either incremental in nature or kept secret. Further dynamics, such as the emergence of new cell technologies, which shifted the focus of inventive activity away from thin-film cells, are revealed. Also differences between countries and their focus on sub-trajectories are uncovered. Here, Asian countries seem to focus on emerging technologies, which have high potential in the future.

The proposed search strategy opens up further avenues for more detailed analysis of the development of the PV system and its sub-trajectories. For example, evaluations of policy instruments with the help of patent data needs to be reconsidered, since effects of demand inducing policies might be overstated, since inventive activity in the dominant cell technology is the lowest. Furthermore, it is possible to analyze in more detail the source of efficiency improvements and factors affecting the learning curve of PV. First descriptive results show high inventive activity in the module component, but not at the cell sub-trajectory. Also the emerging cell sub-trajectory increases its share substantially, which can be used to forecast further technological progress. In Chapter 3 I can show that knowledge recombination by German inventors differs between sub-trajectories, indicating that different competences and knowledge are required for the different sub-trajectories. The possibility to analyze the technological development in more detail can also be useful for studies on the firm and industry level, since technological choice of firms has an effect on its entry (Kapoor and Furr, 2015) and possibly on its survival. With respect to industrial policy, knowing how different sub-trajectories emerge and develop are key determinants for a competitive advantage.

Besides the direct implications on understanding technological progress in the PV system, analyzing sub-trajectories reveals interesting patterns and should be considered in other technologies as well. The concept of sub-trajectories and their emergence, for example via micro-radical innovations (Durand, 1992), helps to understand determinants of progress in more detail. Even though there are several examples of detailed analysis, studies using patent data have neglected this dimension so far. Promising cases are for example sub-trajectories in battery technologies, which emerged over time and provide different characteristics to store electricity and are a vital part to transform the energy system.

However, there are also several shortcomings with the proposed search strategy. First, the keywords and classes do not cover patents which will emerge in the future and updating the search strategy is necessary over time. Also there is a considerable share of patents which is not assigned to the different sub-trajectories, which only gives indication of the distribution of patents per sub-trajectory. Increasing data quality or using different databases could mitigate this shortcoming. Lastly, even though the scope of the search strategy is broad, there are certainly patents which are not considered.

2.7 Appendix

2.7.1 The search strategy for photovoltaic sub-trajectories

The combination of IPCs and keywords for the search strategy is presented in Table 2.3. The patent documents are searched for the keyword in title and abstract while restricted to the specific IPCs. The keywords and IPCs are grouped by their sub-trajectory to reduce the overlap with other adjacent sub-technologies and should be searched accordingly. The "_" and the "%" symbol are used as wildcards for single and multiple characters.

Table 2.3: List of IPCs and keywords for the photovoltaics search strategy.

<table>
<tr><th>Sub-trajectory</th><th>IPCs</th><th>Keyword combination</th></tr>
<tr><td>Silicon wafer cells</td><td>H01L 21%
H01L 31%
C30B 15%
C01B 33%</td><td>((%monocrystalline_silicon% | %monocrystal_silicon% | %crystal_silicon% | %silicon_crystal% | %silicon_wafer%) + (%photovoltai% | %solar%)) | %back_surface_passivation% | (%pyramid% + %etching% + %silicon%) ((%polycrystalline_silicon% | %multicrystalline_silicon% | %poly_Si% | %polysilicon%)</td></tr>
<tr><td></td><td>C30B 15%
C30B 29%
H01L 21%
H01L 31%</td><td>+ (%photovoltai% | %solar%)) | (%ribbon% + (%photovoltai% | %solar% | %silicon%)) | (%edge_defined_film_fed_growth% + %silicon%) | %Metal_wrap_through% | %emitter_wrap_through% | %ribbon_growth%</td></tr>
<tr><td>Thin-film cells</td><td>C23C 14%
C23C 16%
H01L 21%
H01L 27%
H01L 29%
H01L 31%</td><td>((%chemical_vapour_deposition% | %PECVD% | %physical_vapour_deposition% | %PVD% | %solid_phase_crystallization% | %laser_crystallization% | %nanocrystalline% | %microcrystalline%) + (%photovoltai% | %solar% | %silicon%)) | ((%tandem% | %amorphous_silicon% | %silicon_substrate% | %silicon_film%) + (%photovoltai% | %solar%)) | %staebler_wronski%</td></tr>
<tr><td></td><td>C23C 14%
C23C 16%
H01L 21%
H01L 25%
H01L 27%
H01L 29%
H01L 31%</td><td>((%cadmium_telluride% | %CdTe% | %copper_indium_diselenide% | % CIS % | %CuInSe% | %indium_tin_oxide% | %gallium_arsenide% | %GaAs% | %roll_to_roll% | %surface_textur% | %thin_film% | %thinfilm%) + (%photovoltai% | %solar%)) | %copper_indium_gallium_diselenide% | %CuInGeSe% | %CIGS% | %copper_zinc_tin_sulfide% | %CZTS% | %kesterite%</td></tr>
<tr><td>Emerging cells</td><td>C08K 3%
C08G 61%
H01B 1%
H01G 9%
H01L 21%
H01L 31%
H01L 51%
H01M 14%</td><td>((%dye_sensiti% | %titanium_oxide% | %titanium_dioxide% | %TiO2% | %organic% | %polymer%) + (%photovoltai% | %solar)) | %gr_tzel% | %graetzel% | %hybrid_solar_cell%</td></tr>
<tr><td></td><td>H01G 9%
H01L 31%
H01L 51%
H01M 14%</td><td>((%quantum_dot% | %perovskite% | %organic_inorganic% | %plasmon% | %nanowire% | %nanoparticle% | %nanotube%)) + (%photovoltai% | %solar))</td></tr>
<tr><td>PV modules</td><td>H01L 21%
H01L 25%
H01L 27%
H01L 31%
H01R 13%
H02N 6%
H02S 20%
H02S 30%
B64G 1%
E04D 13%</td><td>((%anti_reflection% | %encapsulat% | %back_contact% | %buried_contact% | %bypass_diode% | %rear_surface_protection% | %back_sheet% | %building_integrat% | %mounting_system%) + (%photovoltai% | %solar)) | %solar_panel% | %photovoltaic_panel% | %solar_modul% | %solar_cell_modul% | %photovoltaic_modul% | %solar_cable% | %photovoltaic_wire% | %solar_array% | %photovoltaic_array% | %BIPV% | %solar_park% | (%spacecraft% + (%photovoltai% | %solar_cell%))</td></tr>
<tr><td>BoS</td><td>F21S 9%
G05F 1%
H01L 31%
H02J 3%
H02J 7%
H02M 3%
H02M 7%
H02S 10%
H02S 40%
H02S 50%</td><td>((%off_grid% | %nverter% | %DC_to_AC% | %DC_AC% | %MPP% | %grid_connected%) + (%photovoltai% | %solar%)) | ((%Tracking% | %Tracker% | %Energy_management%) + (%photovoltai% | %solar_cell%)) | (%maximum_power_point% + %track%) | %anti_islanding_protection% | %solar_charge% | %solar_powered%</td></tr>
<tr><td>Unassigned</td><td>B64G 1%
C01B 33%
C08K 3%
C08G 61%
C23C 14%
C23C 16%
C30B 29%
C30B 15%
E04D 13%
F21S 9%
G05F 1%
H01B 1%
H01G 9%
H01L 21%
H01L 25%
H01L 27%
H01L 29%
H01L 31%
H01L 51%
H01M 10%
H01M 14%
H01R 13%
H02J 7%
H02M 7%
H02N 6%
H02S 99%
H02S 20%
H02S 30%
H02J 3%
H02M 3%
H02S 10%
H02S 40%
H02S 50%</td><td>(%photovoltai% | %solar_cell%)</td></tr>
</table>

2.7.2 Search strategy evaluation

Table 2.4: Triadic patent overlap between different search strategies.

	Absolute overlap				Relative overlap		
	Proposed	GI	CPC		Proposed	GI	CPC
Proposed	**2,952**			Proposed	—	0.867	0.763
GI	2,560	**9,865**		GI	0.260	—	0.316
CPC	2,251	3,121	**3,577**	CPC	0.629	0.873	—

Note: In the right table, the bold diagonal represents the number of patents per search strategy while the lower triangle represent the absolute overlap between two search strategies.

Table 2.5: Triadic patents per country and sub-trajectory from 1977-2011.

	Absolute per sub-trajectory						Relative per sub-trajectory					
	US	DE	JP	KR	CN	RoW	US	DE	JP	KR	CN	RoW
Silicon cells	28	21	30	8	1	25	3%	5%	4%	4%	2%	4%
Thin-film cells	291	100	211	56	10	141	34%	22%	25%	29%	20%	24%
Emerging cells	119	69	118	58	24	98	14%	16%	14%	29%	49%	17%
Module	125	107	222	18	2	102	15%	24%	27%	9%	4%	18%
BoS	43	24	49	7	3	29	5%	5%	6%	4%	6%	5%
Unassigned	248	127	198	50	9	184	29%	28%	24%	25%	18%	32%
Total	853	447	828	197	49	578	100%	100%	100%	100%	100%	100%

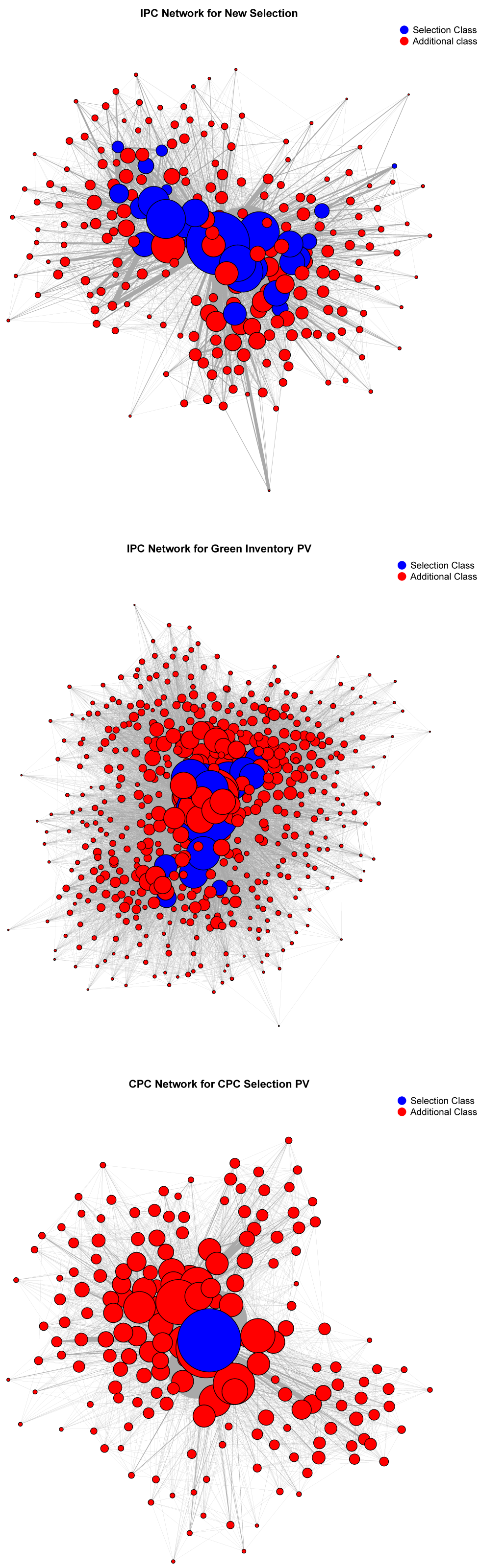


Figure 2.9: Classification co-occurrence for different search strategies.

Figure note: The nodes represent the IPC or CPC classes at the group level, while the edges represent the co-occurence of classes on a patent. The size of the nodes as well as the edges is log-transformed.

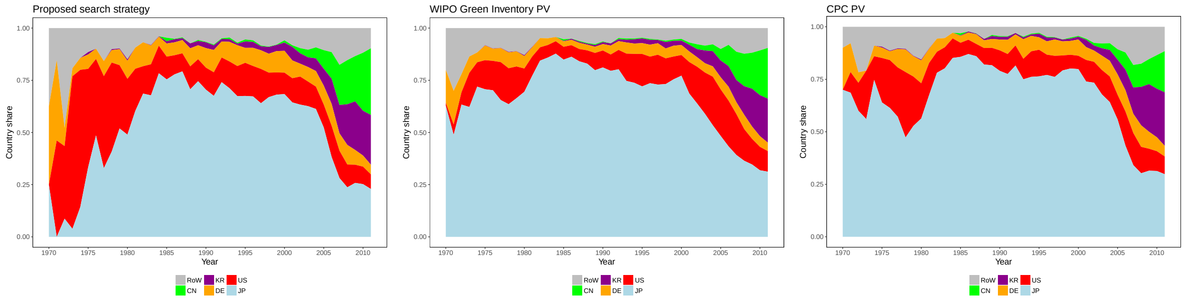


Figure 2.10: Country share of priority patents for different search strategies over time.

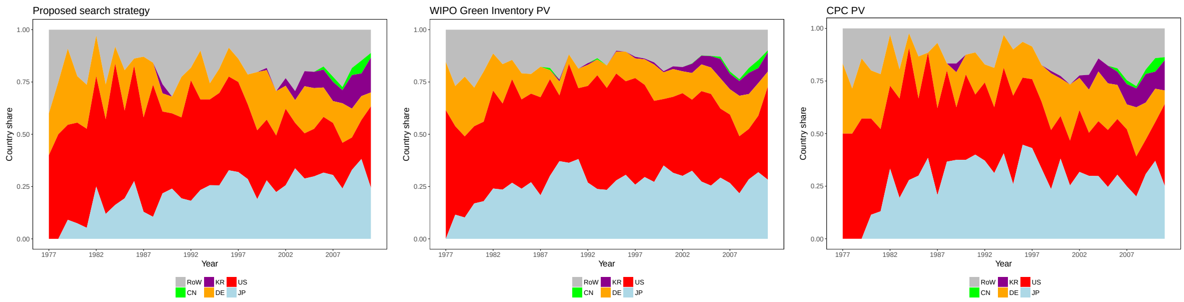


Figure 2.11: Country share of triadic patents for different search strategies over time.

2.7.3 Sub-trajectories in triadic patents

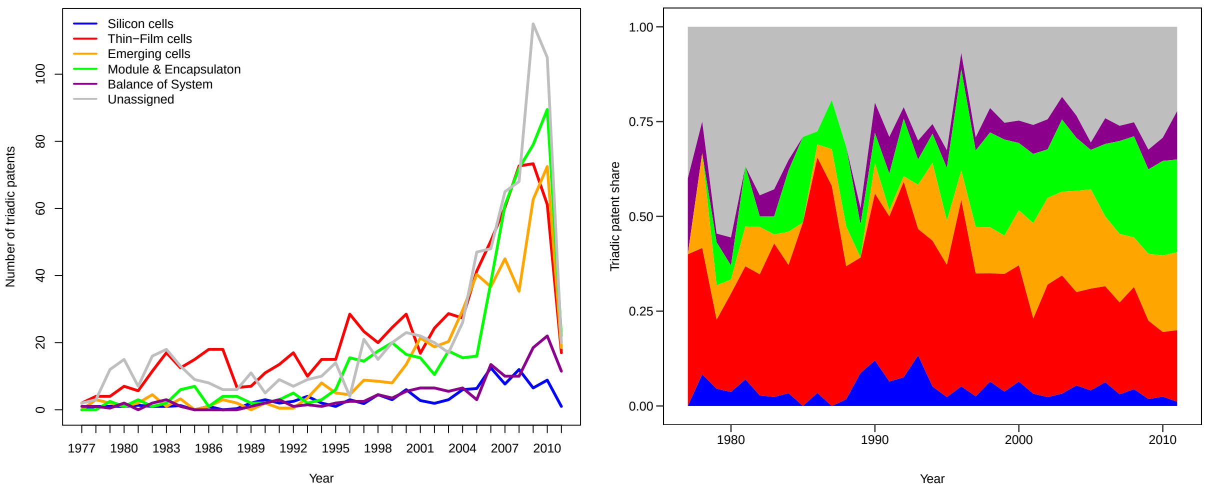


Figure 2.12: Absolute and relative number of triadic patents per sub-trajectory.

Chapter 3

Knowledge recombination along the technology life cycle

3.1 Introduction

Technologies evolve by the inducement of new knowledge into the knowledge base, which is the result of the recombination of already existing knowledge and artifacts (Schumpeter, 1912; Nelson and Winter, 1982; Dosi and Nelson, 2010, 2013). While there is an extensive stream of literature exploring the factors of recombinatorial success at the firm level (Kogut and Zander, 1992; Savino et al., 2017), the influence of knowledge recombination on the technology knowledge base and its evolution over time is so far neglected. It is well known that technologies evolve along their knowledge base, which itself shows certain dynamics and evolves over time (Malerba and Orsenigo, 1996, 2000). Besides internal knowledge accumulation, the in-flow of knowledge from sources external to a technology is crucial for its evolution in terms of initiating, redirecting and refreshing the knowledge accumulation processes (Dosi and Nelson, 2013). The way external knowledge diffuses into a technology, the source it comes from, and the type of actors involved appear to be core determinants of that technology's further development (Grant, 1996; Dosi and Nelson, 2013).

The evolution of a technology can be stylized along a life cycle. Anderson and Tushman (1990) propose a cyclical model of a technological life cycle (TLC). The model distinguishes four phases, an era of ferment, the emergence of a dominant design, an era of incremental change, and a discontinuity, which restarts the cycle. This TLC model has been widely used to analyze technological development and is extended into various dimensions, for example covering the influence of cognitive factors (Kaplan and Tripsas, 2008), specific phases (Murmann and Frenken, 2006) or the level of granularity (Taylor and Taylor, 2012). However, knowledge, the technology's knowledge base, and the influence of different types of knowledge along the TLC are so for neglected from a theoretical and empirical perspective. While there is first empirical

Acknowledgments: Previous drafts of the chapter were presented at the European Meeting on Applied Evolutionary Economics 2013 in Sophia Antipolis, the 2014 SPRU DPhil Day in Brighton, the 15th International Conference of the International Joseph A. Schumpeter Society in Jena, the 5th Governance of a Complex World conference 2016 in Valencia, and at the 16th International Joseph A. Schumpeter Society Conference 2016 in Montreal where it received the best student paper award. The chapter benefited from discussions by and with Stephan B. Bruns, Uwe Cantner, Alex Coad, Holger Graf, Johannes Herrmann, Max-Peter Menzel, Francesco Quatraro, Giorgio Triulzi, Antonio Vezzani, Susanne Walter.

evidence that different kinds of knowledge matter along the technological development (Krafft et al., 2011, 2014a), no theoretical foundation is provided explaining the underlying factors and processes. The aim of the chapter is to close this gap by extending the Anderson and Tushman (1990) model and proposing how recombination of different kinds of knowledge shapes a technology over its life cycle. The extension states that in each TLC phase different sources of knowledge are required for successful recombination and technological progress.

The proposed extension of the Anderson and Tushman (1990) model is empirically tested for wind power (WP) and photovoltaics (PV) in Germany for the period from 1970 until 2006. After the oil crises in the 1970s both technologies were considered as means to reduce the dependency on fossil fuels and to combat climate change (Jacobsson and Johnson, 2000). Since then, severe effort has been put forward to enhance the technologies and both are nowadays competitive with incumbent technologies (REN21, 2016). These makes them ideal cases to analyze how technologies evolve and mature over a life cycle. The period covers several TLC phases and allows to draw conclusions how knowledge recombination patterns change over time. Patent data is used to proxy the technological knowledge base, while inventors and their inventive experience are used to characterize different sources of knowledge. Patent's forward citations are taken as recombinatorial success and proxy the contribution to the knowledge base (Carpenter et al., 1981; Harhoff et al., 1999, 2003; Jaffe and de Rassenfosse, 2016). Negative binomial regressions are run for the overall period as well as for the different TLC phases to estimate the effect of different sources of knowledge. Furthermore, rolling-window regressions are introduced as a novel approach to capture dynamics over time.

The results show that different sources of knowledge matter for technological progress in general but differently in the phases of the TLC, mostly in line with the theoretical model. For the overall technological development, inventors which possess specialized knowledge are most influential. In WP also de-novo inventors matter, who induce knowledge which has not been used before as well as inventors who were previously active in unrelated technologies. Along the phases of the TLC, the era of ferment in WP is mainly shaped by inventors with unrelated knowledge but relevance shifts over time towards specialized and de-novo inventors. In PV, the era of ferment is shaped by several types of inventors, but here also a shift towards specialized inventors takes place over time. The rolling-window regressions provide a more detailed picture and show how different kinds of inventors and their knowledge is relevant over time.

These results contribute to a deeper understanding of the evolution of a technology's knowledge base and which dynamics take place along the TLC. The understanding how knowledge matter in different stages of a technology is crucial for policy maker to implement relevant policies and support the right actors as well as for management to pursue the right R&D strategy. Furthermore, the theoretical contribution by the extension of the Anderson and Tushman (1990) model provides a general framework to understand technological evolution and the respective knowledge dynamics as well as the influence of knowledge from different origins and its integration success into the knowledge base. This complements previous work and allows a more holistic approach to understand technological development along the technology's life cycle. From a methodological point of view, the utilization of previous patents of inventors to distinguish different sources of knowledge allows to analyze long term developments, which can not be captured, for example, by surveys (Conti et al., 2014). Additionally, rolling-window regressions prove to be a useful approach to shed light on dynamics of technological progress in a continuous manner.

In the following, Section 3.2 reviews the literature about knowledge base, knowledge recombination, and their relevance for technological progress and integrates these concepts into the TLC model, providing the theoretical framework for the empirical analysis. Section 3.3 introduces WP and PV as the technologies under consideration and discusses how they develop over time. Section 3.4 presents the data, econometric approach and the results. The last Section discusses findings and concludes.

3.2 Knowledge recombination along the technology life cycle

3.2.1 The technology's knowledge base

The notion of a knowledge base describes a set of knowledge, practices and routines attributed to an object of observation, such as a firm, a technology or a country. The relevance of the knowledge base has been studied extensively at the micro (firm) level (e.g. Nesta and Saviotti, 2005; Krafft et al., 2014a; Roper and Hewitt-Dundas, 2015), but also on more macro dimensions such as the regional (e.g. Leydesdorff and Fritsch, 2006; Cantner et al., 2010), and the country level (e.g. King, 2004; Leydesdorff et al., 2006). The knowledge base is of central importance for innovative activity at the firm level (Nesta and Saviotti, 2005; Antonelli and Colombelli, 2013) and for firm survival (Colombelli et al., 2013). Concerning the knowledge base of a technology, the understanding how the knowledge base shapes technological development is scarce. While some studies focus on the structure of the knowledge inside an industry and show that there are certain dynamics in the knowledge base evolution (Yayavaram and Ahuja, 2008; Krafft et al., 2011, 2014a) and shifts between different regimes (Maleki and Rosiello, 2014), a general understanding how the knowledge base evolves and how the respective technologies are shaped is missing.

The evolution of the knowledge base is driven by knowledge accumulation and introducing new knowledge into it (Malerba and Orsenigo, 1996). This new knowledge stems from the recombination of previously existing knowledge, either from within the knowledge base, or from outside. The idea of knowledge recombination was already proposed by Schumpeter (1912) using the phrase *"Neue Kombinationen"*. This recombination basically leads to a never ending cycle, as Arthur and Polak (2006, p. 23) put it: *"New technologies are never created from nothing. They are constructed—put together—from components that previously exist; and in turn these new technologies offer themselves as possible components—building blocks—for the construction of further new technologies."* This continuous knowledge recombination extends and refreshes the knowledge base with new contributions of previously existing knowledge, which can be utilized to create new products, improve processes and foster economic growth (Weitzman, 1996, 1998).

The process of knowledge recombination an increasingly complex (Jones, 2009) and uncertain task (Fleming, 2001). Several determining factors for success have been identified at the firm level (e.g. Kogut and Zander, 1992; Savino et al., 2017). For example, the previous or stock of knowledge which the firm possess is of importance (Liyanage and Barnard, 2003) as well as its characteristics in terms of structure and complementarity (Dibiaggio et al., 2014). The recombination of knowledge present in the firm is relevant as well as the reconfiguration of existing combinations (Carnabuci and Operti, 2013). Also the combination of new and old knowledge is important for technological advancement (Nerkar, 2003). Especially, the ability to tap on new or external sources of knowledge which can be integrated in the knowledge base is relevant (e.g. labor mobility, hiring specific labor, acquisitions, collaboration, suppliers, customers, ...; see Savino et al., 2017, for an overview).

Knowledge recombination takes place across the knowledge space. A technology can be viewed as a specific area of the knowledge space which constitutes its knowledge base. If knowledge is recombined within such a knowledge base, it can be considered specialized, since it combines parts of knowledge, which is already familiar. The relation between a technology and knowledge which is outside its knowledge base can be characterized by the distance or proximity in the knowledge space. The distance is relevant, for example, in collaborations, where the decision to collaborate is influenced by the distance between partners in the knowledge space (e.g. Cowan et al., 2007; Baum et al., 2010) or the overlap of firms' knowledge bases (Rosenkopf and Almeida, 2003). The knowledge distance for recombination can be constructed either in a continuous way using patent classifications to calculate Euclidean distances or classification overlaps (e.g. Breschi et al., 2003; Benner and Waldfogel, 2008; Bar and Leiponen, 2012; vom Stein et al., 2015), or using binary categories such as related and unrelated knowledge. Applying this binary approach, Nemet and Johnson (2012) show that the use of related knowledge (they use the term "near") leads to more valuable inventions, in terms of forward citations. Youn et al. (2015) distinguish knowledge in "broad" and "narrow" to analyze general recombinatorial patterns for US patents and show that there is an increase of "narrow" recombinations over time.

3.2.2 Knowledge and the technology life cycle

The knowledge base of a technology is central to a technology's evolution. Malerba and Orsenigo (1996, p. 470) propose that the knowledge base itself is dynamic and "*changes in Schumpeterian patterns occurring during a technology and an industry life cycle*". These changes in the knowledge base occur because different kinds of knowledge enter the knowledge base and their contribution to technological development might be conditioned on the stage of the technology. The process of technological evolution can be modeled by a technology life cycle (TLC) similar to the product or industry life cycle. In the TLC neither the actual product is of importance, nor the structure of the firms in the industry, but the application of the technology (see Taylor and Taylor, 2012, for a discussion of the differences). With the technology as the unit of observation, the TLC allows to understand how different kinds of knowledge expand the knowledge base over time.

There are several approaches to model a TLC. According to Taylor and Taylor (2012) these approaches can be generally distinguished into cyclical models based on the Anderson and Tushman (1990) model presenting a macro view on the technology and models using a S-curve depicting the technical progress, usually in terms of cumulative diffusion or technical improvements over time. The S-curve models are closely related to the product life cycle covering a embryonic, growth, maturity, and aging stage (Taylor and Taylor, 2012). These stages are frequently applied to patent data to elaborate in which state a specific technology is (Haupt et al., 2007). In the cyclical model by Anderson and Tushman (1990), a new discovery or breakthrough opens up new technological opportunities or trajectories and starts an era of ferment. This phase is followed by a phase in which a dominant design emerges and a main trajectory is established.[1] After the emergence of a dominant design, an era of incremental change follows in which the technology incrementally evolves along the trajectory until a new technological discontinuity disrupts the technology and the cycle begins again.

While the TLC has been studied frequently in general, so far the underlying knowledge dimension which shapes technological progress has been widely neglected. However, with a focus on the knowledge base, which constitutes a technology, there might be differences in the kind of knowledge which is necessary to alter and extend the knowledge base in different phases of the TLC. While it is widely accepted that a discontinuity in the knowledge base creates a new trajectory leading to a new technology (Dosi, 1982), there is no general model how different kinds of knowledge influences technological development over the TLC. There is the general concept

[1] While Anderson and Tushman (1990) rather see the emergence of a dominant design and a new discontinuity as a point in time, its more a short phase in which these phenomenon emerge, get recognized and development adapts towards it, especially on the technology level, which has different characteristics than the product level. See also Van de Ven and Garud (1993) or Kaplan and Tripsas (2008), who talk about the convergence towards a dominant design.

of exploration and exploitation (March, 1991) and the tendency to move from the former to the latter over time (Utterback and Abernathy, 1975; Klepper, 1996) along with the emergence of a dominant design (Utterback and Abernathy, 1975; Murmann and Frenken, 2006). However, a theoretical framework to integrate knowledge into the different phases of the TLC is missing.

Some empirical analyses try to understand how knowledge matters along the TLC and shape the evolution of a technology. Antonelli et al. (2010) use the co-occurrence of technological classes within patent applications to shed light on the dynamics of knowledge recombination for information and communication technologies, but do not consider a life cycle. Krafft et al. (2011) use social network analysis to elaborate on the relationship in co-occurrence of technological classes and show that in biotechnology the search process changes from exploration to exploitation in the recombination process. Krafft et al. (2014a) use the properties of the biotechnology and telecommunication knowledge base to elaborate on the phases of exploration and exploitation. They show that sectoral differences can be attributed to the phases of the knowledge base. Furthermore, Krafft et al. (2014b) explore the relationship between the structure of the biotechnology knowledge base and technological alliances along the TLC. They find that during the evolution of the biotechnology, search pattern become less random and more organized and knowledge becomes more related. However, they point out that along a trajectory this sequence is not always the case.

In the following, the missing link between the evolution of a technology's knowledge base and the phases of the TLC is established by extending the Anderson and Tushman (1990) TLC model. In each phase of the TLC the relevance of different sources of knowledge is derived and how these knowledge can alter and extend the knowledge base.[2] The result is summarized in Figure 3.1, which expands the initial graphical representation by Tushman and Rosenkopf (1992) with the relevant knowledge in each phase.

1. **Era of ferment**: The era of ferment starts the development of a new technology, following the discovery of a new technological principle, technological disruption, or scientific discovery (Anderson and Tushman, 1990; Tushman and Rosenkopf, 1992). The new technology is not well understood and uncertainty prevails about the technology's characteristics and applications (Kaplan and Tripsas, 2008). The knowledge base is rather small and unstructured (Krafft et al., 2011). Here, experimentation and exploration are the main inventive activities (March, 1991). First applications are derived and (product) variation is high (Van de Ven and Garud, 1993). Niche markets emerge or are created, in which experimentation can take place to gain further understanding of the technology and required characteristics (Kemp et al., 1998).

   Since in the era of ferment the knowledge base is small and unstructured, related and unrelated knowledge from other technological fields is important. This external knowledge is induced into the knowledge base and supports the development of the technology by recombination with existing knowledge already present in the knowledge base. This related and unrelated knowledge is able to provide new combinatorial possibilities from different fields and experimenting with new ways of applications and characteristics are possible. However, due to the high technological uncertainty, failure is very likely (Fleming, 2001).

2. **Dominant design**: The emergence of a dominant design is characterized by increasing economies of scale and scope, network externalities and standardization (Utterback and Abernathy, 1975; Arthur, 1989; Anderson and Tushman, 1990; Klepper, 1996; Murmann and Frenken, 2006). The knowledge base becomes broader and structured which supports

[2] The proposed extension can also be adapted to other models of the TLC, for example the S-shape development proposed in Haupt et al. (2007) or Cetindamar et al. (2016). See also Taylor and Taylor (2012) who try to unify the different approaches of a TLC.

the emergence of the dominant design (Krafft et al., 2011). There are several factors on the firm and environmental level, which are influential as well (Suarez, 2004), such as the emergence of institutions which facilitate knowledge exchange among actors (Kaplan and Tripsas, 2008). The dynamics in the knowledge base play also a role, since the structure of the knowledge base changes and becomes denser (Krafft et al., 2011).

The knowledge base is enhanced with knowledge from related fields, which share the same principles and allow useful recombinations to establish wider levels of application for the dominant design (Murmann and Frenken, 2006). At the same time, the number of variation is reduced so a single trajectory emerges and development focuses along this trajectory (Metcalfe, 1995). Here, specialized and detailed knowledge about the core principles of the technology is relevant to increase performance and application opportunities to expand the number of possible adopters.

3. **Era of incremental change**: After the emergence of a dominant design, incremental change by solving rather small problems along the technological trajectory takes place (Dosi, 1982; Sahal, 1985; Anderson and Tushman, 1990). Here, the knowledge base is large and detailed, the technological principles are well understood and the dominant design is working. This era is characterized by exploitation of the knowledge base by localized search along the trajectory (Nelson and Winter, 1982; Levitt and March, 1988). Incremental improvements occur in a routinized way (Henderson and Clark, 1990) and inertia exists towards switching direction of search (Kaplan and Tripsas, 2008). Social, political and organizational routines are established as well (Tushman and Rosenkopf, 1992). Nevertheless, certain dynamics still exists along the trajectory (Funk, 2009; Dokko et al., 2012; Lee and Berente, 2013).

   In the era of incremental change, specialized knowledge is necessary to solve the incremental problems, which allow further progress. Very detailed knowledge and experience is necessary for the incremental improvements. But also new knowledge might be relevant for further progress. New knowledge might come from a new generation of scientists and researchers, who are not primed towards a specific concept or way of thinking and can integrate their new ideas. Since over time specific educational facilities are established, which provide detailed training in the field, this new knowledge can come up in the era of incremental change (Baumol, 2004; Vona and Consoli, 2015).

4. **Technological discontinuity**: The emergence of a technological discontinuity disrupts the technology and might establish a new trajectory. In this phase, the knowledge base is exhausted and technical opportunities are scarce. The disruption is usually assumed to be exogenous to the technology (Dosi, 1982; Tushman and Anderson, 1986). It can occur if the technology reaches its natural limits (Sahal, 1985), the opportunity space for further improvement is exhausted (Fleming, 2001; Adner, 2004) or customers radically shift their preferences (Tripsas, 2008). However, recently the idea that the discontinuity can emerge out of the incremental improvements, which become radical by accumulation (Funk, 2009), or social interaction (Dokko et al., 2012) is discussed.

   In this stage, the exhausted knowledge base can be rejuvenated by a disruption, which can open up new recombinatorial possibilities. For the further evolution of the knowledge base unrelated knowledge is most likely to refresh the technology in a disruptive way. Radical new ways of recombination can emerge out of these new opportunities. Furthermore, new unexploited ideas and knowledge can induce the discontinuity, especially if accumulated over time. If the unrelated or new knowledge gets successfully recombined with the knowledge base, a rejuvenation of the technology takes place and the life cycle starts again.

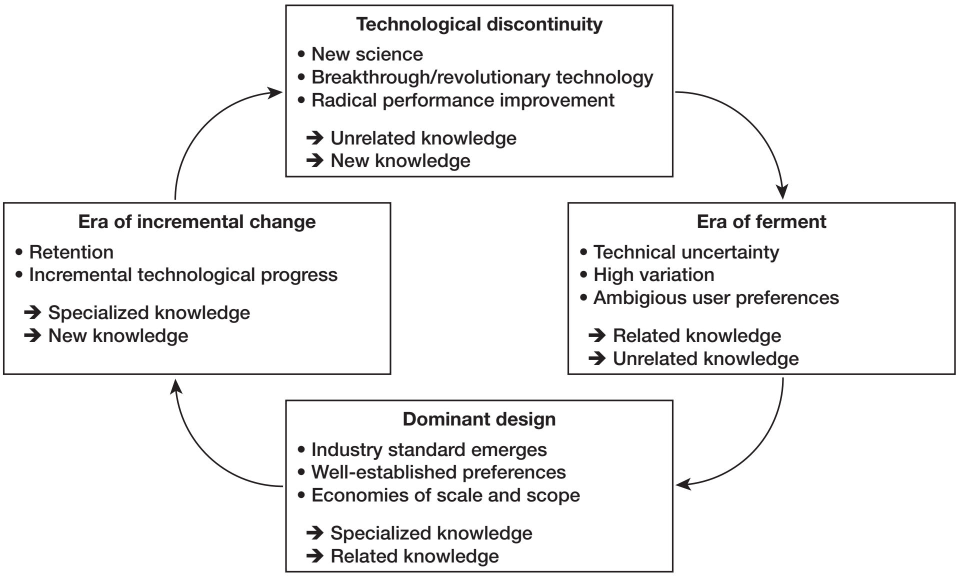


Figure 3.1: Technology life cycle phases and respective relevant knowledge.
Source: Own extention based on the initial representation by Tushman and Rosenkopf (1992).

3.2.3 Inventors and knowledge recombination

To understand the evolution of a technology, it is crucial to determine which factors influence the evolution of the underlying knowledge base. Since the knowledge is embodied in people, the inventor, who is able to create new and recombine existing knowledge, is the core determinant for the evolution of the knowledge base. The individual person possess knowledge and competences, especially tacit ones, which are relevant for recombination and technological advancement (Grant, 1996; Mascitelli, 2000). The inventor can gain and use his knowledge from learning-by-doing, experimentation and application (Arrow, 1962a). This extends the inventor's stock of knowledge and makes the inventor more effective in future inventive activity in recombination (Conti et al., 2014), but with diminishing returns to novelty (Audia and Goncalo, 2007; Conti et al., 2014). However, the process of recombination is influenced by uncertainty about the usefulness of the outcome of the recombination process (Fleming, 2001) and specific characteristics of the inventor play an important role for recombinatorial success.

Several findings reveal which inventor characteristics lead to successful recombinations and inventions. Gruber et al. (2013) show that the kind of education an inventor received influences the ability to combine knowledge from different fields. They show that scientists are better in integrating distant knowledge than engineers. Besides the kind of training the inventor receives, also the breadth and depth of the knowledge the inventor possess has an influence, as shown by Boh et al. (2014), while Conti et al. (2014) find that the previous inventive activity positively influences new inventions. In addition to that, Mohammadi and Franzoni (2014) show that for scientists knowledge relatedness influences the technological value of inventions. Meyer (2006) demonstrate that scientists in nanotechnology, who invent at the same time are more effective than non-inventing scientists. Scandura (2013) shows that the success of inventors is influenced by the type of knowledge they use. She shows based on survey data that combining scientific and market knowledge enhances inventive output.

While the characteristics of the inventor are of importance, the origin in the knowledge space may also play a role. Mobile inventors, which enter a technology from outside the technologies' knowledge domain, may alter a technology's knowledge base and enhance recombination possibilities. Those inventors can transport or spill over their knowledge about a specific technology to a new one by moving between technologies and industries and carrying their knowledge and experience with them (Song et al., 2003; Hoisl, 2007). By entering a technology, in terms of creating an invention in this field, the knowledge these people possess may increase the knowledge base of the technology they move into. It can be assumed that during the process of invention, the knowledge an inventor holds is recombined with knowledge present in the technology that the inventor moves to and increases the knowledge base, especially if the invention is followed up by other inventors. This transfer of knowledge is important for the technology's progress and shapes the direction into which a technology may develop (Schoenmakers and Duysters, 2010). Here, the distance in the knowledge space plays a role again, since these inventors can originate from related technologies, which are near or familiar with the technology, or from unrelated technologies, which do not share common principles. Their movement from one technological field to another allows them to combine their previous knowledge with the one present in the technology's knowledge base they move into.

Based on the different characteristics and technological origin of inventors, inventors can be distinguished into four different groups based on their inventive experience. The characteristics these inventors have may influence their success of recombination, especially in different phases of the TLC. The distinction between different kinds of inventors can be drawn from the inventor's personal knowledge and the knowledge base of a technology.

1. **New Inventors**: Inventors may have no inventive experience, which implies that their first invention contributes to the technology's knowledge base. They may have gotten educational training in this field (Vona and Consoli, 2015), but have no experience with inventive activities yet. They can be customers who want specific features or characteristics of a technology and introduce them on their own (von Hippel, 1976, 1988; Bogers et al., 2010) or the classical tinkerer (Bettiol et al., 2014). They have the advantage that they are not primed by any previous inventive activity and can bring novel and unexploited ideas with them. However, they lack experience and tacit knowledge in inventive activity and may not fully understand the technology.

2. **Specialized Inventors**: Specialized inventors have contributed to the technology's knowledge base by previous inventive activity. Due to their repetitive inventive activity, they benefit from learning-by-doing (Arrow, 1962a) and have accumulated knowledge in the technology which gives them a deep understanding of the technology (Conti et al., 2014). They are able to see opportunities for further improvement of the technology or their previous inventions. However, it can be assumed that they face diminishing returns of success, since they might follow an exploitative path, as suggested by Audia and Goncalo (2007).

3. **Related Inventors**: Related inventors have contributed to a technological field, which is related to the technology they move to. They have previously invented in fields related to the technology or underlying technological principles. These inventors are familiar with the technological field and can transfer related knowledge from other technologies or technical applications to the knowledge base under consideration. These inventors are able to recombine their previous knowledge with the knowledge already present in the knowledge base. Uncertainty about the recombinatorial success should be low, but radical contributions are not that likely.

4. **Unrelated Inventors**: Unrelated inventors show no inventive background, which is related to the technology's knowledge base. These inventors generated inventive output in unrelated technologies and changed their field of inventive activity. By the shift from one technology to another, they carry with them specific knowledge from the former field of activity which may not be present in the technology's knowledge base and they may combine

this knowledge with the knowledge present already in the knowledge base. However, the knowledge they possess for recombination might be difficult to integrate into knowledge present in the technology and unsuccessful recombinations are likely (Fleming, 2001).

These different types of inventors are the carrier of specific knowledge and can by their inventive activity recombine their knowledge with the knowledge present in a technology. In line with the extension of the Anderson and Tushman (1990) model, they provide the necessary new knowledge, which influences the technological progress along the TLC. In the following the extended model and the influence of different kinds of inventors along the technology life cycle is tested with renewable energy technologies in Germany.

3.3 Technology life cycles in renewable energy technologies

3.3.1 Wind power and photovoltaics in Germany

To test the proposed extension and the effect of different sources of knowledge along the TLC, wind power (WP) and photovoltaics (PV) are chosen from the field of renewable energies. In the light of emerging environmental problems such as climate change, but also resource scarcity and rising energy consumption, alternative energy technologies are demanded. Since the oil crises in the 1970s, renewable energy technologies, especially WP and PV, emerge and diffuse in the electricity market (Jacobsson and Johnson, 2000). During the last 40 years, these technologies underwent a remarkable development to catch up with incumbent technologies in terms of efficiency and cost competitiveness. The evolution of these technologies is driven by inventions and knowledge accumulation extending the knowledge base of the technologies. Nowadays, WP and PV are cost competitive and contribute a substantial share of electricity in several countries (REN21, 2016).

While the technologies develop globally, in the following the situation in Germany from 1970 until 2012 is considered. Germany can be seen as a forerunner for both technologies due to high inventive activity, installed capacity, and policy support. The German government implemented various policy instruments to support the development and served in some period as the largest market (Lauber and Mez, 2004). Figure 3.2 shows the R&D expenditures as well as the diffusion (by annually installed capacity) of both technologies over the last 40 years as well as the main demand policies. Over time, there is a shift from direct R&D subsidies to demand inducing policies, which create a niche market for the technologies and supported their diffusion. This favorable environment helped the technologies to develop and the different instruments induced inventive activity (Johnstone et al., 2010; Wangler, 2013; Cantner et al., 2016).

3.3.2 Technology life cycle phases in wind power and photovoltaics

Several attempts to distinguish technological phases for WP and PV are proposed in the literature, which mimic the TLC but also to some extend an industry life cycle. For example, Bergek and Jacobsson (2003) distinguish two phases in the worldwide WP development, a phase of experimentation from about 1975 until 1989 and a phase of turbulence and growth from 1990 until 1999. Wilson (2012) derives similar phases for the development in Denmark. Harborne and Hendry (2009) argue, that even though a dominant design seemed to emerge in the end of the 1980s, variation and experimentation is still high at the end of the 1990s. According to Huenteler et al. (2016b), WP follows a complex-products and systems life cycle (Davies, 1997) and a dominant design emerges already in the late 1980s. Since then WP is in the era of incremental change. Hemmelskamp (1998) does not analyze a TLC in particular, but points out

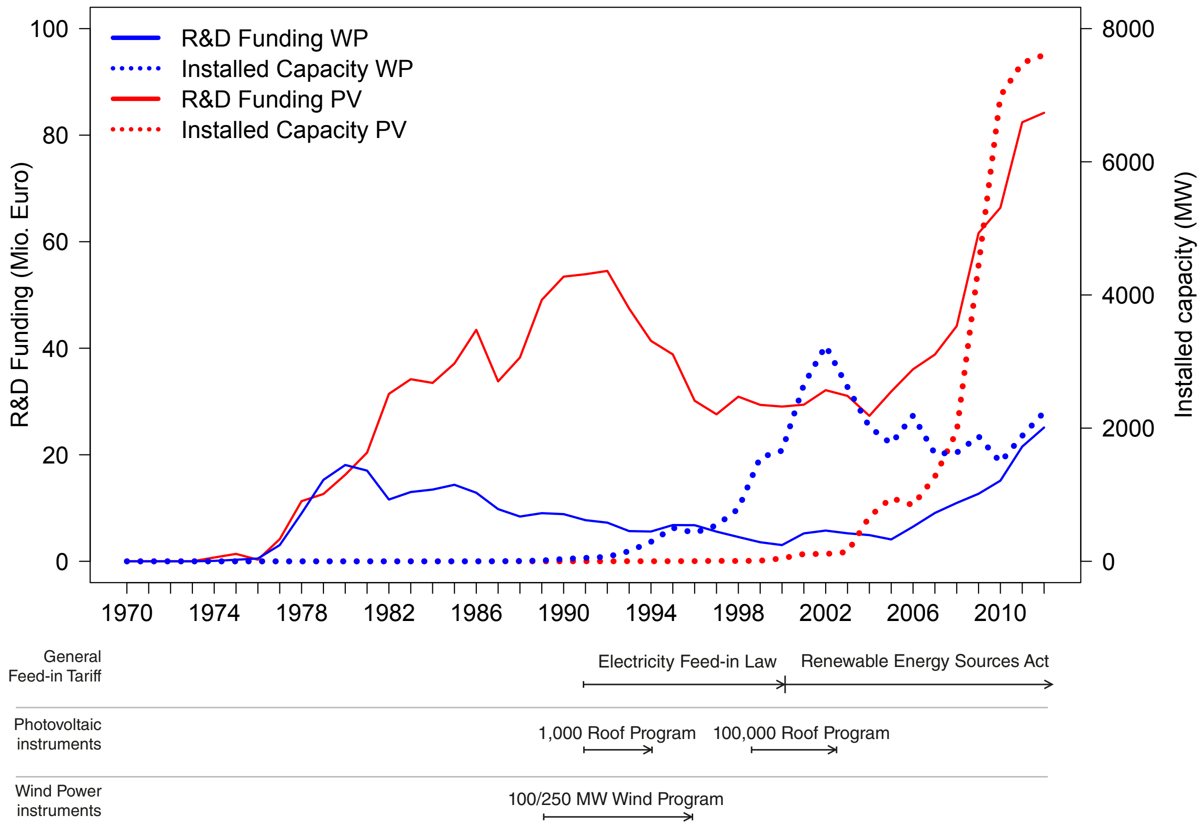


Figure 3.2: Policy instruments supporting wind power and photovoltaics in Germany. **Data source**: Cantner et al. (2016).

that even two dominant designs emerge for small and large scale wind turbines in the middle of the 1990s. For Germany, the development for WP can according to Bruns et al. (2009) and Bruns and Ohlhorst (2011) be distinguished in a pioneering phase from 1975 to 1985, followed by a rethinking/adopting framework period until 1990, succeeded by a breakthrough period until 1995. Then a three year transitory setback period is proposed, followed by a second boom period until 2002. After 2002, consolidation in the industry took place and according to them a divergence of the trajectory takes place.

PV can according to Peters et al. (2012) be distinguished in three phases on the global level. The period 1974-1985 is a first boom phase, followed by a stagnation phase until 1994 and from 1995 onwards a second boom phase. Huenteler et al. (2016b) analyze the technology in detail and conclude that PV follows a mass-produced goods life cycle (Abernathy and Utterback, 1988) and a dominant design emerges in the early 1990s. Since then, PV is in the era of incremental change. For the development specifically in Germany, Jacobsson et al. (2004) distinguish the development of PV in two phases, a first until 1989 which they consider a science-based experimentation phase and a growth phase from 1990 until 2001. Bruns et al. (2009) distinguish the development of PV in five phases. They attribute the period 1970-1985 as a pioneering phase, followed by a phase with reduced private and public R&D until 1991, when a demand inducing policy instrument was implemented, which allowed first larger scale tests. From 1994 till 1998 was a phase of slow down and uncertainty, followed by a breakthrough phase form 1999 until 2003, and from 2004 onwards a booming phase.

Since there is no clear distinction of the TLC phases in the literature, the technologies are separated in phases based on the diffusion and the political support they received in Germany (see Fig. 3.2).[3] For this purpose the distinction between demand-pull and technology-push policies is useful (Mowery and Rosenberg, 1979), since the policy support changed over time towards more demand oriented support. Several studies show that policy instruments decisively influenced the technological development, especially demand pull policies (Johnstone et al., 2010; Wangler, 2013; Cantner et al., 2016). These policies induced demand for the technologies which reaped economies of scale and helped to establish a dominant design.

In the case of WP, the technological development can be separated into three phases until today.[4] The era of ferment starts in Germany around 1970 and lasts until 1995. This period covers the experimental phase in the beginning of the 1980s where the large scale pilot turbine GROWIAN was constructed but failed in operation (Bergek and Jacobsson, 2003). However, first successful small scale applications were supported by the 100/250 MW wind program in the end of the 1980s which proved the technological feasibility (Harborne and Hendry, 2009). Additionally, the first feed-in tariff was introduced in 1991 and supported technology independent diffusion of renewable energy (see Bergek and Jacobsson, 2003; Bruns et al., 2009, for a detailed discussion of the policy instruments). These instruments created a niche market which provided opportunities and testing ground for commercial applications. The emergence of a dominant design took place from 1996 until 2000 and is characterized by massive up-scaling of the turbine size and a surge in installed capacity in Germany due to demand policies. The turbine design converged to a three blade rotor facing the wind with a variable-speed gearbox (Harborne and Hendry, 2009; Milborrow, 2011; Huenteler et al., 2016b). This so called Danish-design is used in nearly all wind turbines until today. The era of incremental change starts in 2001 and is characterized by a reduced annual installed capacity, but increasing exports and further up-scaling. The focus of inventive activity switched to other components, such as mounting and encapsulation or grid connection of turbines (Huenteler et al., 2016a), which are not fundamental to the technical principle. Also offshore turbines are developed and installed, however they do not substantially differ from onshore turbines and a discontinuity seems not to emerge yet.

In the case of PV[5], the era of ferment covers the years from 1970 until 1997 and is characterized by massive R&D subsidies and first experimental demand policies which create a niche market (Jacobsson et al., 2004). In this phase various actors engaged in PV R&D and research institutes were founded, providing scientific infrastructure and public funding allowed experimentation with the technology (Jacobsson et al., 2004; Herrmann and Töpfer, 2017). The emergence of a dominant design lasts from 1998 until about 2006 and covers the vast increase in installed capacity due to implemented demand policies and cost reductions. The 100,000 roof program created favorable economic conditions to install PV and the later introduced renewable energy source act substantially improved the investment conditions and created strong market demand, which provided secure grounds to invest in R&D. During this period, manufacturing capacity and automation of production processes were established, which lead to severe cost

[3] Since technological development unfolds over time, retrospective identification of phases is difficult and depends on the point in time the distinction is made. This explains the above variation in periods and assessments in the future will most likely derive different phases than the ones distinguished in the following. However, there are methods available to distinguish TLC phases based on patent data (e.g. Haupt et al., 2007; Lizin et al., 2013; Chang and Fan, 2016), but this approach is neglected since the same data will be used to explain changes in the phases later on.

[4] In the case of WP it is hard to track a discontinuity, which opened up the trajectory. The underlying technological principle is used for several hundred years in wind-mills to create mechanical energy. The first wind turbine to produce electricity was constructed in 1888 and the technology was used in small scale until 1950 but then disappeared in favor of other technologies until its renaissance after the oil crises (Shepherd, 1994; Nielsen, 2010).

[5] The photovoltaic effect was discovered already in 1839, but the first conventional photovoltaic cell was developed in 1954 (Chapin et al., 1954). This can be seen as the emergence of the trajectory. However, due to high costs, application was limited and PV was mainly used to power satellites and off-grid applications (Perlin, 2002). Only after the oil crises, PV was seriously considered for large scale electricity production.

reductions and economies of scale. From 2007 onwards, the era of incremental change begins with reduced policy support and international competition for German PV cell producers.

However, in PV the phases represent only a general pattern of the trajectory, since there are several PV sub-trajectories with respect to the different cell types, as discussed in the previous Chapter 2. For example, the emerging cell sub-trajectory, are still in an emerging state and their efficiency and costs are far from silicon wafer or thin-film cells. The sub-trajectories emerged at different points in time and are in different phases of the development (see for example Lizin et al., 2013, who look at the life cycle of organic PV cells).[6]

Table 3.1: Overview of the technology life cycle phases for wind power and photovoltaics.

	Wind power	Photovoltaics
Era of ferment	1970-1995	1970-1997
Dominat design	1996-2000	1998-2006
Era of incremental change	2001-	2007-

3.4 Econometric approach

In the following, the extended TLC model is empirically tested for the TLC of WP and PV. Using negative-binomial regression the effect of different sources of knowledge on the success of knowledge recombination is tested. Data, variables, and the econometric approach are explained next, followed by the results. Descriptive statistics and correlations can be taken from Appendix 3.6.2 and 3.6.3.

3.4.1 Data and variables

3.4.1.1 Patent data

The technological advancement and evolution of the renewable energy technologies and their knowledge base can be observed in patent data. Patents are, despite their broadly discussed disadvantages, a good proxy for inventive activity and a technology's knowledge base (Griliches, 1990; Hall and Harhoff, 2012). Even though only a part of all inventions are patented (Arundel and Kabla, 1998; Cohen et al., 2000), the codification of knowledge in a patent allows other inventors to utilize the knowledge and build upon it.

Patent data for the analysis is retrieved from the Worldwide Patent Statistical Database (PATSTAT) (EPO, 2014). Patents for WP and PV are extracted by a combination of technology specific IPC (International Patent Classification) classes and keywords (see Appendix 3.6.1 for details). All priority filings by German inventors in the period from 1970 to 2011 are considered. A patent is selected if at least one of its inventors resides in Germany. Since the database contains missing information on the inventor's country code, the country code was manually added if conclusive evidence is provided (e.g. German address). The overall data set comprises 3,765 WP patents and 3,589 PV patents. However, for the following analysis, only a subset until 2006 is considered, since the patents need some time to receive forward citations. For the set until 2006, there are 1,984 WP patents and 1,691 PV patents which are the units of analysis.

[6] It could also be argued that the presence of sub-trajectories indicates that no dominant design emerged yet. But these sub-trajectories have also partly different fields of application from application in space to integration in textiles or windows and are hardly competing in their specific field of application. Furthermore, physical boundaries will eventually prevent progress in the market-dominating sub-trajectory and other sub-trajectories will most likely outperform them.

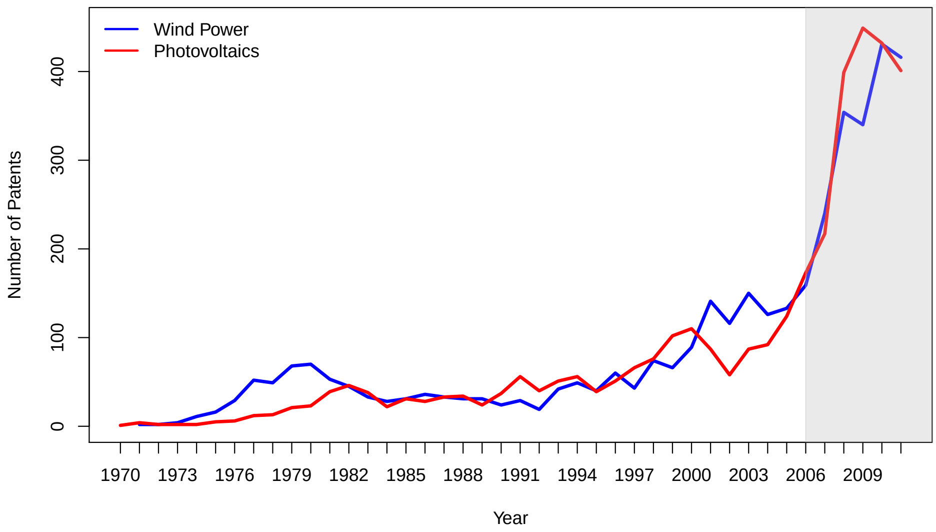


Figure 3.3: Wind power and photovoltaics patents by German inventors.

3.4.1.2 Dependent variable: Forward citations

The success of knowledge recombination and the contribution of a patent to the knowledge base can be approximated by the forward citations it receives. A forward citation of a patent is a citation of this patent by another patent, which considers the cited patent as prior art. The general assumption is that the more forward citations a patent receives, the more valuable in technological terms it is for the evolution of a specific technology (Carpenter et al., 1981; Trajtenberg, 1990; Harhoff et al., 1999, 2003; Czarnitzki et al., 2011; Jaffe and de Rassenfosse, 2016). If a patent receives many citations it can even be considered radical or breakthrough (Ahuja and Lampert, 2001; Conti et al., 2014) while if it receives no citations, it is most likely that the recombination was a failure and the patent has no value for the knowledge base or further inventions.

The forward citations are collected on the patent family level in the first five years after the priority application (Bakker et al., 2016). This five year truncation is used to grant all patents the same time span to receive citations and avoid a bias towards older patents (Lanjouw and Schankerman, 2004). Forward citations added by examiners are not considered separately, even though they indicate higher importance of the cited patent (Alcácer and Gittelman, 2006; Yasukawa and Kano, 2014). Figure 3.4 displays the number of forward citations. The number is highly skewed and about 33% of the PV and 40% of the WP patents receive no citation in the first five years after application. On average, WP receives about 2.6 citations and PV 2.7 citations per patent in the first five years after application in the sample.

3.4.1.3 Independent variables: Type of inventor

To understand the influence of different sources of knowledge on the technological evolution, the inventors on the patent are assigned to the four different groups elaborated in section 3.2.3. Since the assignment to the different groups is sensitive to the data quality, cleaning up the patent data is necessary. The inventor names were manually harmonized by correcting obvious typos[7],

[7] There have been different algorithms proposed to clean patent data (Raffo and Lhuillery, 2009; Miguélez and Gómez-Miguélez, 2011) but they were not able to provide appropriate results. However, there are several sets of harmonized inventor names, but these sets were either not available for different application offices or were specified for a certain group of inventors, such as scientists.

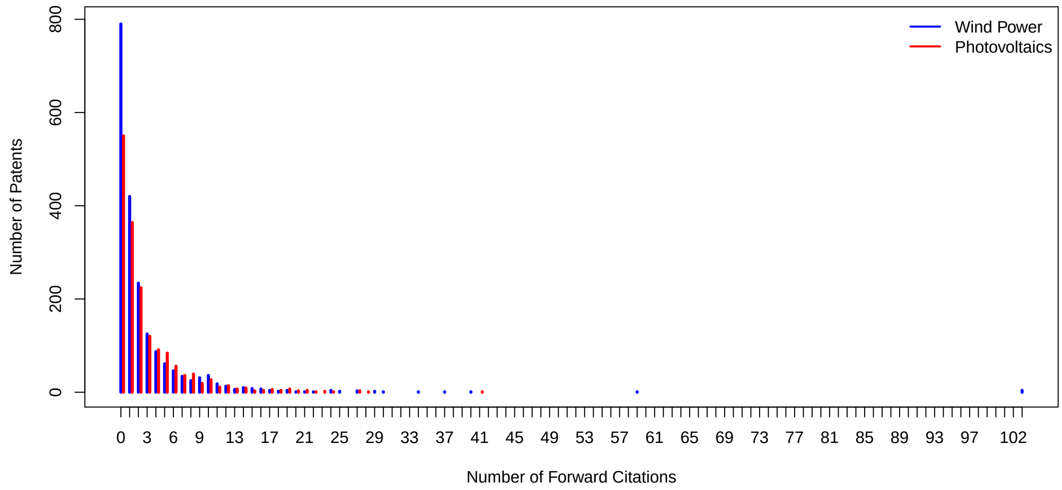


Figure 3.4: Distribution of forward citations per patent.

academic titles or name order, controlling for patent applicant, address and year of application, to avoid inflating the number of inventors.[8] In total there are 1,675 unique inventors on WP patents and 2,203 unique inventors on PV patents.

All filed patents for each inventor are collected from PATSTAT to construct the inventor's patenting history (similar to Jones, 2009). This patenting history is used to determine the type of inventor. The inventors can be assigned to the four different groups. The first group, *New Inventors*, are those without previous patenting experience, so there is no patenting history. The second group of inventors, *Specialized Inventors*, contains inventors who patented previously only in the respective technology. For the third and fourth group of inventors, who have an inventive history in either related or unrelated technologies, the distinction becomes a bit different: The field of former patenting activity of an inventor is indicated by the IPCs his previous patents are assigned to. The inventor is considered to be related to the technology, so a *Related Inventor*, if one of the IPCs in the personal portfolio has also been used in the respective technology before, if not, the inventor is considered an *Unrelated Inventor*.[9] The IPCs of all previous patents in WP or PV are collected over time and compared to the inventor's patenting history.[10] If any of the inventor's patents coincides with an IPC which is already used in the technology, the inventor belongs to *Related Inventors*. This approach allows a dynamic change of the criteria for *Related Inventors* and *Unrelated Inventors* if new concepts are introduced into the knowledge base. The first time an IPC is introduced by an inventor in the technology, it is no longer unrelated to the technology but related.[11]

The distinction between *Related Inventors* and *Unrelated Inventors* is influenced how detailed the technological relatedness is constructed. The minuteness of detail of the technological relatedness can be proxied by the hierarchical nature of the IPC classification. The IPC classes consists of 8 different fields, e.g. physics or electricity. These fields have several classes and subclasses (about 640, usually referred to as four-digit IPC class). Several studies use these four-digit IPC class to distinguish between different technological fields (e.g. Nemet and Johnson, 2012). There are furthermore also groups (about 7,000) and subgroups (more than 70,000)

[8] Technically, the different person-IDs from the PATSTAT database for one person are attributed to one unique identifier used to describe the inventor.

[9] If an inventor has patented in related and unrelated fields, the inventor is assigned to the *Related Inventors*.

[10] Patents from 1965 until 1969 are used to create an initial set of ICP classes, otherwise the first inventors would be unrelated by default.

[11] Since this is a rather strong assumption, a robustness test is done where the inventor is assigned to the related or unrelated group if the patent belongs to a similar technology field or not. See section 3.4.4.

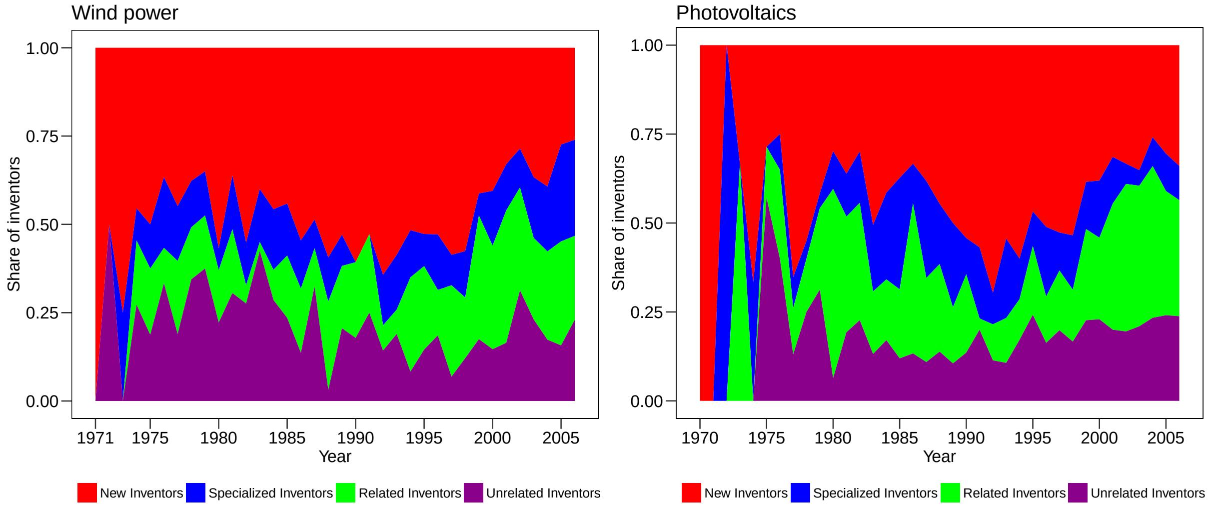


Figure 3.5: Share of inventor types per technology over time.

which represent more fine grained distinctions of the technology. In the current case, the level of groups is used to assign the inventors to the related and unrelated category. Using the subgroup level would drastically reduce the related group, since there would be no overlap on a higher level, while using only the subclasses would drastically reduce the unrelated group, since general technological principles would be the same in most cases.

The share of the different kinds of inventors over time is presented in Figure 3.5. In both technologies, *New Inventors* are the largest group. This is persistent over time, indicating that there is a high number of new people starting inventive activity in these technologies. Furthermore, since inventions are a rare event, a considerable amount has only one invention, or they change their focus and continue their inventive activity in other domains (Menon, 2011). *Related Inventors* are the second biggest group in both technologies. But in WP *Unrelated Inventors* have a high share in the early years, indicating an experimental phase. *Specialized Inventors* are the smallest group in both technologies, indicating that specialization on one technology does not take place that much. Further information about the number of patents per inventor and the overall number of inventors is provided in Appendix 3.6.4.

To better understand the effect of separating different kinds of inventors, intermediate groups are created to see the effect if the inventors are separated into the different types. Two intermediate groups are constructed: First *Experienced Inventors* who are all the inventors who have patenting history, (sum of *Specialized Inventors*, *Related Inventors* and *Unrelated Inventors*) to test if it matters if an inventor has previous experience. The second group, *Knowledable Inventors*, are the inventors who come from outside the technology's domain and patented in related and unrelated fields (sum of *Related Inventors* and *Unrelated Inventors*).

3.4.1.4 Control variables

While the source of knowledge embodied in inventors and their success of recombination has an influence on the received forward citations, other influential factors may be related to the patent itself. In the following, the relevant control variables are discussed.[12]

Team Size: An influential factor for the success of a patent, and also for knowledge recombination, is invention in teams. Patents invented in teams have a higher technological value than inventions by a single inventor (e.g. Wuchty et al., 2007; Jones, 2009). The number of inventors on the patent is the aggregation of the different types of inventors.

Foreign Inventors: International collaboration has a positive effect on research and inventive activity in general (Adams, 2013; Kerr and Kerr, 2015). Patents might be invented in international teams and inventors from other countries are counted.

IPC Classes: The technological breadth of the patent influences its technological importance. More basic patents, which can be applied to different kinds of technologies, might me more relevant for future development than highly specified patents (Lerner, 1994). To approximate the breadth of the patent, the number of IPC groups a patent comprises is counted.

Family Size: The size of the patent family the patent belongs to is considered to be relevant for the technological importance of a patent. The bigger the family of a patent, which means that the priority patent is registered in other patent offices as well, the higher the number of forward citations (Putnam, 1996; Lanjouw et al., 1998; Harhoff et al., 2003). Here, the size of the DocDB family is calculated (Martínez, 2011).

Backward Citations: The previous knowledge the inventor used to create the patent may influence the technological value of a patent (Harhoff et al., 2003). However, it can be the case that patents with many backward citations are rather incremental compared to patents with no or only a few backward citations (Lanjouw and Schankerman, 1999).

Granted Patent: If the patent is granted is usually a good indicator for its novelty and relevance (Guellec and van Pottelsberghe de la Potterie, 2000).

PCT Patent: If a patent is filed under the Patent Cooperation Treaty (PCT) the technological value can be higher (Guellec and van Pottelsberghe de la Potterie, 2000).

New Combination: A patent can introduce a new IPC class into the knowledge base which has not been used in the technology. This might be a new combination which can be of higher value. Arts and Veugelers (2015) use a similar idea to capture previously uncombined technologies. The dummy variable is constructed by comparing all previous IPCs used in the technology and the patent under consideration.

USPTO: Patents filed at the United States Patent and Trademark Office (USPTO) receive usually a higher number of forward citations, since the USPTO requires to indicate all prior art which could be relevant and this leads to a higher number of forward citations than a patent from the German or European patent office would receive (Michel and Bettels, 2001; Nagaoka et al., 2010).

[12] Besides the variables presented, there are several other which could have been considered, but are not used due to several reasons. For example, triadic patents are indicators of high value (Dernis and Khan, 2004; Sternitzke, 2009), but they are highly correlated with the family size and in favor of the family size neglected. Cited non-patent literature is also frequently used, but the data has hardly any such references and is according to Harhoff et al. (2003) only relevant in for pharmaceutical and chemical patents. Claims per patent are also frequently counted (Lanjouw and Schankerman, 1999), but most patents are filed at the German patent office, which does not publish the number of claims.

Year Effects: Year dummies capture time variant effects such as macroeconomic changes, political support, patent legislation changes or other factors which may influence patenting activity and quality in a specific year. Furthermore, the variable captures also the effect that due to the general increasing patenting trend younger patents have a larger pool of patents which could cite them.

PV sub-trajectories: For PV, the technology is more complex and consists of different components and sub-trajectories, which develop intertwined with each other. There are different approaches to utilize the photovolatic effect based on different light-absorbing materials. The first cell sub-trajectory uses silicon wafer to generate electricity, while over time the thin-film sub-trajectory emerged and nowadays a sub-trajectory for emerging cells is present. Since the sub-trajectories emerge at different points in time, they might require different kinds of inventive activity and have overlapping life cycle phases. To account for this, the patents for PV are distinguished into *PV Modules*, which is a generic component for all cell type and deals with the overall construction and installation of the cell, and the actual *PV Cells*, which can be further distinguished based on their material into *Silicon Wafer Cells*, *Thin-Film Cells* and *Emerging Cells*. However, not all patents can be attributed to a specific technology. A detailed elaboration about sub-trajectories in PV is given in Chapter 2.

3.4.2 Econometric approach

The dependent variable, the forward citations per patent, measures the success of the knowledge recombination and the resulting technological contribution to the knowledge base. Since forward citations are a rare event, the count data is over-dispersed (the variance exceeds the mean of the data). This requires a negative binomial regression model (Cameron and Trivedi, 1986; Hilbe, 2011). These models are commonly used for patent data. Since the patent is the object of analysis (i), the data set is cross sectional but has time information. The stylized regression model is

$$Forward\ Citation_i = \boldsymbol{\beta} Inventor\ Types_i + \boldsymbol{\gamma} Controls_i + \epsilon_i \tag{3.1}$$

where $\boldsymbol{\beta}$ is a vector of the coefficients of the estimated effects of the different inventor types and $\boldsymbol{\gamma}$ is a vector of the estimated effects of control variables.

In the following, there seven models for WP and six models for PV are used to estimate the effect of the different types of inventors on the forward citations. The first four models (see Section 3.4.3.1) cover the full period and are used to elaborate the relevance of the different inventor types in general. The first model uses only the *Team Size* of the inventor team to estimate if the number of inventors on a patent has an effect. In the second model, the inventors are separated into *New Inventors* and *Experienced Inventors* to see if it makes a difference if previous knowledge is present. The third model separates the *Experienced Inventors* into *Specialized Inventors* which only invent in the respective technology and *Knowledable Inventors* which have experience in other fields. Model four furthermore separates the *Knowledable Inventors* into *Related Inventors* and *Unrelated Inventors* to estimate if the kind of previous knowledge has an effect. In the case of PV, two alternatives are estimated as well, which distinguishes PV in sub-trajectories. Model 4a controls for patents which belong to *PV Modules* and *PV Cells*. Model 4b separates the PV Cells further into *Silicon Wafer Cells*, *Thin-Film Cells* and *Emerging Cells* to account for different developments of PV sub-trajectories.

The next models (see Section 3.4.3.2) cover the different periods of the TLC derived in Section 3.3. In models five to seven for WP the first three stages of the TLC are analyzed. For PV, only two periods are considered. Model five covers the period 1970-1997 and model six 1998-2006. Again, distinction between the PV module and cell sub-trajectories are made.

Since the proposed sub-periods in the last models are static and results could be sensitive to the exact separation of periods, rolling-window regressions are used to illustrate the importance of different types of inventors over time. Rolling-window regressions (alternatively called moving-window regressions) are usually applied to time series data to analyze if structural changes occur in a specific subsample of a time-series (Fama and MacBeth, 1973; Nyakabawo et al., 2015). The approach uses a fixed window of years sequentially from the start to the end of the overall observation period by dropping one year from the end and adding one to the beginning. In the current case, a time-series is not present, but based on the filing year of the patent, time periods can be constructed. When using this method, the selection of the window of years is of importance and has to make a trade-off between the accuracy of the effect, the power of the estimation, and the coverage of the relevant period. This is especially a problem for time-series (see Pesaran and Timmermann, 2005, for a discussion), but not necessarily for the current case, since multiple observations are present in each period, providing sufficient power. However, if the selected time period is too short, overall time variant effects which are otherwise captured by year dummies might influence the result. In the following a time period of eight years is considered covering a sufficient large time period and power per window. Furthermore, robustness tests for five and eleven years are provided in Section 3.4.4.

3.4.3 Results

3.4.3.1 Overall influence of different inventor types

The regression results for the influence of different types of inventors for WP and PV can be taken from Table 3.2. In the case of WP, the first model, the baseline, illustrates the overall influence of patent characteristics on forward citations. As suggested in the literature, most control variables influence the number of forward citations positively except *PCT Patent*, which is not significant. However the negative effect of *New Combination* is surprising. The introduction of a new IPC class into the technology seems to have a negative effect on the contribution to the knowledge base. This indicates that the extension of the knowledge base by bringing in new principles seems not to contribute. This is however in line with the argumentation by Fleming (2001), who claims that recombination is risky and may lead to failure. The negative effect can also indicate that the trajectory is already defined and integrating further technological principles in the knowledge base does not provide useful recombinations. In model 2 the inventors are separated into *New Inventors* and *Experienced Inventors*. We see that both have a strong positive effect, indicating that both sources of knowledge are relevant. This effect sustains if the *Experienced Inventors* are further separated in *Specialized Inventors* and *Knowledgeable Inventors* in model 3. However, in model 4 the separation of the *Knowledgeable Inventors* reveals that only *Unrelated Inventors* are weakly significant, while the *Related Inventors* do not play a significant role in WP. In all models also *Foreign Inventors* contribute, indicating that international knowledge spillover are relevant for the technological development.

The regression results for PV show that in the baseline model 1, the results are nearly similar to the ones for WP, but here, *Granted Patent* is not significant. Again, *New Combination* is negative significant, indicating that inducing new principles into the PV knowledge base is also not successful or necessary. Model 2 shows that in PV *New Inventors* seem not to play a role, but *Experienced Inventors*. This indicates that recombination in PV is only successful if inventors possess previous experience and knowledge. Model 3 presents the distinction between *Specialized Inventors* and *Knowledgeable Inventors*. Both are significant, but especially the *Specialized Inventors* are of importance, indicating that knowledge accumulation seems to matter more than a diverse set of knowledge. In model 4 we see that only *Specialized Inventors* contribute to the technological development and the distinction between *Related Inventors*

Table 3.2: Regression results for different types of inventors.

Negative binomial regressions: Dependent variable: Forward citations per patent

	Wind Power				Photovoltaics					
	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 1 Full Period	Model 2 Full Period	Model 3 Full Period	Model 4 Full Period	Model 4a Full Period	Model 4b Full Period
Team Size	0.160 ***				0.049 **					
	(0.025)				(0.019)					
New Inventors		0.157 ***	0.163 ***	0.166 ***		0.032	0.032	0.033	0.037	0.033
		(0.040)	(0.039)	(0.039)		(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Experienced Inventors		0.170 ***				0.069 ***				
		(0.033)				(0.027)				
Specialized Inventors			0.424 ***	0.424 ***			0.154 ***	0.155 ***	0.167 ***	0.169 ***
			(0.055)	(0.055)			(0.056)	(0.056)	(0.057)	(0.055)
Knowledable Inventors			0.080 **				0.049 *			
			(0.041)				(0.029)			
Related Inventors				0.069				0.042	0.058 *	0.056 *
				(0.047)				(0.030)	(0.030)	(0.029)
Unrelated Inventors				0.114 *				0.117	0.117	0.116
				(0.066)				(0.076)	(0.075)	(0.075)
PV Modules									-0.027	-0.045
									(0.072)	(0.072)
PV Cells									-0.215 **	
									(0.088)	
Silicon Wafer Cells										-0.933 ***
										(0.326)
Thin Film Cells										-0.236 **
										(0.099)
Emerging Cells										-0.010
										(0.151)
Foreign Inventors		0.152 ***	0.142 ***	0.141 ***		0.017	0.021	0.023	0.016	0.013
		(0.040)	(0.041)	(0.041)		(0.059)	(0.059)	(0.060)	(0.059)	(0.058)
IPC Classes	0.081 ***	0.081 ***	0.092 ***	0.093 ***	0.135 ***	0.134 ***	0.138 ***	0.140 ***	0.139 ***	0.135 ***
	(0.025)	(0.025)	(0.024)	(0.024)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)
Backward Citations	0.012 ***	0.012 ***	0.012 ***	0.012 ***	0.017 ***	0.017 ***	0.016 ***	0.016 ***	0.016 ***	0.016 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
New Combination	-0.145 *	-0.146 *	-0.139	-0.143 *	-0.212 **	-0.213 **	-0.204 **	-0.206 **	-0.214 **	-0.217 **
	(0.087)	(0.088)	(0.086)	(0.085)	(0.100)	(0.100)	(0.099)	(0.100)	(0.101)	(0.100)
Family Size	0.066 ***	0.066 ***	0.068 ***	0.069 ***	0.132 ***	0.131 ***	0.129 ***	0.130 ***	0.128 ***	0.126 ***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
PCT Patent	0.267	0.266	0.127	0.127	-0.094	-0.085	-0.097	-0.126	-0.113	-0.061
	(0.234)	(0.235)	(0.225)	(0.225)	(0.400)	(0.404)	(0.420)	(0.411)	(0.408)	(0.398)
Granted Patent	0.359 ***	0.359 ***	0.319 ***	0.321 ***	0.056	0.056	0.057	0.057	0.057	0.062
	(0.066)	(0.067)	(0.067)	(0.067)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)	(0.065)
USPTO	1.146 ***	1.154 ***	1.033 ***	1.028 ***	0.979 ***	1.035 ***	1.031 ***	1.038 ***	1.141 ***	1.137 ***
	(0.165)	(0.161)	(0.159)	(0.159)	(0.175)	(0.192)	(0.194)	(0.194)	(0.202)	(0.205)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1984	1984	1984	1984	1691	1691	1691	1691	1691	1691
df	1940	1938	1937	1936	1646	1644	1643	1642	1640	1638
loglik	-3478.858	-3478.796	-3462.796	-3462.620	-3356.730	-3356.106	-3354.165	-3353.734	-3350.518	-3343.702
AIC	7047.715	7051.591	7021.592	7023.240	6805.459	6808.211	6806.330	6807.468	6805.035	6795.403
McFadden R^2	0.142	0.142	0.146	0.146	0.074	0.074	0.074	0.075	0.075	0.077

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

and *Unrelated Inventors* seems not to explain recombinatorial success. However, controlling for different sub-trajectories in model 4a and 4b reveals that *Related Inventors* have a weak significant effect, indicating that sub-trajectories interfere with each other and that the relevance of related knowledge is conditioned on the sub-trajectory. Contrary to WP, *Foreign Inventors* do not matter and inventive activity for PV in Germany does not benefit from international collaboration.

Overall, different sources of knowledge are relevant and the distinction reveals that knowledge embodied in different types of inventors influences recombinatorial success. There are differences between the technologies as well. While in WP *New Inventors* have a significant effect, they do not matter in PV. Also the kind of knowledge from domains external to the technology's knowledge base matters. While in WP *Unrelated Inventors* are able to provide useful recombinations, in PV *Related Inventors* are successful. Also the difference concerning *Foreign Inventors* is remarkable. However, the systemic difference between WP and PV on the technological level has also been shown by Cantner et al. (2016) and Huenteler et al. (2016b), but not with respect to the relevant knowledge.

3.4.3.2 Technology life cycle phases

In this section, the phases of the TLC are analyzed and regression results are presented in Table 3.3. For WP, model 5 shows the era of ferment in which *New Inventors* and especially *Unrelated Inventors* play a significant role. While it was proposed in the extended TLC model that *Related Inventors* and *Unrelated Inventors* are decisive in this phase, only *Unrelated Inventors* seem to be able to successfully integrate distant knowledge into the knowledge base. The significance of *New Inventors* is interesting, since it shows that the technology benefited from inventors which started their inventive activity in WP. Here, anecdotal evidence supports the results. Inventors in the era of ferment were tinkerers and engineers who wanted to improve environmental conditions and provide technical alternatives to conventional energy production (Simmie et al., 2014). Concerning the control variables, *IPC Classes* and *Backward Citations* lose their significance as well as the negative effect of *New Combination* compared to the full model. Interestingly, *Foreign Inventors* have a negative effect, indicating that knowledge from other countries lead to a reduction in recombinatorial success. Here, it could be that German inventors follow their own trajectory and concepts developed in other countries seem not to be relevant in this phase.

Model 6 presents the results for the emergence of the dominant design. Here, *New Inventors* as well as *Specialized Inventors* are decisive. It was however supposed that *Specialized Inventors* and *Related Inventors* are relevant sources of knowledge in this phase. The results indicate that the dominant design in WP emerges out of the established trajectory and rely on acquired and accumulated knowledge and does not need further knowledge from related fields. Concerning the control variables, *Foreign Inventors* still have a negative coefficient, but the size of the effect decreases. Interestingly, *PCT Patent* shows a significant negative effect.

In the era of incremental change, presented in model 7, again *New Inventors* and *Specialized Inventors* play a significant role, which is in line with the proposed model. Additionally, *Related Inventors* are able to integrate knowledge from adjacent technologies into the WP knowledge base. This could hint towards an upcoming discontinuity maybe related to offshore WP. There is some evidence that the struggling German ship-building industry diversifies in offshore WP and provides competences for the development of offshore turbines and components (Fornahl et al., 2012). In this phase, *Foreign Inventors* have a positive significant effect, possibly integrating knowledge which is not present in the knowledge base yet and increases the knowledge base. The other control variables show no unusual pattern, except *Granted Patents*, which is no longer significant.

Table 3.3: Results for the technology life cycle phases.

Negative binomial regressions: Dependent variable: Forward citations per patent

	Wind Power			Photovoltaics					
	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 5 Era of Ferment 1970-1997	Model 5a Era of Ferment 1970-1997	Model 5b Era of Ferment 1970-1997	Model 6 Dominant Design 1998-2006	Model 6a Dominant Design 1998-2006	Model 6b Dominant Design 1998-2006
New Inventors	0.163 *	0.275 ***	0.146 ***	0.084 *	0.086 **	0.085 *	-0.007	-0.003	-0.008
	(0.091)	(0.065)	(0.053)	(0.044)	(0.043)	(0.044)	(0.039)	(0.040)	(0.040)
Specialized Inventors	0.080	0.485 ***	0.499 ***	0.120	0.138 *	0.132 *	0.174 **	0.181 **	0.190 ***
	(0.175)	(0.165)	(0.060)	(0.077)	(0.075)	(0.076)	(0.075)	(0.076)	(0.072)
Related Inventors	0.236	-0.170	0.091 *	0.084	0.092 *	0.110 **	0.030	0.041	0.036
	(0.176)	(0.113)	(0.049)	(0.055)	(0.055)	(0.056)	(0.036)	(0.036)	(0.035)
Unrelated Inventors	0.337 **	-0.042	0.082	0.170	0.178	0.177	0.070	0.076	0.074
	(0.141)	(0.149)	(0.098)	(0.110)	(0.110)	(0.110)	(0.108)	(0.108)	(0.107)
PV Modules					-0.189 *	-0.196 *		0.048	0.026
					(0.111)	(0.110)		(0.093)	(0.093)
PV Cells					-0.481 ***			-0.085	
					(0.144)			(0.109)	
Silicon Wafer Cells						-1.665 ***			-0.833 **
						(0.450)			(0.368)
Thin-Film Cells						-0.371 **			-0.136
						(0.155)			(0.130)
Emerging Cells						-0.368			0.126
						(0.311)			(0.169)
Foreign Inventors	-1.130 *	-0.764 **	0.172 ***	0.087	0.034	0.043	-0.006	-0.007	-0.011
	(0.641)	(0.342)	(0.042)	(0.085)	(0.087)	(0.086)	(0.074)	(0.074)	(0.074)
IPC Classes	0.125	0.086 **	0.087 ***	0.158 ***	0.156 ***	0.155 ***	0.116 **	0.118 **	0.108 **
	(0.078)	(0.043)	(0.032)	(0.028)	(0.027)	(0.027)	(0.046)	(0.046)	(0.045)
Backward Citations	0.025	0.024	0.011 ***	0.021 ***	0.022 ***	0.023 ***	0.012 **	0.012 **	0.012 **
	(0.022)	(0.015)	(0.002)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)
New Combination	-0.194	-0.190	-0.132	-0.256 **	-0.297 **	-0.301 **	-0.167	-0.165	-0.163
	(0.204)	(0.146)	(0.120)	(0.125)	(0.123)	(0.123)	(0.154)	(0.156)	(0.154)
Family Size	0.147 ***	0.057 ***	0.076 ***	0.121 ***	0.112 ***	0.111 ***	0.134 ***	0.135 ***	0.132 ***
	(0.024)	(0.008)	(0.006)	(0.013)	(0.014)	(0.014)	(0.010)	(0.010)	(0.010)
PCT Patent	-0.595	-0.821 ***	0.110	-32.345 ***	-31.298 ***	-31.321 ***	0.108	0.122	0.188
	(0.983)	(0.306)	(0.225)	(0.526)	(0.536)	(0.534)	(0.404)	(0.405)	(0.393)
Granted Patent	0.342 **	0.640 ***	0.131	0.065	0.081	0.076	0.064	0.056	0.065
	(0.147)	(0.136)	(0.091)	(0.094)	(0.092)	(0.093)	(0.094)	(0.094)	(0.092)
USPTO	1.895 ***	0.741 *	1.016 ***	1.104 ***	1.272 ***	1.214 ***	1.041 ***	1.103 ***	1.107 ***
	(0.511)	(0.404)	(0.166)	(0.212)	(0.236)	(0.226)	(0.266)	(0.271)	(0.279)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	827	332	825	782	782	782	909	909	909
df	790	315	807	742	740	738	888	886	884
loglik	-832.361	-673.535	-1928.075	-1314.259	-1307.914	-1305.916	-2029.824	-2029.360	-2024.069
AIC	1740.723	1383.071	3894.151	2710.518	2701.829	2701.833	4103.649	4106.719	4100.139
McFadden R^2	0.082	0.073	0.096	0.070	0.074	0.075	0.059	0.059	0.062

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

For the different phases of the TLC in PV, model 5 and 6 present the results for the era of ferment and the emergence of a dominant design. Model 5 indicates that only *New Inventors* contribute to technological development. However, controlling for different sub-trajectories in model 5a and 5b reveals that also *Specialized Inventors* and *Related Inventors* have a positive effect. *Unrelated Inventors*, as proposed, do not matter, but *New Inventors* as well as *Specialized Inventors* do. A diverse set of knowledge is integrated in the knowledge base in this phase. Related literature shows that especially in the 1980s and 1990s a diverse set of actors (firms, research institutes, universities, ...) engage in PV R&D (Jacobsson et al., 2004) and the Fraunhofer Institute for Solar Energy Systems ISE was founded, which is until today central in Germany's PV research (Herrmann and Töpfer, 2017). Furthermore, contrary to WP, PV had in the era of ferment various applications to power off-grid solutions from calculators to satellites (Perlin, 2002; Jacobsson et al., 2004). This diverse areas of application could explain the different sources influencing the technology, especially at the sub-trajectory level where either costs (mass production) or efficiency (space application) are relevant. The control variables show except from the very large coefficient for *PCT Patents* no unusual results and are invariant towards controlling for sub-trajectories. Similar to the overall results, *Foreign Inventors* have no significant effect.

During the emergence of the dominant design, only *Specialized Inventors* contribute to the technological development, irrespectively controlling for sub-trajectories or not. Contrary to the theoretical expectation, *Related Inventors* do not matter. The shift towards the *Specialized Inventors* from experimentation in knowledge recombination to a more routinized inventive process could be a result of the complexity of PV. If the basic principle of the material to convert radiation into electricity is understood, improvements require a sound understanding of the material to improve it further. This specialized knowledge seems to be generated according to Jacobsson et al. (2004) by inventors in research institutes and universities. Considering the control variables, it is interesting to see that the negative effect of *New Combiantions* is not significant anymore.

Overall it is eminent that the knowledge relevant to advance the technologies changes over time from an explorative way to a more exploitative or routinized approach as suggested by March (1991). Partially in line with the proposed model, the relevant sources shift from knowledge outside the knowledge base towards knowledge present in the knowledge base over the course of the TLC. In WP the era of ferment is influenced from knowledge provided by *New Inventors* and *Unrelated Inventors* and in PV *New Inventors*, *Specialized Inventors* and *Related Inventors*. The dominant design is shaped in both cases by *Specialized Inventors*, in WP also by *New Inventors*. *Related Inventors* as proposed in the model do not matter in both cases. The era of ferment in WP is as proposed influenced by *New Inventors* and *Specialized Inventors*, but also by *Related Inventors* which could lead the way towards a discontinuity. Noteworthy is also that in WP *Foreign Inventors* become important over time, indicating that either knowledge from outside the country's domain becomes relevant, or inventors emigrate but still collaborate with German inventors.

3.4.3.3 Rolling-window regressions

The dynamics along the technological development can be analyzed more fine grained by rolling-window regressions. They allow to analyze changes in the effect of different types of inventors over time. The rolling-window regressions use an eight-year window sequentially from the start to the end of the overall observation period by dropping on year from the end and adding one to the beginning. For WP, model 4 is used and for PV model 4b to estimate the rolling-window

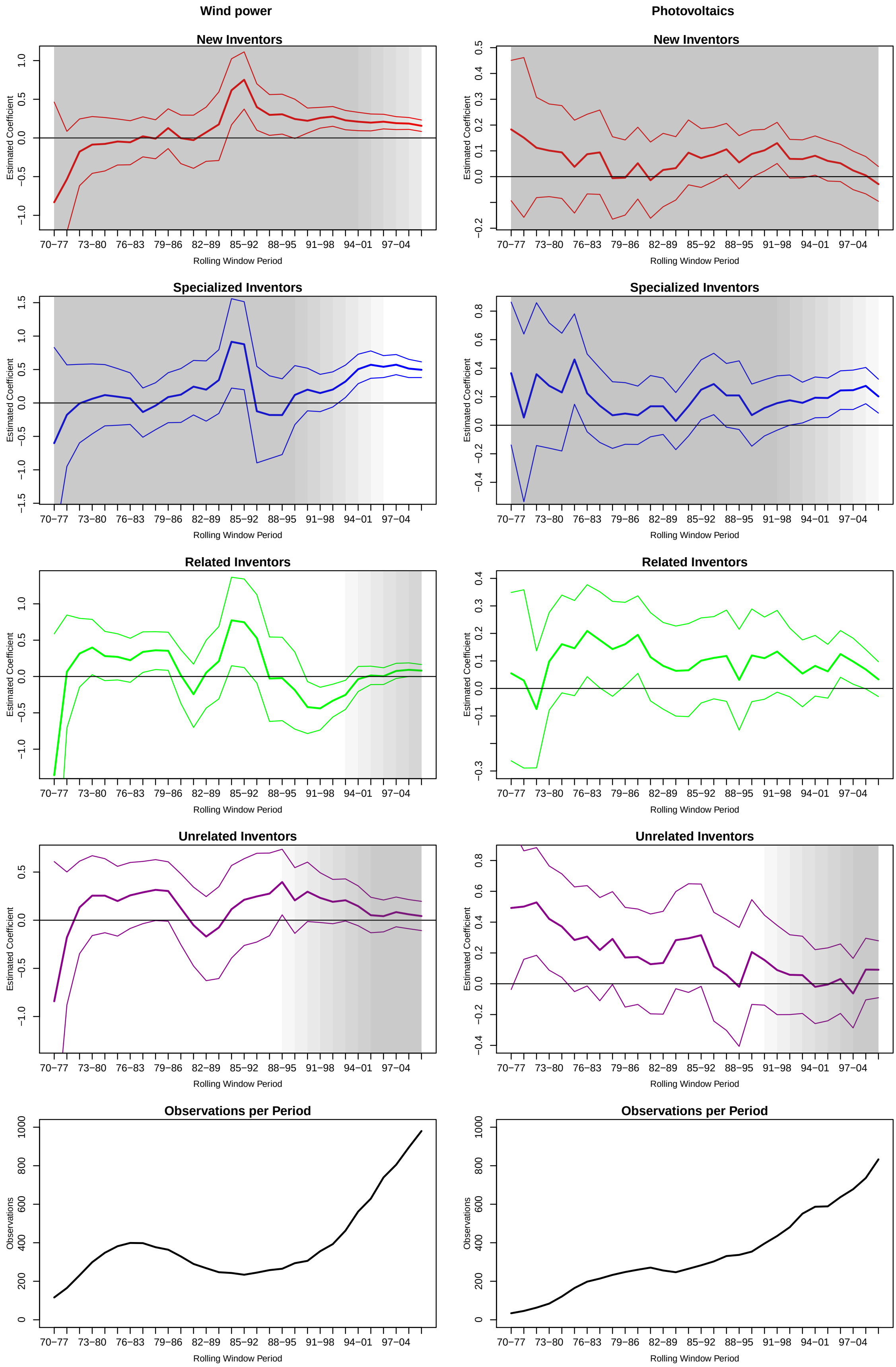


Figure 3.6: Eight year long rolling-window regression results for wind power and photovoltaics.

regressions. Figure 3.6 presents the results for WP and PV graphically.[13] The coefficients for the different inventors of the regressions are plotted along with the 10% confidence intervals for each eight-year period.[14] To test the proposed TLC model, the time periods in which the respective inventor type should have an effect are non-shaded in Figure 3.6. Since the periods are overlapping, the transition periods are symbolized by an increasing brightness, indicating the increasing relevance of the respective inventor type.

In the rolling-window regressions for WP, *New Inventors* should have an effect in the era of incremental change, which begins in 2001. There is however a significant effect already from the end of the 1980s onward which is persistent until the end of the observation period, indicating that fresh knowledge is constantly recombined and introduced into the knowledge base. Shedding more light on the results from the analysis of the TLC phases, we see that in the era of ferment *New Inventors* do not matter for about the first 15 years, but have a substantial effect onward, which is partly captured by the regression of the complete era of ferment. The influence of *New Inventors* can be the result of the changing approach towards WP in Germany after the failure of the GROWIAN project. Since this large scale wind turbine failed, focus was put on small scale turbines and new actors entered the technology (Bergek and Jacobsson, 2003). *Specialized Inventors* are supposed to be relevant in the emergence of the dominant design and the era of incremental change. The results show how these inventors become relevant from the beginning of the 1990s onwards and contribute substantially to the technological development until the end of the observation period. Besides two periods in the 1980s, they are not relevant in the era of ferment. Here, the results are in line with the results from the TLC regressions.

Related Inventors should play a role in the era of ferment and the emergence of the dominant design. In the era of ferment they have a significant effect only in a few periods and even reduce the number of forward citations a patent receives in some periods covering the emergence of the dominant design. Only towards the end of the observation period, the *Related Inventors* become slightly significant and seem to play a role again, which is also shown in the TLC regression. The rolling-window regressions reveal a significant negative effect in some periods which is unnoticed in the TLC regressions. *Unrelated Inventors* are supposed to have an effect in the era of ferment. The results show basically no effect at all. Only in some periods in the era of ferment, the coefficient is close to significant. This contrasts the results from the regression for the era of ferment, which finds an effect. However, the number of observation is low in these rolling-window regressions, which could explain that a significant effect does not show up. Towards the end of the observation period, there is no effect of these inventors at all, indicating that knowledge from outside the technology's domain does not matter and *Unrelated Inventors* seem not to disrupt the technology until then.

In PV, only the first two stages can be analyzed in which *New Inventors* are not supposed to have an influence. Concerning the results, this seems to be the case. Only in a few periods in the beginning of the 1990s there is a significant positive effect. This small effect is also present in the TLC regression conducted earlier. *Specialized Inventors* are supposed to matter while the dominant design emerges. Here, we can see an increase of the effect in this period in line with the model. In the earlier periods, there are only a few periods in which these inventors are relevant as well.

Related Inventors should have an influence in both periods. However, the results indicate only a few periods where these inventors actually have a significant effect. While the TLC regressions show that in the era of ferment the *Related Inventors* have a quite strong effect,

[13] The variation in the plotted graph is the result of the drop of observations from the last year and the inclusion of the added year. Furthermore, the number of observation changes, which also influences the regression results. This implies that each period can be considered on its own, but changes from one period to another should be interpreted with caution.

[14] Sensitivity tests for five and eleven years are discussed in Section 3.4.4.

the rolling-window regressions reveal that in the different periods the effect is not that strong, however this might be influenced by the low number of observations in each window. *Unrelated Inventors* are supposed to successfully recombine their knowledge in the era of ferment. The results indicate that especially in the early years this is the case, but over time this effect vanishes. However, the TLC regression finds no effect in the era of ferment at all, neglecting the effect in the early years of this phase.

Overall, the rolling-window regression provide further insights into the technological development. In both technologies we see shifts of relevance of different inventors over time. For WP, we can observe that *New Inventors* and *Specialized Inventors* become relevant, *New Inventors* even much earlier than expected. Also in line with the model, but only partially significant in the era of ferment, are *Related Inventors* and *Unrelated Inventors*. Contrary to the expectation, *Related Inventors* have a negative effect while the dominant design emerges. In PV the results are in general not that pronounced, but partially in line with the model. *New Inventors* play basically no role, as expected, and *Specialized Inventors* only have a significant effect while the dominant design emerges. *Related Inventors* should have an effect along the whole observation period, but show only a significant effect in some periods. *Unrelated Inventors* show as expected an effect early on, but not during the whole era of ferment. The results of the rolling-window regression mirror pretty much the results of the TLC phases in WP, while in PV there are some differences which show up in the era of ferment and are not captured by the TLC regressions.

3.4.4 Robustness

Several robustness test are performed concerning the distinction of inventors, possible team effects and the rolling-window length (see Appendix 3.6.5). The distinction of the inventors into *Related Inventors* and *Unrelated Inventors* is based on the presence of the IPCs in the knowledge base of the technology. This criterion changes over time as the knowledge base grows. A robustness test is done to see if this distinction and the change of classification criteria influences the overall results. The assignment of inventors to the two groups is in the following exogenously imposed using technology fields based on an extended version of the OST-INPI/FhG-ISI technology nomenclature classification (OECD, 1994; Schmoch, 2008). This classification contains five main technological fields and 35 subgroups. The subgroups provide the possibility to assign the inventor type according to the general field of previous application. To distinguish between *Related Inventors* and *Unrelated Inventors*, inventors which possess experience in the technological field "electrical machinery, apparatus, energy" for both technologies, and "engines, pumps, turbines" for WP and "semiconductors" for PV are assigned to be *Related Inventors*. These fields cover the underlying principles of the technologies and most IPCs of the WP and PV patents are assigned to these fields. If inventors do not have experience in these fields, they are supposed to be *Unrelated Inventors*.

Table 3.9 shows the results for WP and PV for model 4 and the TLC phases. For WP, we see in model 4 that the *Unrelated Inventors* are no longer significant. In the first phase of the TLC, the effect of *Unrelated Inventors* becomes stronger, but surprisingly *New Inventors* are no longer significant. In the second phase, the *Unrelated Inventors* become significant again, however, with a negative coefficient. In the last phase, no changes occur. In PV, Model 4b shows basically no differences, while in the era of ferment *Specialized Inventors* loose their weak significance. In the second phase, no changes occur. In general the results show that there is some sensitivity towards the distinction between *Related Inventors* and *Unrelated Inventors*, but the effects are only marginal and do not affect the overall pattern.

While the results show that different kinds of inventors are relevant for successful knowledge recombination along the TLC, inventive activity is increasingly conducted in teams (Wuchty et al., 2007). While the general trend of increasing team size over time is captured by the year dummies, the team composition is not accounted for. The effect of team composition and heterogeneous teams on knowledge recombination and creativity is an increasing stream of literature (Singh and Fleming, 2010; Uzzi et al., 2013; Lee et al., 2015). To account for possible effects of team composition, interactions between the different kinds of inventors are estimated.

The results of the interaction of different inventors are presented in Table 3.10. In general, the average team size is rather low with 1.4 for WP and 2.1 in PV and heterogeneous teams are a rare event, as shown in Figure 3.8. For WP, accounting for different interactions does not change the results in the model 4, but increases the coefficients. The interactions are mostly negative and significant, indicating that knowledge recombination in heterogeneous teams does not increase the invention's usefulness in general. In the era of ferment, the results do not change neither, but here the interaction between *Related Inventors* and *Unrelated Inventors* is positive and significant, indicating that in this phase combining knowledge from different fields external to the technology fosters technological development. The phase in which the dominant design emerges shows deviating results. *New Inventors* and *Specialized Inventors* are no longer significant and *Related Inventors* are negative and significant. The interaction terms however show that again *Related Inventors* and *Unrelated Inventors* but also *Specialized Inventors* and *Related Inventors* are positive and significant. In this phase, the team composition really seem to matter and influence the emergence of the dominant design. However, the number of team compositions is very low. For example the very large and negative coefficient of *Specialized Inventors* and *Unrelated Inventors* is striking, but this team composition occurs only three times. The era of incremental change shows again no deviation and the interactions are mostly negative and significant.

In the case of PV, there are differences in the model 4b. Here, *New Inventors* and *Unrelated Inventors* become significant as well. Concerning the interactions, there is a negative, significant effect of the combination of *New Inventors* and *Unrelated Inventors*. This indicates that their joint inventive activity produces less valuable patents as if they invent on their own. *Specialized Inventors* and *Related Inventors* keep their positive and significant effect. In the era of ferment, we observe that *Specialized Inventors* and *Related Inventors* are no longer significant, but *Unrelated Inventors* become significant. However, non of the interactions is significant. This result is quite puzzling. In the emergence of the dominant design, there are no deviations from the initial model. Here, also the interaction *New Inventors* and *Unrelated Inventors* has a negative effect.

Overall the general results seem to be robust towards the inventor interaction and the effect of heterogeneous teams matter in WP for the emergence of the dominant design and in PV for the era of ferment. In most cases heterogeneous teams exhibit a negative effect which is contrary to the previous findings in the literature. Especially in PV controlling for team composition reveals effects for New Inventors and *Unrelated Inventors* in the full model. Furthermore, there are some hints that also the effect of team composition changes along with the TLC, but a more detailed analysis is left for further research.

The rolling-window regression provided interesting insights about the dynamics over time. However, the effects might be dependent on the length of the time window. Shorter time periods should increase the volatility, since the number of observation is decreased and opposing effects might not be averaged out. Longer time windows will increase power and outlier effects are not that pronounced. To illustrate and analyze the sensitivity of the previously applied eight-year window, a five-year as well as an eleven-year window are estimated to capture more short term as well as long term patterns. The results are presented in Appendix 3.6.5.

As expected, with a shorter time window the results are more volatile and not as often significant as in the eight-year case. Here, the lower number of observation per regression is a problem and the first five periods are omitted because they cannot be reliably estimated. The overall pattern however stays in both technologies the same. In the eleven-year case the volatility of the coefficients is smaller and also the confidence intervals are smaller. However, the overall results converge and smaller changes are not that frequent anymore. In general the results stay the same as in the eight-year case.

3.5 Discussion and conclusion

The aim of the paper is to understand how recombination of different kinds of knowledge extends the knowledge base of a technology along its life cycle. For this purpose, from a theoretical perspective, the Anderson and Tushman (1990) model is extended to integrate different kinds of knowledge in the technology life cycle (TLC) phases. The proposed model extension is empirically tested for the TLC of wind power (WP) and photovoltaics (PV) in Germany. Different kinds of knowledge are proxied by inventors' patenting experience. This experience can be absent in case of new inventors, specialized in the technology or earned by inventive activity in related or unrelated fields. Overall, the results indicate that different kinds of knowledge matter along the TLC and are partly in line with the theoretical elaborations. While it has been proposed that the utilization of knowledge changes from exploration towards exploitation over time (March, 1991; Klepper, 1996), the results presented here reveal a more detailed picture of the utilization of knowledge along the TLC. The different phases of the TLC are characterized by specific knowledge and even inside the phases, relevant sources of knowledge change, providing a more detailed picture compared to previous empirical findings (Krafft et al., 2011, 2014a). The results help to better understand the process of knowledge recombination, technological development and provides relevant insides for policy and management.

Summarizing the results reveals technological differences in the relevance of knowledge for technological advancement, but the general expected shift of different sources of knowledge over time is evident. For the overall technological development from 1970 until 2006 specialized knowledge is relevant in both technologies. While WP is also influenced by new and unrelated knowledge, PV benefits from related knowledge, indicating first technological differences. In the era of ferment, WP requires unrelated knowledge as expected, however, not related knowledge. In PV its the opposite: related knowledge is relevant, but unrelated not. While PV uses the same material as the semiconductor technologies which explains the strong influence of related knowledge, WP seems not to have such an adjacent technology which it can benefit from, but relies on unrelated knowledge from other fields instead. Furthermore, both technologies benefit from new knowledge and PV also from specialized knowledge, indicating that a diverse set of knowledge is required for technological development in this phase. The emergence of the dominant design is as expected highly influenced by specialized knowledge in both technologies. However, related knowledge, as proposed in the model, does not matter. In WP, also new knowledge is of importance. The era of incremental change can only be observed in WP and is as proposed highly influenced by new and specialized knowledge. Furthermore, related knowledge contributes to some extend, maybe paving the way towards a discontinuity in offshore WP. The results are overall robust to an alternative distinction between related and unrelated knowledge, as well as controlling for team composition.

Rolling-window regressions, introduced as a new method in this stream of literature, reveal a finer-grained picture of the relevance of different kinds of knowledge along the TLC. They allow to observe the effect of different sources of knowledge in a continuous way and are not bound to the pre-defined phases of the TLC. In general, the relevance of different kinds of knowledge varies over time similar to the TLC phases. However, the rolling-windows reveal some differences. In WP, the earliest windows show that no specific kind of knowledge seems to matter, but this could be attributed to the rather small sample size in the early periods. In the beginning of the 1980s related and unrelated knowledge have an effect in some windows, which is in line with the theoretical proposition. However, not noticed in the TLC regression, related knowledge has a negative effect in some periods later on. New knowledge becomes relevant from the 1990s onwards and some years later specialized knowledge as well. These time nuances cannot be observed in normal regressions. In PV, new knowledge matters hardly for technological development. Specialized knowledge is very relevant towards the end of the observation period and an increasing trend is observable. Related and unrelated knowledge is relevant in some periods in the era of ferment, but the magnitude is smaller than suggested in the normal regressions. Since the effects of different kinds of knowledge vary over time and are not always in line with an imposed distinction of TLC-phases, using rolling-window regression to determine the TLC phase of a technology can be used as new way to characterize technological development in a continuous way.

These findings help to better understand the development of both technologies and their innovation process. As shown previously, WP and PV show different patterns in their development (e.g. Cantner et al., 2016; Huenteler et al., 2016a). This holds also for knowledge, which is used for technological advancement. Especially in WP it is evident that various kinds of knowledge are recombined to generate useful inventions. In line with qualitative evidence (Bergek and Jacobsson, 2003; Fornahl et al., 2012; Simmie et al., 2014), external knowledge and competencies refresh the knowledge base continuously over time. In PV, knowledge accumulation is the main diving force and specialization on the technology seems to be key for successful inventive activity. Since PV became a mass-market product over time, technological advancement is rather incremental (Huenteler et al., 2016b), where this specialized knowledge is of particular importance. However, in PV different sub-trajectories are present and developing simultaneously, but have partly different areas of application. They have their own life cycle, as previously shown by Lizin et al. (2013) for organic PV cells. In WP these different technological concepts are not present, but as shown by Huenteler et al. (2016a) the design hierarchy matters and the focus on different components changes over time. For both technologies further research is necessary to provide a more detailed understanding how knowledge is relevant for technical progress in different sub-trajectories or components.

From a theoretical perspective, integrating a knowledge related dimension in the Anderson and Tushman (1990) model joins the TLC concept with research on knowledge recombination and with research concerning inventor's personal characteristics. The proposed framework proved useful to analyze knowledge and knowledge recombination along the TLC and has implications for further research. First, the paper provides a theoretical foundation and empirical evidence for a more profound understanding of the relevance of knowledge along the TLC and that recombinatorial patterns change over time. Previously, these dynamics have not been considered, but different kinds of knowledge seem to be decisive for recombinatorial success and technological development in the TLC phases. Second, the results show that the technology's knowledge base is shaped over time by different kinds of knowledge. Knowledge accumulation and refreshing the knowledge base with knowledge from outside the technology's knowledge domain are necessary, but conditioned on the TLC phase. This provides some implications for studies on industrial dynamics. The dynamics in a sector's underlying technology allow to infer towards the life cycle of the sector as well, since here actors transform the knowledge into products. This knowledge is however generate by a diverse set of actors, such as research institutes, universities, users, tinkerers and knowledge is not bound to the firm. Integrating the overall TLC in studies on industrial dynamics helps to understand how technologies and the related sector and firms co-evolve. Third, the personal characteristics of inventors seems to be relevant for knowledge recombination. This dimension was absent in previous studies on knowledge recombination and the actual persons involved in the recombinatorial process need further research. Fourth, the chosen technologies provide new cases besides the commonly used biotech and ICT studies considered for knowledge recombination. Using WP and PV, it is demonstrated that the success of recombination is technology dependent and expanding the set of considered technologies enhances the general understanding of recombinatorial processes.

From a methodological point of view, using rolling-window regressions provide an interesting approach to track dynamics over time and should be included in the toolbox for research on dynamics in economics of innovation. Furthermore, the use of inventor's previous patents to reason about the embodied knowledge and experience seems to provide interesting possibilities to observe aggregated phenomena but also individual inventive biographies. However, here manual data cleaning was necessary and applying it to larger scale studies requires higher data quality. Nevertheless, this approach has several advantages compared to surveys, which are limited in size and time period and reachability of inventors.

The results lead to several policy and managerial implications. First, different kinds of knowledge are relevant in different phases of technological development. These changing requirements need to be considered in instrument and funding decisions for policy makers. While the effect of different types of policy instruments has been studied previously (Mowery and Rosenberg, 1979; Peters et al., 2012; Cantner et al., 2016; Rogge and Reichardt, 2016), the effect of instruments in specific phases of the TLC needs to be on the policy maker's agenda as well. If policy aims to support R&D of a technology in the era of ferment, funding should be granted to actors from diverse fields, while increasing the efficiency along the established trajectory, specialized actors should be in the focus. The same principle holds for firms and their decision whom to hire for inventive activity. Second, technological development is not a uniform process across technologies but different kinds of knowledge are relevant for each technology. The technology inherent differences need to be considered, which is however a difficult task for policy making.

The analysis faces certain shortcomings and limitations, which leave room for further research. First, the proposed framework has been only applied to two technologies in Germany. Here, further technologies and broader geographical coverage are necessary. Also, not all phases of the TLC could be analyzed due to the technologies' nature. Applying this approach to technologies which faced a discontinuity would shed light on this phase as well. The Framework can also be refined and extended to capture other dimensions of knowledge, such as tacit components or search behavior. Second, there are several areas which could not be explored in more detail, such as the team composition, which seems to matter partly and changes along the TLC. Sub-trajectories play a role in the TLC and a more detailed analysis could provide further insights on technological development. Third, the analysis relies on patent data only and not all inventions are patented. To complement the understanding of knowledge recombination along the TLC, other sources such as publication data, related product characteristics or interviews with inventors can be considered to overcome limitations of patent data.

3.6 Appendix

3.6.1 Patent selection approach

The WP and PV patents were queried from Patstat (EPO, 2014) by combining IPC classes and keywords. The title and abstract of patent documents are searched for the keyword while restricted to the specific IPC classes. The selection criteria for WP is based on the suggestions from the WIPO Green Inventory for wind power and own elaboration. For PV, search strategy developed in Chapter 2 is used. However, the balance of system component is excluded from the analysis, since it covers a partly different technological approach and could interfere with the aim of the analysis. The keywords and IPCs are grouped for specific sub-trajectories. The "_" and the "%" symbol are used as wildcards for single and multiple characters.

Table 3.4: List of IPCs and keywords for patent search strategies.

<table>
<tr><th>Technology</th><th>IPCs</th><th>Keyword combination</th></tr>
<tr><td>Wind power</td><td></td><td></td></tr>
<tr><td></td><td>F03D%</td><td></td></tr>
<tr><td></td><td>H02K 7/18
B63B 35/00
E04H 12/00</td><td>(%wind% + (%turbine% | %power% | %mill% | %energ%))</td></tr>
<tr><td>Photovoltaics</td><td></td><td></td></tr>
<tr><td>Silicon wafer cells</td><td>H01L 21%
H01L 31%
C30B 15%
C01B 33%</td><td>((%monocrystalline_silicon% | %monocrystal_silicon% | %crystal_silicon% |
%silicon_crystal% | %silicon_wafer%) + (%photovoltai% | %solar%))
| %back_surface_passivation% | (%pyramid% + %etching% + %silicon%)
((%polycrystalline_silicon% | %multicrystalline_silicon% | %poly_Si% | %polysilicon%)</td></tr>
<tr><td></td><td>C30B 15%
C30B 29%
H01L 21%
H01L 31%</td><td>+ (%photovoltai% | %solar%)) | (%ribbon% + (%photovoltai% | %solar% | %silicon%))
| (%edge_defined_film_fed_growth% + %silicon%) | %Metal_wrap_through% |
%emitter_wrap_through% | %ribbon_growth%</td></tr>
<tr><td>Thin-film cells</td><td>C23C 14%
C23C 16%
H01L 21%
H01L 27%
H01L 29%
H01L 31%</td><td>((%chemical_vapour_deposition% | %PECVD% | %physical_vapour_deposition% | %PVD% |
%solid_phase_crystallization% | %laser_crystallization% | %nanocrystalline% | %microcrystalline%)
+ (%photovoltai% | %solar% | %silicon%)) | ((%tandem% | %amorphous_silicon% |
%silicon_substrate% | %silicon_film%) + (%photovoltai% | %solar%)) | %staebler_wronski%</td></tr>
<tr><td></td><td>C23C 14%
C23C 16%
H01L 21%
H01L 25%
H01L 27%
H01L 29%
H01L 31%</td><td>((%cadmium_telluride% | %CdTe% | %copper_indium_diselenide% | % CIS % | %CuInSe% |
%indium_tin_oxide% | %gallium_arsenide% | %GaAs% | %roll_to_roll% | %surface_textur% |
%thin_film% | %thinfilm%) + (%photovoltai% | %solar%)) | %copper_indium_gallium_diselenide% |
%CuInGeSe% | %CIGS% | %copper_zinc_tin_sulfide% | %CZTS% | %kesterite%</td></tr>
<tr><td>Emerging cells</td><td>C08K 3%
C08G 61%
H01B 1%
H01G 9%
H01L 21%
H01L 31%
H01L 51%
H01M 14%</td><td>((%dye_sensiti% | %titanium_oxide% | %titanium_dioxide% | %TiO2% | %organic% | %polymer%)
+ (%photovoltai% | %solar)) | %gr_tzel% | %graetzel% | %hybrid_solar_cell%</td></tr>
<tr><td></td><td>H01G 9%
H01L 31%
H01L 51%
H01M 14%</td><td>((%quantum_dot% | %perovskite% | %organic_inorganic% | %plasmon% | %nanowire% |
%nanoparticle% | %nanotube%)) + (%photovoltai% | %solar))</td></tr>
<tr><td>PV modules</td><td>H01L 21%
H01L 25%
H01L 27%
H01L 31%
H01R 13%
H02N 6%
H02S 20%
H02S 30%
B64G 1%
E04D 13%</td><td>((%anti_reflection% | %encapsulat% | %back_contact% | %buried_contact% | %bypass_diode% |
%rear_surface_protection% | %back_sheet% | %building_integrat% | %mounting_system%)
+ (%photovoltai% | %solar)) | %solar_panel% | %photovoltaic_panel% | %solar_modul% |
%solar_cell_modul% | %photovoltaic_modul% | %solar_cable% | %photovoltaic_wire% |
%solar_array% | %photovoltaic_array% | %BIPV% | %solar_park% | (%spacecraft% +
(%photovoltai% | %solar_cell%))</td></tr>
<tr><td>Unassigned</td><td>B64G 1%
C01B 33%
C08K 3%
C08G 61%
C23C 14%
C23C 16%
C30B 29%
C30B 15%
E04D 13%
F21S 9%
G05F 1%
H01B 1%
H01G 9%
H01L 21%
H01L 25%
H01L 27%
H01L 29%
H01L 31%
H01L 51%
H01M 10%
H01M 14%
H01R 13%
H02J 7%
H02M 7%
H02N 6%
H02S 99%
H02S 20%
H02S 30%</td><td>(%photovoltai% | %solar_cell%)</td></tr>
</table>

3.6.2 Decriptive statistics

Table 3.5: Descriptive statistics for wind power and photovoltaics.

	Tech.	Min.	Median	Mean	Max.	SD
Forward Citation	WP	0	1	2,628	103	6,202
	PV	0	1	2,723	41	4,008
New Inventors	WP	0	0	0,546	6	0,753
	PV	0	1	0,820	10	1,053
Specialized Inventors	WP	0	0	0,208	4	0,475
	PV	0	0	0,260	4	0,574
Related Inventors	WP	0	0	0,362	6	0,633
	PV	0	1	0,808	8	1,052
Unrelated Inventors	WP	0	0	0,221	4	0,454
	PV	0	0	0,136	3	0,379
Team Size	WP	1	1	1,384	8	0,886
	PV	1	2	2,132	13	1,465
Experienced Inventors	WP	0	1	0,791	7	0,776
	PV	0	1	1,205	8	1,129
Knowledable Inventors	WP	0	0	0,583	7	0,715
	PV	0	1	0,944	8	1,075
Foreign Inventors	WP	0	0	0,047	7	0,405
	PV	0	0	0,108	5	0,477
IPC Classes	WP	1	2	2,042	10	1,343
	PV	1	2	2,381	10	1,414
Backward Citations	WP	0	2	3,236	171	7,307
	PV	0	3	4,263	154	6,388
New Combination	WP	0	0	0,148	1	0,355
	PV	0	0	0,225	1	0,418
Family Size	WP	1	1	3,033	35	4,682
	PV	1	1	2,957	31	3,059
PCT Patent	WP	0	0	0,011	1	0,102
	PV	0	0	0,008	1	0,091
Granted Patent	WP	0	0	0,29	1	0,454
	PV	0	0	0,357	1	0,479
USPTO	WP	0	0	0,027	1	0,161
	PV	0	0	0,018	1	0,132
PV Modules	PV	0	0	0,215	1	0,411
PV Cells	PV	0	0	0,167	1	0,373
Silicon Wafer Cells	PV	0	0	0,021	1	0,142
Thin-Film Cells	PV	0	0	0,100	1	0,300
Emerging Cells	PV	0	0	0,054	1	0,227

3.6.3 Correlation tables

Table 3.6: Correlation table for wind power.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Forward Citation	—															
2	New Inventors	-0.022	—														
3	Specialized Inventors	0.216	-0.177	—													
4	Related Inventors	0.033	-0.269	-0.137	—												
5	Unrelated Inventors	-0.081	-0.245	-0.120	-0.168	—											
6	Team Size	0.243	0.428	0.268	0.315	0.113	—										
7	Experienced Inventors	0.112	-0.471	0.430	0.634	0.376	0.487	—									
8	Knowledable Inventors	-0.022	-0.394	-0.197	0.779	0.487	0.350	0.800	—								
9	Foreign Inventors	0.358	-0.021	0.091	-0.027	-0.018	0.459	0.023	-0.035	—							
10	IPC Classes	0.131	0.003	-0.051	0.147	-0.062	0.046	0.052	0.090	-0.006	—						
11	Backward Citations	0.603	0.005	0.112	0.028	-0.082	0.155	0.043	-0.027	0.246	0.115	—					
12	New Combination	0.006	0.041	-0.048	0.048	0.013	0.039	0.017	0.051	-0.024	0.510	0.012	—				
13	Family Size	0.247	-0.127	-0.006	0.215	-0.088	0.010	0.121	0.135	0.027	0.241	0.102	0.085	—			
14	PCT Patent	0.027	-0.016	0.090	-0.005	-0.018	0.022	0.041	-0.015	0.000	-0.007	0.042	-0.029	0.047	—		
15	Granted Patent	0.220	0.029	0.138	0.027	-0.091	0.118	0.054	-0.034	0.102	0.180	0.239	0.111	0.242	-0.066	—	
16	USPTO	0.489	0.004	0.217	-0.060	-0.053	0.207	0.053	-0.087	0.344	0.006	0.419	0.001	0.041	-0.017	0.204	—

Table 3.7: Correlation table for photovoltaics.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	Forward Citation	—																			
2	New Inventors	-0.005	—																		
3	Specialized Inv.	0.071	-0.046	—																	
4	Related Inv.	0.145	-0.158	-0.156	—																
5	Unrelated Inv.	0.011	-0.048	-0.051	-0.119	—															
6	Team Size	0.165	0.566	0.235	0.520	0.101	—														
7	Experienced Inv.	0.175	-0.187	0.346	0.812	0.199	0.638	—													
8	Knowledable Inv.	0.146	-0.172	-0.171	0.937	0.236	0.545	0.865	—												
9	Foreign Inv.	0.105	-0.026	0.004	0.025	-0.055	0.312	0.006	0.005	—											
10	IPC Classes	0.083	0.018	-0.097	0.081	0.015	0.036	0.030	0.084	-0.001	—										
11	Backward Cit.	0.076	0.015	0.058	-0.048	-0.022	0.017	-0.022	-0.054	0.070	-0.005	—									
12	New Combination	-0.015	0.021	-0.069	-0.001	0.075	0.004	-0.011	0.025	-0.006	0.532	-0.010	—								
13	Family Size	0.378	0.041	0.088	0.180	-0.014	0.227	0.208	0.171	0.115	0.124	0.042	0.056	—							
14	PCT Patent	0.011	-0.022	0.061	-0.033	0.002	-0.008	0.001	-0.032	0.020	-0.029	0.025	-0.049	-0.009	—						
15	Granted Patent	0.051	0.064	0.047	-0.003	-0.023	0.079	0.014	-0.011	0.070	0.044	0.248	0.041	0.105	-0.068	—					
16	USPTO	0.122	-0.024	0.025	-0.031	-0.048	0.077	-0.032	-0.047	0.364	-0.046	0.265	-0.008	-0.020	-0.012	0.105	—				
17	PV Modules	-0.052	-0.060	-0.012	-0.097	-0.055	-0.151	-0.115	-0.115	-0.058	-0.038	0.041	-0.117	-0.158	0.000	0.015	-0.038	—			
18	PV Cells	-0.029	0.039	0.067	0.162	-0.027	0.179	0.176	0.148	0.048	-0.013	0.016	-0.029	-0.039	0.029	0.023	0.132	-0.084	—		
19	Silicon Wafer Cells	-0.056	-0.007	0.064	0.105	-0.019	0.095	0.125	0.096	0.011	-0.024	-0.016	-0.029	-0.014	0.078	-0.030	-0.020	-0.076	0.324	—	
20	Thin-Film Cells	-0.052	0.021	0.076	0.036	0.021	0.086	0.079	0.043	0.028	-0.069	0.049	-0.048	-0.055	-0.030	0.101	0.149	-0.059	0.743	0.021	—
21	Emerging Cells	0.048	0.076	-0.032	0.163	-0.059	0.160	0.116	0.139	0.050	0.105	-0.036	0.052	0.028	0.036	-0.081	0.027	-0.024	0.535	-0.017	-0.019

3.6.4 Inventor types

In this section, more detailed information about the number of the different kinds of inventors, their patents and team composition are presented. Table 3.8 shows the number of different types of inventors. These numbers do not sum up to the total number of inventors, since the inventor type can change over time, for example if a *New Inventor* continues his inventive activity and becomes a *Specialized Inventor*.

Table 3.8: Number of inventors of wind power and photovoltaic patents.

	Wind power	Photovoltaics
New Inventors	1083	1387
Specialized Inventors	413	440
Related Inventors	596	920
Unrelated Inventors	560	677

Figure 3.7 displays the number of patents each inventor possesses in the technologies. The very skewed distribution is common for patent data (Menon, 2011) and scientific output in general (Lotka, 1926). It is not possible to infer from the number of patents to the type of inventor. *Related Inventors* and *Unrelated Inventors* can have only one patent or inventors, which start and continue their inventive activity have more than one patent. Remarkably is the WP inventor with 127 patents. This inventor is Aloys Wobben, founder of the German wind turbine manufacturer Enercon.

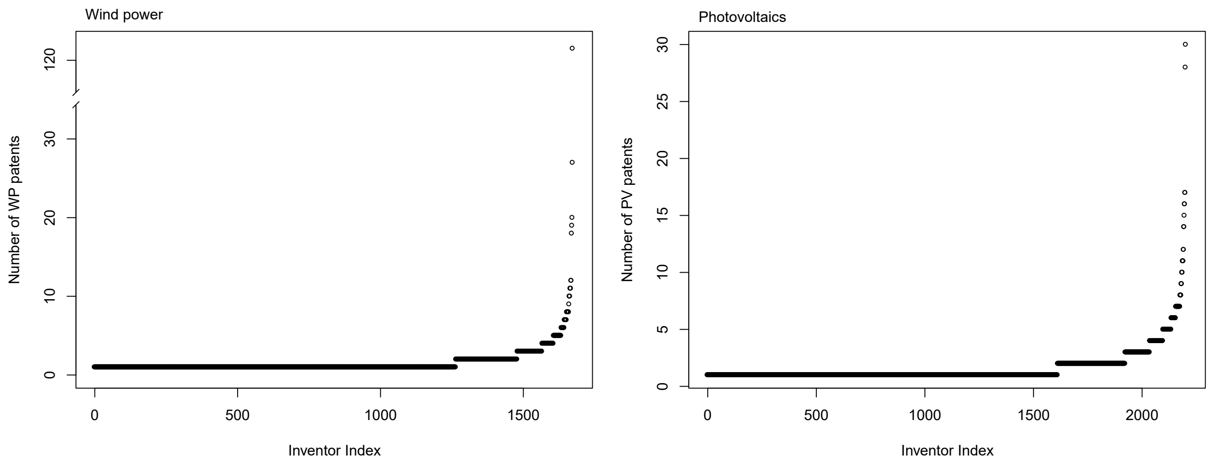


Figure 3.7: Number of wind power and photovoltaics patents each inventor possess.

Figure 3.8 depicts the team composition in WP and PV. A edge between two different kinds of inventor is established if they are present on the same patent. The loops for each inventor consists of patents invented by only one type of inventor, regardless of the amount (patents with only one inventor are included in the loop as well). WP has hardly any heterogeneous teams and most patents are filed by one or multiple inventor of the same type. In both technologies, teams comprising *New Inventors* and *Related Inventors* as well as *New Inventors* and *Specialized Inventors* are the most frequent.

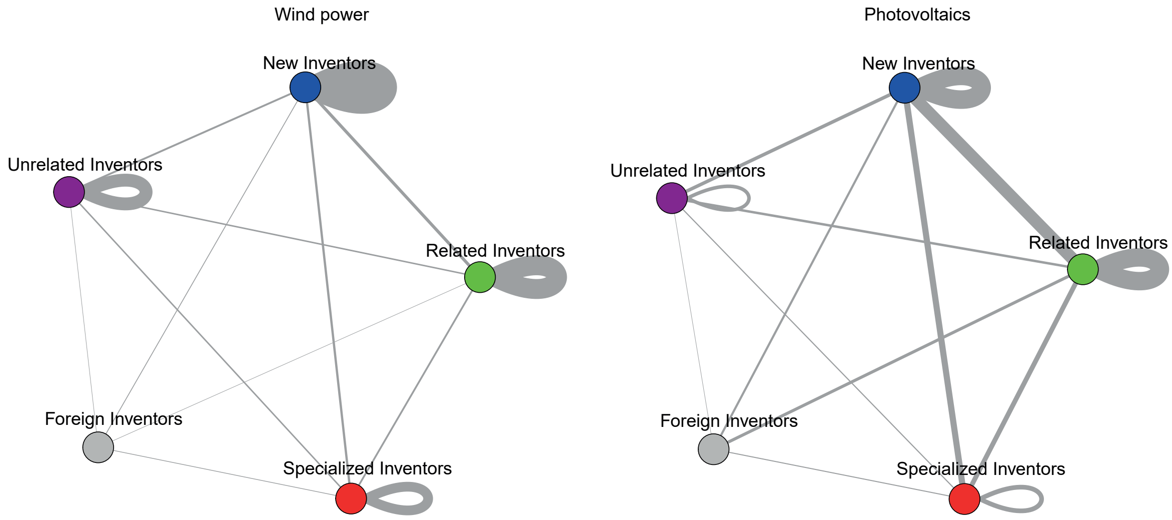


Figure 3.8: Team structures in wind power and photovoltaics.

3.6.5 Robustness tests

Table 3.9: Regression results for alternative inventor specification.

Negative binomial regressions: Dependent variable: Forward citations per patent

	Wind Power				Photovoltaics		
	Model 4 Full Period 1970-2006	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 4b Full Period 1970-2006	Model 5b Era of Ferment 1970-1997	Model 6b Dominant Design 1998-2006
New Inventors	0.163 ***	0.142	0.269 ***	0.146 ***	0.033	0.083 *	-0.007
	(0.039)	(0.094)	(0.067)	(0.053)	(0.030)	(0.044)	(0.040)
Specialized Inventors	0.425 ***	0.052	0.489 ***	0.508 ***	0.164 ***	0.123	0.186 ***
	(0.055)	(0.180)	(0.166)	(0.060)	(0.055)	(0.075)	(0.072)
Related Inventors alt.	0.088	0.071	-0.049	0.148 **	0.092 **	0.174 **	0.060
	(0.054)	(0.199)	(0.121)	(0.062)	(0.038)	(0.069)	(0.047)
Unrelated Inventors alt.	0.073	0.377 ***	-0.258 *	0.025	0.004	0.030	-0.001
	(0.054)	(0.135)	(0.140)	(0.060)	(0.040)	(0.069)	(0.048)
PV Modules					-0.046	-0.179	0.022
					(0.072)	(0.110)	(0.093)
Silicon Wafer Cells					-0.935 ***	-1.708 ***	-0.829 **
					(0.342)	(0.458)	(0.383)
Thin-Film Cells					-0.234 **	-0.351 **	-0.139
					(0.098)	(0.155)	(0.129)
Emerging Cells					-0.039	-0.400	0.103
					(0.151)	(0.318)	(0.168)
Foreign Inventors	0.142 ***	-1.181 *	-0.670 *	0.170 ***	0.007	0.034	-0.016
	(0.041)	(0.648)	(0.373)	(0.042)	(0.058)	(0.086)	(0.073)
IPC Classes	0.092 ***	0.120	0.085 *	0.084 ***	0.135 ***	0.147 ***	0.110 **
	(0.024)	(0.076)	(0.044)	(0.032)	(0.025)	(0.027)	(0.044)
Backward Citations	0.012 ***	0.021	0.025	0.011 ***	0.016 ***	0.024 ***	0.012 **
	(0.002)	(0.022)	(0.016)	(0.002)	(0.004)	(0.008)	(0.005)
New Combination	-0.139	-0.123	-0.192	-0.130	-0.212 **	-0.270 **	-0.167
	(0.086)	(0.205)	(0.149)	(0.121)	(0.098)	(0.119)	(0.152)
Family Size	0.068 ***	0.149 ***	0.053 ***	0.074 ***	0.126 ***	0.113 ***	0.131 ***
	(0.005)	(0.024)	(0.009)	(0.006)	(0.008)	(0.014)	(0.010)
PCT Patent	0.128	-0.584	-0.511	0.117	-0.027	-30.337 ***	0.212
	(0.225)	(0.977)	(0.339)	(0.228)	(0.415)	(0.533)	(0.406)
Granted Patent	0.320 ***	0.315 **	0.617 ***	0.137	0.060	0.088	0.058
	(0.067)	(0.147)	(0.136)	(0.090)	(0.064)	(0.092)	(0.092)
USPTO	1.034 ***	1.945 ***	0.734 *	1.025 ***	1.129 ***	1.186 ***	1.108 ***
	(0.159)	(0.518)	(0.403)	(0.166)	(0.205)	(0.218)	(0.280)
Year Dummies	yes	yes	yes	yes	yes	yes	yes
N	1984	827	332	825	1691	782	909
df	1936	790	315	807	1638	738	884
loglik	-3462.770	-830.673	-673.111	-1926.998	-3342.420	-1304.780	-2023.636
AIC	7023.541	1737.347	1382.222	3891.996	6792.841	2699.559	4099.271
McFadden R^2	0.146	0.084	0.074	0.096	0.078	0.076	0.062

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

Table 3.10: Regression results for inventor interactions.

Negative binomial regressions: Dependent variable: Forward citations per patent

	Wind Power				Photovoltaics		
	Model 4 Full Period 1970-2006	Model 5 Era of Ferment 1970-1995	Model 6 Dominant Design 1996-2000	Model 7 Era of incremental change 2001-2006	Model 4b Full Period 1970-2006	Model 5b Era of Ferment 1970-1997	Model 6b Dominant Design 1998-2006
New Inventors	0.202 ***	0.252 **	0.100	0.179 ***	0.081 *	0.109 *	0.020
	(0.052)	(0.114)	(0.158)	(0.069)	(0.047)	(0.063)	(0.065)
New Inventors x Specialized Inventors	-0.098 *	-0.641	-0.195 **	-0.138 **	-0.026	-0.038	0.008
	(0.052)	(0.601)	(0.098)	(0.061)	(0.043)	(0.057)	(0.063)
New Inventors x Related Inventors	0.057	-0.893 **	0.288	0.065 *	-0.022	0.002	-0.006
	(0.035)	(0.429)	(0.225)	(0.037)	(0.019)	(0.049)	(0.022)
New Inventors x Unrelated Inventors	-0.166 **	-0.041	-0.147	-0.246 *	-0.191 ***	-0.174	-0.172 *
	(0.082)	(0.187)	(0.209)	(0.127)	(0.069)	(0.106)	(0.099)
Specialized Inventors	0.524 ***	0.307	0.218	0.617 ***	0.207 ***	0.119	0.258 ***
	(0.073)	(0.237)	(0.261)	(0.079)	(0.075)	(0.110)	(0.086)
Specialized Inventors x Related Inventors	-0.168 **	-0.433	0.885 ***	-0.231 ***	0.015	0.131	-0.100
	(0.076)	(0.334)	(0.333)	(0.082)	(0.061)	(0.098)	(0.071)
Specialized Inventors x Unrelated Inventors	-0.155	-0.226	-37.941 ***	0.075	-0.176	-0.112	-0.219
	(0.170)	(0.358)	(0.805)	(0.180)	(0.112)	(0.182)	(0.154)
Related Inventors	0.098	0.291	-0.563 **	0.134 **	0.074 *	0.081	0.041
	(0.062)	(0.200)	(0.251)	(0.059)	(0.042)	(0.073)	(0.053)
Related Inventors x Unrelated Inventors	-0.061	0.928 **	0.479 **	-0.164	0.047	0.066	0.071
	(0.074)	(0.431)	(0.188)	(0.101)	(0.061)	(0.126)	(0.079)
Unrelated Inventors	0.213 **	0.385 **	-0.353	0.195	0.259 **	0.285 **	0.188
	(0.090)	(0.180)	(0.277)	(0.126)	(0.107)	(0.130)	(0.179)
PV Modules					-0.032	-0.187 *	0.030
					(0.072)	(0.110)	(0.092)
Silicon Wafer Cells					-0.917 ***	-1.592 ***	-0.790 **
					(0.331)	(0.456)	(0.374)
Thin-Film Cells					-0.232 **	-0.358 **	-0.124
					(0.100)	(0.157)	(0.132)
Emerging Cells					-0.009	-0.342	0.119
					(0.151)	(0.322)	(0.167)
Foreign Inventors	0.137 ***	-1.138 *	-0.940 ***	0.164 ***	0.020	0.054	-0.002
	(0.042)	(0.643)	(0.324)	(0.043)	(0.058)	(0.085)	(0.074)
IPC Classes	0.093 ***	0.139 *	0.065	0.084 ***	0.132 ***	0.152 ***	0.103 **
	(0.024)	(0.076)	(0.045)	(0.032)	(0.025)	(0.027)	(0.046)
Backward Citations	0.012 ***	0.027	0.017	0.011 ***	0.015 ***	0.021 ***	0.012 **
	(0.002)	(0.022)	(0.015)	(0.002)	(0.004)	(0.008)	(0.005)
New Combination	-0.140 *	-0.220	-0.155	-0.123	-0.212 **	-0.299 **	-0.146
	(0.084)	(0.203)	(0.146)	(0.119)	(0.100)	(0.123)	(0.154)
Family Size	0.070 ***	0.147 ***	0.063 ***	0.077 ***	0.127 ***	0.113 ***	0.133 ***
	(0.005)	(0.024)	(0.009)	(0.006)	(0.008)	(0.014)	(0.010)
PCT Patent	0.135	-0.737	36.429 ***	0.110	-0.113	-31.327 ***	0.124
	(0.227)	(1.024)	(0.798)	(0.236)	(0.391)	(0.535)	(0.386)
Granted Patent	0.322 ***	0.323 **	0.658 ***	0.135	0.065	0.083	0.059
	(0.067)	(0.142)	(0.137)	(0.092)	(0.064)	(0.092)	(0.091)
USPTO	1.030 ***	1.858 ***	1.019 **	1.035 ***	1.150 ***	1.239 ***	1.099 ***
	(0.163)	(0.505)	(0.406)	(0.172)	(0.206)	(0.228)	(0.281)
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1984	827	332	825	1691	782	909
df	1930	784	309	801	1632	732	878
loglik	-3457.785	-827.086	-667.408	-1921.658	-3339.656	-1303.689	-2021.261
AIC	7025.570	1742.172	1382.817	3893.315	6799.311	2709.377	4106.523
McFadden R^2	0.147	0.088	0.082	0.099	0.078	0.077	0.063

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

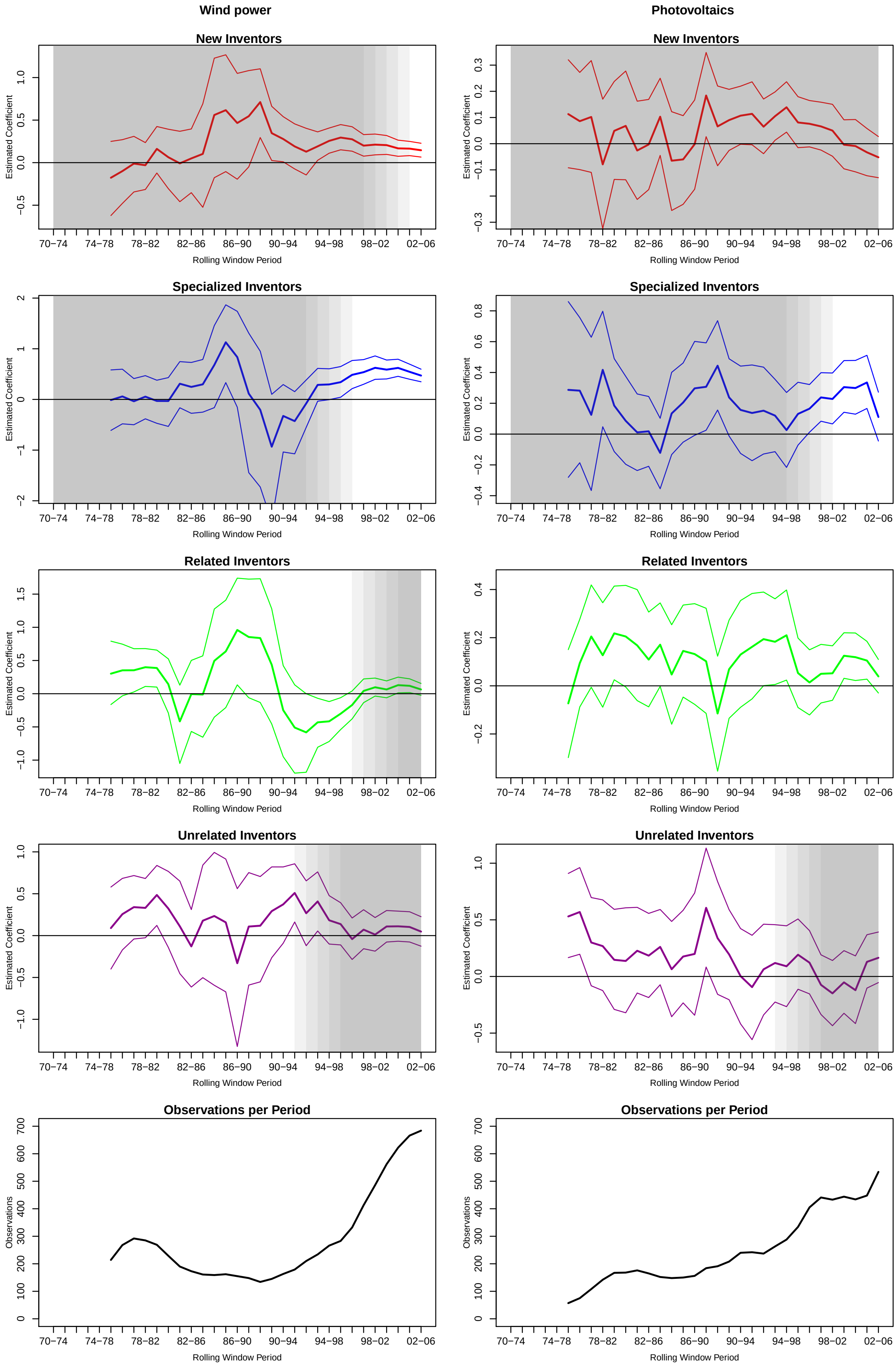


Figure 3.9: Five year long rolling-window regression results for wind power and photovoltaics.

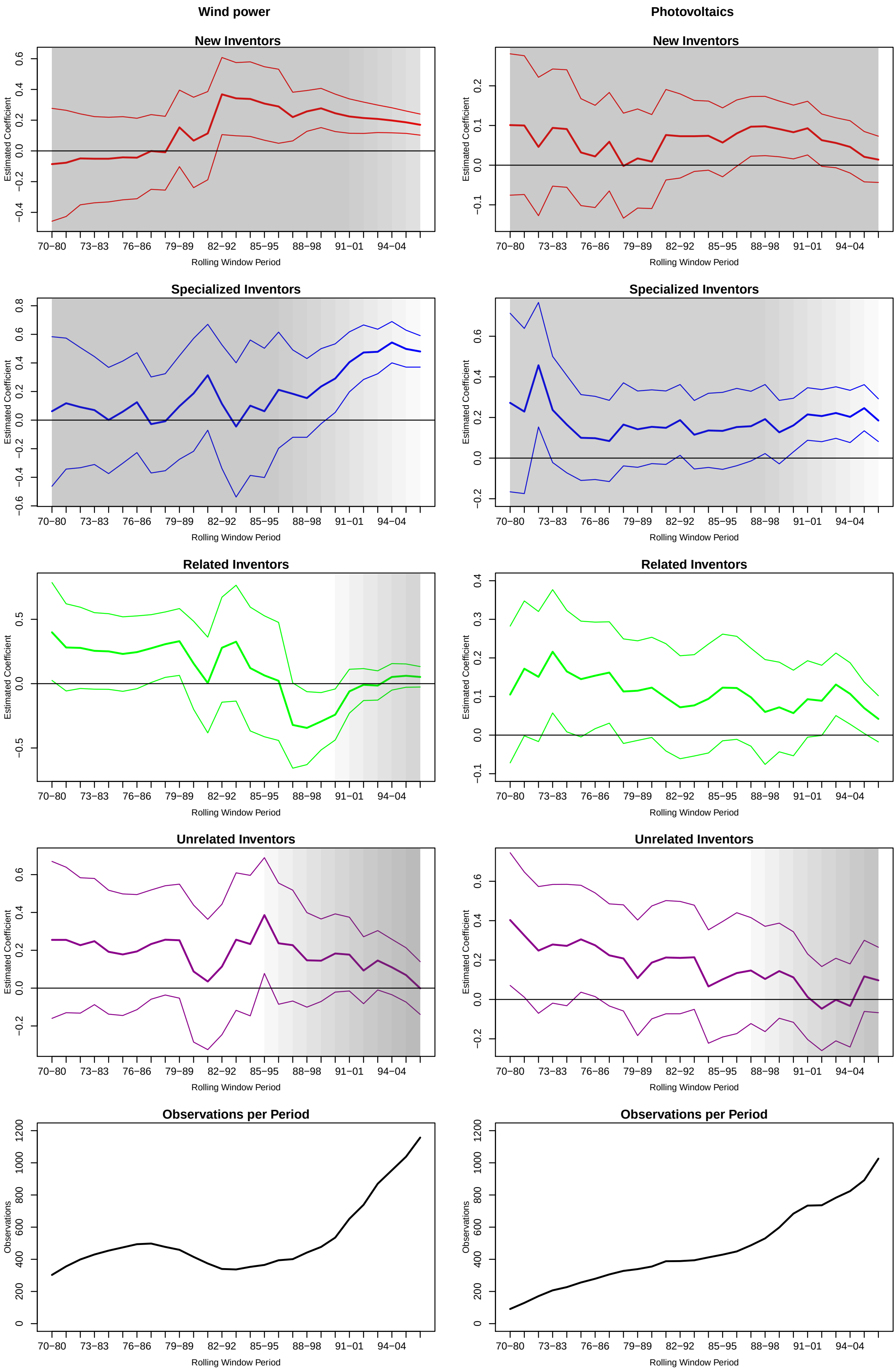


Figure 3.10: Eleven year long rolling-window regression results for wind power and photovoltaics.

Chapter 4

Inventor networks in renewable energies: The influence of the policy mix in Germany

Co-authored with Uwe Cantner, Holger Graf and Johannes Herrmann

4.1 Introduction

During the last decades, the global capacity for electric power generation by renewable sources (excluding hydropower) increased substantially from 85 GW in 2004 to 657 GW in 2014 (REN21, 2015). In Germany, the share of renewable energies in electric power production reached 27% in 2014 (BMWi, 2015). This development is mainly driven by political support and technological progress in the specific technologies. Several studies have shown that policies and environmental regulations are important drivers of innovative activities in environmental technologies, especially in renewable energies (Johnstone et al., 2010; Grau et al., 2012; Peters et al., 2012; Wangler, 2013; Dechezleprêtre and Glachant, 2014; Costantini et al., 2015b). In particular, inventive activities, largely induced by policies for wind power (WP) and photovoltaic (PV) technologies, increased tremendously over the last decades.

Policies have been implemented in an attempt to influence the development and diffusion of renewable power generation technologies (RPGT), especially PV and WP, from different directions. Demand pull instruments affect innovative activities indirectly by creating demand for RPGT, e.g. through feed-in tariffs (FIT) or investment support, and thus increase market size. Technology-push instruments directly affect inventive and innovative activities by means of

Acknowledgements: This chapter was written as part of the research project GRETCHEN (The impact of the German policy mix on technological and structural change in renewable power generation technologies, `www.project-gretchen.de`), which is funded by the German Ministry of Education and Research (BMBF) within its funding priority "Economics of Climate Change" under the funding label Econ-C-026. We gratefully acknowledge this support. Johannes Herrmann also thanks the German Research Foundation (DFG) for financial support within the DFG-GRK 1411 "The Economics of Innovative Change". We would like to thank the GRETCHEN team members and especially Karoline Rogge for the valuable discussions. We are grateful to Jens J. Krüger and participants of the 13th IAEE European Conference in Düsseldorf, the International Conference on Policy Mixes in Environmental and Conservation Policies in Leipzig, the 15th International Conference of the International Joseph A. Schumpeter Society in Jena, as well as the seminar in Turin for discussions of earlier versions of this chapter. We would also like to thank Moritz Böhmeke-Schwafert for his valuable research assistance. Three anonymous referees greatly helped to improve the chapter.

R&D subsidies or through performing public R&D in research institutes. Systemic instruments, such as cooperative R&D programs, clusters or infrastructure provisions, provide support for collaboration and knowledge transfer (Smits and Kuhlmann, 2004). The combination of these policies constitutes an instrument mix,[1] which needs to be consistent to support fully innovative activity.

With respect to technology push policies, while their influence on investments in R&D is quite clear, two important aspects of policy impact are less obvious. First, while demand pull instruments increase incentives to invest in production facilities, do they also increase incentives for innovation and investment in R&D? And if so, is it an immediate effect or rather a consequence of the change in market size and structure? Regarding the second aspect, it is common knowledge that internal investments in R&D are only one input in the innovation process. External knowledge, captured through technological spillovers, increases the knowledge-base of innovative actors and therefore has a positive influence on innovation output (Cassiman and Veugelers, 2006). Several channels of technological spillovers have been identified in the economics of innovation, with personal contact through cooperation or job mobility being one of the most important (Singh, 2005; Breschi and Lissoni, 2009; Edler et al., 2011). These modes of interaction constitute a network of actors, being either organizations or individuals. Networks of knowledge exchange are widely viewed as a central driver for inventive activity and it is most likely that they are affected by different policies as well (Cantner and Graf, 2011; Phelps et al., 2012; Broekel et al., 2015). What we do not know is how the mix of policies influences the structure of these networks.

The aim of this research is to understand how the different instruments of the policy mix as well as the consistency of this mix influence the process of invention and innovation in WP and PV. We focus on Germany because of the strong political support for renewable energies and the high share of German inventors in these specific industries. In addition, Germany represented a good fraction of the world market for RPGTs in our observation period (1978–2012). This is especially true for PV, where Germany represented between 30 and 60 per cent of the world market from 2001 to 2010 (IEA, 2010). Our approach adds three important aspects to the existing literature. First, in addition to the level of inventive activity, we put the focus on the structure of relations within the network of collaboration. Second, regarding policy instruments, we distinguish between R&D subsidies that are granted to single organizations and research grants aimed at fostering collaboration and which can, therefore, be regarded as systemic (Smits and Kuhlmann, 2004). Third, we test for the consistency of a set of instruments within a policy mix. Here, the effects of single policy instruments as well as of changes in the policy mix on networks of cooperation are studied by mapping co-inventor networks in the PV and WP industries in Germany.

We use patent applications in WP and PV by German inventors to reconstruct co-inventor networks and estimate the effects of several policies as well as their mix on the size and structure of these networks. By and large, the size of the networks is increased by technology push as well as systemic instruments, whereas demand pull policies seem especially effective in PV. The structure of the co-inventor networks is driven by systemic instruments, especially in WP. For both technologies, surprisingly, demand pull policies are very important in facilitating collaboration. The mix of these instruments shows strong consistency in most cases.

The remainder of this chapter is organized as follows: in the following section, we give a short review of the literature on innovation networks and innovation policy and derive respective hypotheses. In section 4.3, a short overview of relevant policy instruments in Germany is

[1] The terms instrument mix and policy mix are not clearly defined and sometimes are used interchangeably. Here we rely on the distinction by Rogge and Reichardt (2016), where the instrument mix is an essential part of a broader policy mix.

provided. Section 4.4 describes the data and our empirical approach. Section 4.5 presents our results and discusses their robustness. In the last section, we discuss our findings and conclude.

4.2 Policy influence on innovation, collaboration and networks

4.2.1 The innovation–network nexus

Inventive activity, and innovative activity in general, is an interactive process of knowledge creation and accumulation (Kline and Rosenberg, 1986) in which novelty is created by combining knowledge from a diverse set of actors (Kogut and Zander, 1992). This knowledge re-combination is especially successful in teams that are able to combine diverse sets of knowledge (Wuchty et al., 2007; Bercovitz and Feldman, 2011). Corresponding networks of knowledge transfer and learning constitute one important driver of innovation (Dosi, 1988; Powell et al., 1996; Ahuja, 2000). These networks can be studied by the use of social network analysis, which maps actors and their relations in the context of innovation and knowledge transfer.[2] Knowledge transfer can be traced through different types of networks, such as co-authorship networks (e.g. Barabasi et al., 2002; Newman, 2004; Moody, 2004; Acedo et al., 2006), co-invention (e.g. Balconi et al., 2004; Fleming and Frenken, 2007; Casper, 2013), university-industry research collaborations (e.g. Balconi et al., 2004; Ponds et al., 2010; Guan and Zhao, 2013) and industry collaborations (e.g. Ahuja, 2000; Hagedoorn, 2002; Schilling and Phelps, 2007).

The motives to engage in collaborations and to exchange knowledge are manifold (Cantner and Graf, 2011) and the objective is to increase the inventive and innovative performance. Indeed, as empirical research finds, collaboration and networking in R&D in general lead to a higher research output than individual R&D activities (e.g. Czarnitzki et al., 2007; Fornahl et al., 2011). While there are relatively few studies on the relation between network structure and its performance, theoretical as well as empirical results suggest a positive influence of increased interaction (Powell and Grodal, 2005; Fritsch and Graf, 2011; Phelps et al., 2012). The speed of information diffusion increases with the connectivity of the network and the probability of knowledge transfer between individuals decreases the longer the paths connecting them (Singh, 2005). Average innovative performance is higher in well-connected networks (Fleming et al., 2007). Analyzing these networks helps us to understand how knowledge is generated and distributed and the way in which it affects the actors in the networks.

4.2.2 Policy instruments fostering innovation and collaborations

4.2.2.1 Rationale for policy intervention

Due to the costly and uncertain nature of inventive and innovative activity, policy intervenes to enhance and increase research and development activities. Furthermore, there are several market failures that hamper inventive and innovative activity, such as knowledge externalities or technological lock-ins and path dependencies (Arthur, 1989; Griliches, 1992; Cecere et al., 2014).

Concerning cooperation in R&D, the implied knowledge transfer between the actors and the underlying network structures tends to be affected by system failures of complementarity (Do the diverse piece of knowledge and hence the actors behind fit together?), reciprocity (Is the network based exchange of knowledge governed by trust and reciprocity?) and intermediation

[2] See Borgatti and Foster (2003) for a general overview of social network analysis and Cantner and Graf (2011) for an overview and application in the context of innovation networks.

(Are the eventual network partners aware of all potential cooperation partners?). Answering a "no" to any one of these questions leads to a rationale for policy intervention in order (i) to reduce the monetary risk of non-complementarity and/or non-reciprocity and (ii) to bear the costs of searching for appropriate partners (Carlsson and Jacobsson, 1997; Klein-Woolthuis et al., 2005; Cantner et al., 2011). In this context, various types of policies may have different influences on network formation, thereby affecting the rate of knowledge transfer and consequently influencing the speed at which technologies are developed. For example, R&D subsidies are frequently and increasingly awarded only if actors collaborate on these projects to overcome such failures and incentivize joint research efforts (Broekel and Graf, 2012).

Furthermore, environmentally friendly innovations generate positive externalities for society by reducing emissions and resource extraction that cannot be fully internalized. Therefore, these eco-innovations are subject to a double or multiple externality problem (Rennings, 2000; Jaffe et al., 2005; Cecere et al., 2014).

To deal with these externalities, and to directly or indirectly foster inventive activity various instruments originating from different policy fields can be implemented. The main fields are *innovation policy*, where policy needs to address the underinvestment in R&D due to spillovers and non-excludability of new knowledge, path dependency, lock-ins and network effects; *environmental policy*, which deals with the negative external effects concerning emissions from conventional technologies; and *climate policy* which focuses especially on the adverse effects of greenhouse gas emissions.[3] A broad set of instruments from these fields supports and induces environmental innovations to overcome these externalities and increases innovation and the diffusion of clean technologies (Jaffe et al., 2002; Kemp and Pontoglio, 2011; Costantini and Crespi, 2013; Groba and Breitschopf, 2013). These sets of instruments can be conventionally classified in technology push and demand pull instruments. Furthermore, there is an increasing attention towards instruments affecting the above mentioned failures related to the systemic nature of the innovation process (Smits and Kuhlmann, 2004; Wieczorek and Hekkert, 2012), so called systemic instruments.

On this basis, we are interested in how the mix of these instruments influences inventive activities in environmentally friendly technologies. Taking into account the importance of cooperation in those activities, we focus on networks of inventive activity and formulate hypotheses regarding their size and structure. The former reflects the attractiveness of the system in terms of the number of inventive actors, while the structure is of particular importance for the potential knowledge transfer within networks (Cowan and Jonard, 2004; Schilling and Phelps, 2007).

4.2.2.2 Technology push instruments

There are several measures directly targeted at overcoming the above mentioned externalities and enhancing inventive activity. The most prominent instruments directly influencing inventors' activity are R&D subsidies or other means, such as tax incentives, to reduce the private costs of R&D activities. In his seminal report, Bush (1945) addressed the necessity to fund directly R&D activities to increase the knowledge stock and to increase research cooperation between actors. Since then, there has been a long debate about the effectiveness of direct R&D support and its benefits for inventive activity (cf. David et al., 2000; García-Quevedo, 2004). Growing empirical evidence indicates that direct R&D funding increases inventive output (e.g Czarnitzki and Hussinger, 2004; Alecke et al., 2012), despite frequent concerns regarding crowding-out of private R&D investments (see Zúñiga-Vicente et al., 2014, for a review).

[3] Of course, other policy fields also influence inventive activity, such as energy policy in general, industrial policy or trade policy.

Several empirical studies have analyzed the effect of direct R&D subsidies in environmentally friendly technologies, especially renewable energies. Most of them use patent data as an output of the R&D process and estimate how R&D subsidies influence patenting activity. Johnstone et al. (2010) estimate for a panel of 25 countries that public R&D expenditure fosters inventive activity, especially in WP and PV. Wangler (2013) as well as Böhringer et al. (2014) focus their analyses on inventive activity in Germany and find that public R&D expenditure has a positive effect on inventive activity. Costantini et al. (2015b) find no positive effect for mature biofuel technologies, but a positive effect for less mature technologies that are still in the early stage of development. Costantini et al. (2017) show for a panel of 23 OECD countries that technology push policies increase inventive performance in energy efficiency technologies. However, Nesta et al. (2014) find no significant effect of public R&D expenditure on green patents.

With our focus on collaboration and networking in R&D, we extend these analyses by looking at the effects of technology push instruments on inventor networks. First, since patents are the basis for the size of the co-inventor network, we expect that technology push instruments foster inventive activity and thereby increase the size of the network.

Hypothesis 1. *Technology push instruments increase the size of the co-inventor network*

Second, concerning the structure of inventor networks, we do not expect an effect of individual funding. Technology push instruments are not designed to influence connectivity within the network, since by its very nature individual R&D funding does not aim at encouraging cooperation. In addition, inventors working for private companies may be concerned about secrecy and may prefer not to cooperate to inhibit an outflow of knowledge. This leads us to the following hypothesis:

Hypothesis 2. *Technology push instruments have no effect on cooperation within the co-inventor network*

4.2.2.3 Systemic instruments

Systemic instruments are designed to provide support at the systemic level of inventive activity and reduce system failures (Chaminade and Edquist, 2006; Wieczorek and Hekkert, 2012). This includes the provision of infrastructure, especially to facilitate learning and knowledge exchange, to enhance cooperation, for example by cluster initiatives, or to foster cooperation between inventive actors (Smits and Kuhlmann, 2004). The aim of such policies is to connect different actors, such as firms, universities and research institutes, to create a network of knowledge transfer, encourage learning processes and open up possibilities of resource and capability sharing. The most common systemic instrument is subsidizing research collaboration with the requirement to involve different actors in a R&D project. Such cooperative grants lead to higher inventive output compared to individual grants (e.g Czarnitzki et al., 2007; Fornahl et al., 2011).

Concerning the effect of systemic instruments on inventive activity, Branstetter and Sakakibara (1998, 2002); Czarnitzki and Fier (2003) and Czarnitzki et al. (2007) find that firms that participate in publicly funded R&D consortia have a higher inventive output than non-funded or non-participating firms. Fornahl et al. (2011) find that R&D funding for German biotech firms has only a minor effect on inventive output, while collaborative R&D funding increase inventive output to some extent. Falck et al. (2010) show that a cluster initiative in Bavaria, Germany, increased the amount of innovation and eased the access to foreign knowledge for participating firms. Indirect support of networking within a Japanese cluster policy has been shown to be effective in increasing innovative output (Nishimura and Okamuro, 2011).

In view of this evidence and parallel to the analysis of technology push instruments, we are interested in the effects of systemic instruments on co-inventor networks. Since many types of systemic instruments provide financial support for joint R&D activity, they should increase inventive activity similar to technology push instruments. Furthermore, by providing incentives to form cooperation with (often) previously unknown partners, they could increase the size of the network by attracting new actors to these technologies. Hence, we suggest the following hypothesis:

Hypothesis 3. *Systemic instruments increase the size of the co-inventor network*

The instruments at the systemic level are especially designed to increase the connectivity inside the network. They attract new actors to the network and integrate them by providing incentives to establish linkages. Even though evidence on the link between systemic instruments and network formation is scarce, some studies find positive effects of collaborative R&D funding or cluster policies on collaboration (Giuliani and Pietrobelli, 2011; Nishimura and Okamuro, 2011; Cantner et al., 2014). In view of this evidence, we propose the following hypothesis:

Hypothesis 4. *Systemic instruments increase cooperation inside the co-inventor network*

4.2.2.4 Demand pull instruments

The notion of a demand effect on inventive and innovative activity was introduced by Schmookler (1962, 1966), who postulates that markets with high expected profitability provide incentives to engage in inventive activity. This relationship has been widely discussed in the literature (e.g. Mowery and Rosenberg, 1979; Kleinknecht and Verspagen, 1990) with recent empirical evidence indicating that market demand induces inventive output in general (Peters et al., 2012) and especially fosters process innovations (Fontana and Guerzoni, 2008).

Environmentally friendly technologies compete with incumbent technologies that have cost-advantages due to negative externalities and path-dependencies and are therefore left with sub-optimal market shares from a societal perspective. To establish demand for these technologies, a protected niche marked is required that allows the technologies to emerge and improve (Kemp et al., 1998; Nill and Kemp, 2009). Demand pull instruments can create such niche markets and provide incentives for firms to enter the market or to innovate and expand production capacity. With revenues generated on this market, firms can grow to appropriate economies of scale and learning effects that allow the development of more efficient production processes or investment in new machinery (Arrow, 1962a; Peters et al., 2012; Lindman and Söderholm, 2012); thereby they reduce production costs and generate revenues, which can be re-invested in R&D (Nemet, 2009; Hoppmann et al., 2013). Different demand inducing policies can be thought of, such as public procurement, demand subsidies, deployment policies, and fiscal incentives, or soft instruments such as standards and labels or initiatives to reduce information asymmetries (Edler, 2010).

The effect of niche markets for environmentally friendly technologies has been observed in case studies and broader empirical settings. For energy efficiency technologies, Costantini et al. (2017) find that a general energy tax, which induces demand for energy efficiency applications, increase inventive output. In a case study on PV module producers, Hoppmann et al. (2013) show that an increase in market size also increases the innovative investments, with gained revenues being partly reinvested. Nemet (2009) finds the opposite effects for WP in California, where demand policies did not trigger non-incremental inventions. In an econometric framework, Johnstone et al. (2010) show that feed-in tariffs have only a significant effect for solar technologies and a negative effect for WP on inventive output, while certificates and obligations increase inventions in general. Costantini et al. (2015b) show that demand induces innovation and, especially for less-mature technologies, price-based demand instruments enhance invention more than quantity-based ones. Peters et al. (2012) consider domestic and foreign demand policies for PV and find that both have an effect on inventive output. Wangler (2013) finds that an increase in market size has a positive effect on inventive activity in Germany.

As stated above, the evidence for the effect of demand pull instruments on invention is inconclusive and apparently technology dependent. We assume that demand pull instruments may have an indirect effect on the size of co-inventor networks. First and foremost, they establish markets and/or increase market size. Furthermore, with a larger market, more actors will see an opportunity to serve that market. Hence, with inventive activity being a prerequisite for survival in the market, due to the increased competition, indirectly more inventions are induced. Hence, for the size of inventor networks we suggest:

Hypothesis 5. *Demand pull instruments increase the size of the co-inventor network*

Demand pull instruments increase the number of actors, but we have no good reason to expect that they change cooperative behavior within the network. While an increasing number of actors positively affects the number of potential partners, it might at the same time increase the fear of unintended knowledge spillovers if competition becomes fiercer. Therefore we hypothesize for the structure of inventor networks:

Hypothesis 6. *Demand pull instruments have no effect on cooperation in the co-inventor network*

4.2.3 Consistency of the instrument mix

All the above mentioned instruments seem relevant for increased inventive activity and are frequently implemented simultaneously, thereby constituting an instrument mix for innovation. In the literature, it is acknowledged for quite some time that such a mix of instruments is necessary to increase inventive activity, especially for eco-innovations (Mowery and Rosenberg, 1979; Kemp et al., 1992).

Recently, the interaction, interdependency and possible coordination failures within the instrument mix for innovation have caught the attention of researchers. Several theoretical contributions argue that the optimal reduction of emissions is achieved by emission control policies combined with the direct support of inventive activity (see Lehmann, 2012, for a survey). Concerning the interaction of implemented instruments to support inventive activity, the evidence is scarce.[4] Buen (2006) shows for WP in Denmark and Norway that supply and demand subsidies should be implemented at the same time and be predictable over time to create an environment in which actors can successfully engage in inventive activity. Bérubé and Mohnen (2009) show for a sample of Canadian firms that the presence of tax credits as well as R&D subsidies increase inventive output more than tax credits alone. Guerzoni and Raiteri (2015) find for a sample of European firms that, if supply and demand side policies positively interact, innovation expenditures are highest.

Various conceptualizations of a broader policy mix have been proposed. Within the innovation system approach, Borrás and Edquist (2013) suggest how an instrument mix with systemic characteristics should be designed. Flanagan et al. (2011) emphasize several dimensions (policy space, governance space, geographical space and time) of innovation policy mix interactions on various levels. A recent conceptualization of the policy mix is proposed by Rogge and Reichardt (2016), who argue that the instrument mix is part of a wider policy mix for innovation.

[4] There is distinct stream of literature focusing on instrument mixes in environmental policy in general (e.g. OECD, 2007) and the interaction of the EU ETS and the diffusion policies for renewable energies and their emission reduction in particular (e.g. Sorrell et al., 2003; del Río González, 2007; del Río, 2010; Lehmann, 2012).

This policy mix consists of different elements that capture the policy strategy to define certain objectives, the instruments used to achieve the strategies' objectives, and the mix of these instruments. These elements furthermore have certain characteristics. A particularly important one is the consistency of the elements in the policy mix that includes, among others, the consistency between the instruments and their interaction.

According to Rogge and Reichardt (2016), the consistency of the instrument mix can be assessed by interaction analysis and can have three degrees of interaction: strong, if the instruments reinforce each other, weak, if the interaction is neutral, and inconsistent if the interaction effect is negative. They argue that due to the conflicting objectives, perfect consistency may not be possible (Flanagan et al., 2011), and may sometimes not even be desirable (Quitzow, 2015). Costantini et al. (2017) show how an inconsistent mix of instruments, characterized by an excess of implemented instruments, can deter inventive performance in energy efficiency technologies. They find that if too many policies are implemented, complexity increases and inconsistencies emerge that reduce inventive performance. Guerzoni and Raiteri (2015) find strong consistency for the interaction between public procurement and direct subsidies. Inventive expenditures of firms are found to be higher if the instruments interact compared with the sum of the individual effects of both instruments.

Based on the previous empirical findings, we argue that market demand must be present to encourage inventors to engage in R&D activity. Here, we expect that demand pull interacts with technology push instruments and enhances the size of the network. Both policies create incentives: demand pull instruments promise customers for products based on each technology and technology push instruments lower barriers to the pursuit of R&D activities. Expecting strong consistency, we can formulate the following hypothesis:

Hypothesis 7. *The size of the co-inventor network is positively affected by the interaction of demand pull and technology push instruments*

A similar line of reasoning can be put forward regarding the structure of the network. Market demand is required for actors to engage in R&D activity. Systemic instruments provide incentives to collaborate on R&D, especially between previously unknown partners. We expect that the interaction between the two instruments increases the connectivity inside the network and therefore shows strong consistency.

Hypothesis 8. *Collaboration within the co-inventor network is positively affected by the interaction of demand pull and systemic instruments*

4.3 Policies for renewable energy in Germany

The development of RPGT and especially WP and PV received broader attention in the 1970s in reaction to the oil crises and due to the growing awareness of resource depletion and environmental concerns in society. Governmental support of R&D in these technologies started in Germany in 1974 (Lauber and Mez, 2004). This development has been accompanied and pushed by various policy initiatives. They are designed to aim at technological improvement and cost competitiveness directly via subsidizing R&D activities leading to cost reduction, or indirectly via feed-in-tariffs, i.e. guaranteeing a cost covering price that induces demand and allows reaping scale and learning economies by increased production. The rationale for such policies is seen in the initially low competitiveness of the new compared to incumbent technologies as well as in the external effects associated with these infant technologies (Painuly, 2001).

While both technologies were at an infant stage when policy support in Germany started, there are noteworthy differences between them. Windmills as a source of mechanical energy have long been known and even though modern WP installations differ greatly from traditional windmills, the concept of using wind as a source of energy was familiar (see Shepherd, 1994, for a historical review). Furthermore, many auxiliary technologies that were used to develop wind turbines could be adapted from other fields (e.g. wind tunnels in aviation), which may ease technological progress. The first photovoltaic cell was only introduced in 1954 and provided a new way of utilizing solar energy. While there was not much previous knowledge to build on, photovoltaic applications benefitted from simultaneous developments within the emerging semiconductor industry (Sze, 1981). This leads to differences in efficiencies and production costs, which partly explains political support patterns described below.

4.3.1 Technology push instruments

For RPGTs in Germany, the main technology push instrument is R&D funding by the German federal government. Federal R&D spending is documented in the German Förderkatalog (2014), a database containing all federal granted research projects from 1968 until today (see Broekel and Graf, 2012, for a detailed description of the database). We identify research projects relevant for the technologies under concern by conducting a keyword search.[5] Overall, funding can be divided into funding for individual research projects at an institute or a company and collaborative research projects. We separate these two kinds of funding since they have different effects and select for the technology push instrument only projects attributed to one recipient. We collect the data from 1978 until 2011, which covers 259 research projects with a total amount of €283.4 million in WP and 590 projects with a total of €934.9 million in PV (in 1995 Euros).[6]

Overall funding as well as its breakdown into individual and cooperative funding is depicted in Fig. 4.1. Regarding the respective overall funds, we observe similar patterns for both technologies with an early first maximum around 1980 (WP) and 1990 (PV), followed by a decline that lasts for several years and a sharp increase during the 2000s.

Individual funding in both technologies follows the same pattern most of the years but the upsurge during the last years is not as pronounced as in overall funding due to a policy shift towards cooperative funding. However, between the two technologies, there are also some notable differences with respect to the timing and the amount of funding. Spending for PV reaches its maximum ten years later than WP which reflect differences in the maturity of these technologies. The Government also seems to perceive a greater need for funding or puts higher expectations in PV, since the maximum level of spending on PV is about five times higher than on WP. In general, spending for PV is more volatile than for WP.

4.3.2 Systemic instruments

Systemic instruments support the research infrastructure by facilitating learning and knowledge exchange, enhancing cooperation, or fostering cooperation between inventive actors (Smits and Kuhlmann, 2004). In Germany, institutional funding for research institutes such as the Fraunhofer Institute for Solar Energy Systems ISE or the establishment of dedicated chairs at universities are examples of this type of instrument. Furthermore, cooperative research projects ("Verbundforschung") are widely used to connect public actors with partners from industry and

[5] The keywords used are: "wind", "pv", "photovoltai*", "solar". We remove projects not directly relevant for inventive activity, such as energy related educational programs, as well as projects that focus on upstream technologies, but not on WP and PV directly, manually from the dataset. Furthermore, funding for demand pull instruments, especially the 100/250 MW wind program, are removed as well.

[6] The project grants are equally distributed over the project duration to account for the length of the project. This means, if €1 million is granted to a research project running for five years, we allocate €0.2 million per year.

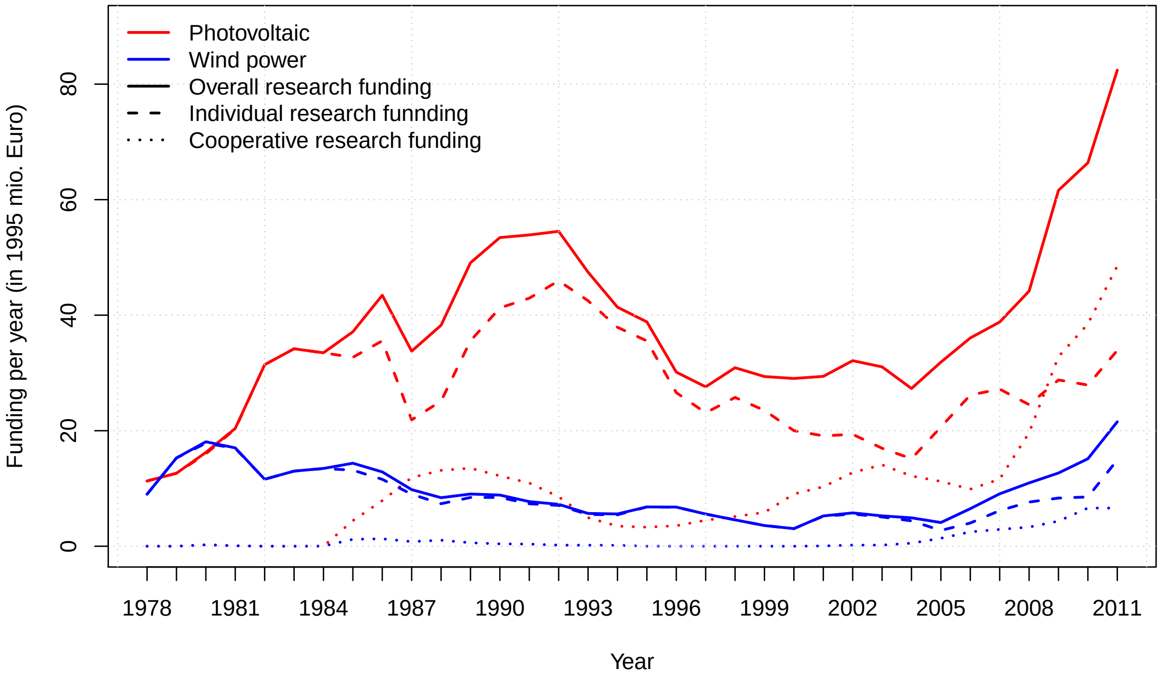


Figure 4.1: Federal funding of research projects in wind power and photovoltaics. **Source:** Own calculation based on Förderkatalog (2014).

also among each other. Cluster policies such as the funding of the SolarValley fall into this category as well.

We select grants for cooperative research also from the Förderkatalog (2014).[7] There are 216 cooperative research projects for PV and 55 for WP in the timespan from 1978 until 2011. The amount of funding for the projects was €35.1 million for WP and €344.2 million for PV, respectively (see Fig. 4.1). Cooperative research grants were introduced in WP and PV at the beginning of the 1980s, and especially in PV it had a substantial and increasing share in the following years with a short period of decline during the early 1990s. By 2011, more than half of overall funding in PV was granted to cooperative projects. In WP, the systemic instrument was not frequently applied until 2000. Afterwards, cooperative funding increased and by 2011 it accounted for one third of total funding in WP.

4.3.3 Demand pull instruments

In the beginning of the development of RPGT in the 1970s, demand pull instruments did not play a major role. Only some local demonstration programs were in place, trying to overcome the cost disadvantages especially faced by PV (Jacobsson and Lauber, 2006). These agreements, most of the time between municipal services and the installation owner, granted a payment per electricity unit in relation to production costs. With the Electricity Feed-in Law ("Stromeinspeisungsgesetz"), the first German FIT, a profound demand side policy was introduced in 1991. This national law granted renewable energy producers a fixed feed-in tariff of 90% of the regular customer's electricity price (computed on the price two years before the granting year) for WP and PV. This fixed price permitted RE producers to sell their electricity to the grid operators, which were obliged to purchase. This removed market and price uncertainty for RPGT. The incentives were sufficient for WP to diffuse, but did not create high demand for PV, due to the low

[7] We identify collaborative grants by the term "Verbundforschung" in the project title, which is specifically used to describe these cooperative grants. This also includes funding for clusters.

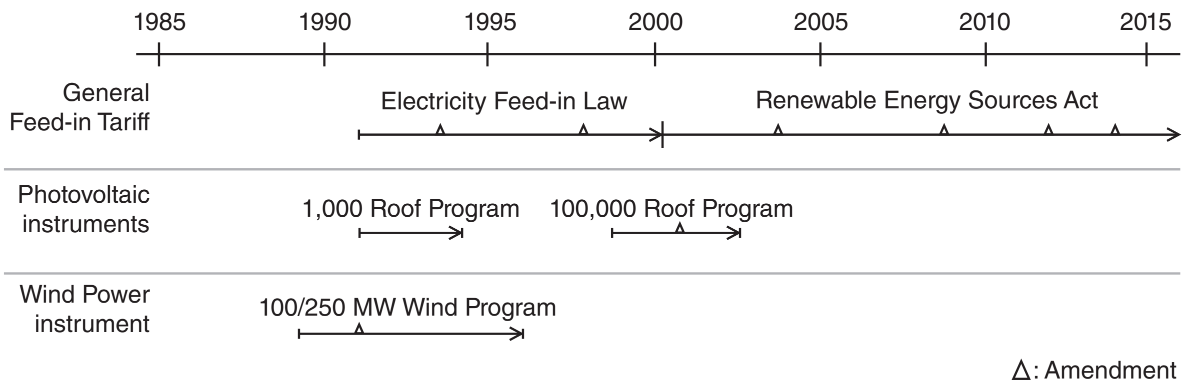


Figure 4.2: Main demand pull instruments for wind power and photovoltaics in Germany. **Source:** Own elaboration based on Bruns et al. (2009).

FIT compared to the high system costs of PV (Jacobsson and Lauber, 2006). This overarching policy was continued by the Renewable Energy Sources Act ("Erneuerbare Energien Gesetz", EEG) in 2000, which extended the FIT and distinguished further between different kinds of technologies and increased the support for PV and other technologies (see Hoppmann et al., 2014, for the development of the EEG, especially for PV). The EEG was amended several times to differentiate further between technologies and to adjust for unexpected cost reductions.

Besides these main instruments, which created a stable environment for investments in RPGT, other demand inducing policies were in place. For WP, the 100/250 MW wind program supported the diffusion of WP as well. The program started in 1989 and granted the owner of a wind turbine either an investment support or an additional payment for each unit of electricity feed into the grid. This could be combined with the Electricity Feed-in Law and created strong incentives to invest in WP. In 1996, the program ended, covering about 1,500 installations with 350 MW installed capacity (see Durstewitz et al., 2000, for an evaluation).

Similar demand supporting programs were in place for PV. In 1991, the 1,000 roof program was enacted, which provided PV installations support of 70% of installation costs. Until 1994, 2,250 installations were installed and created the biggest market for PV installations in Europe (Kiefer and Hoffmann, 1994). In 1999, a second program to support the diffusion of PV was introduced, the 100,000 roof program. The program also granted investment subsidies, but only up to 30% of the investment costs, and provided interest reduced loans for PV installations. The program was a big success and was amended to keep up with the demand for support (Bruns et al., 2009). Eventually, the program ended in 2003 and was integrated in the amended version of the EEG in 2004. An overview of the most important demand pull instruments and their amendments is provided in Fig. 4.2.

4.4 Data and empirical strategy

To test our hypotheses, we run a set of OLS time series regressions, which estimate the effect of different of policy instruments and their mix on the development of the size and the structure of co-inventor networks. In the following, we explain how the networks for WP and PV are derived from patent data, continue with the policy instruments and control variables (see Table 4.1), and describe our empirical strategy.

4.4.1 Dependent variables: co-inventor networks

4.4.1.1 Reconstructing co-inventor networks from patent data

We use patent data to identify cooperation at the inventor level. The dataset for the analysis is retrieved from the Worldwide Patent Statistical Database (PATSTAT) (EPO, 2014). Subsets for WP and PV are extracted by a combination of technology specific IPC (International Patent Classification) classes and keywords (the same data and search strategy is used as described in Chapter 3 and the corresponding Appendix 3.6.1). We consider all priority applications in the timespan from 1980 to 2011. The dataset consists of 3,985 patents for WP and 3,763 patents for PV invented by German inventors. A patent is selected if at least one of its inventors resides in Germany. After extensive manual cleaning of the dataset, controlling for patent applicant, address and year of application, the final dataset consists of 3,603 unique WP and 4,761 PV inventors. The development of the patents and inventors over time can be seen in Fig. 4.3.

We use a social network approach to reconstruct and analyze the structure and evolution of the undirected inventor networks in the two technologies. For the reconstruction of inventor networks, we link inventors via joint patents. If two or more inventors are named on the same patent (co-invention), we assume that they have collaborated and exchanged knowledge during the process of invention (Breschi and Lissoni, 2004). The technology specific networks are constructed using 3-year moving windows to account for persistence, while also allowing for decay of the linkages (Fleming et al., 2007; Schilling and Phelps, 2007). These moving windows help to map the invention process, because the patent is just the point in time when the result occurs, while the inventive process itself is continuous and interaction between the actors takes place before filing the patent and might persist afterwards.

4.4.1.2 Development of network structures over time

Based on the inventor networks, different properties can be observed concerning their size and structure (Fig. 4.3). Looking at the size of the networks based on the underlying patent data, we can observe a steady increase in patents over time, rather exponentially during the last years. The nodes in the network, which represent the individual inventors, show a similar pattern. The edges in the network, which represent the number of connections between the inventors, increase as well. Average team size, i.e. the number of inventors per patent, shows a significant difference between the technologies. The average team in PV is larger than in WP by about one inventor per patent throughout most of the periods. The gap becomes smaller during the last observations, but still accounts for 0.5. This could partly be caused by the existence of very successful individual inventors in WP, for example, the founder of the German wind turbine company Enercon, Aloys Wobben, who filed about 3.5% of all WP patents in the observed time period on his own.

The change of the network structure over time can be described by statistics that measure characteristics of the network as a whole or describe the individual position of network actors. A broad overview of these measurements and detailed calculations can be found in Wassermann and Faust (1994). Concerning network structure, the mean degree, which is the average number of edges per node, shows an upward development, indicating an increase in cooperative behavior over time. However, in both networks, density, i.e. the share of active links in all possible links, decreases over time. Since density is a function of network size, this fact is not surprising, because the size of the network, in terms of nodes, is increasing over time as well. In the first years of observation, density is much higher in the PV-network than in the WP-network, but, by the end of our observation period, both are equal. Degree centralization, which accounts for the concentration of edges across the nodes, is in both technologies quite volatile but has no trend, indicating that no actor is important or dominates the network. The largest component in the network, which represents the largest group of connected inventors, has a surprisingly low share and is quite volatile in both technologies. However, in both networks, the share of the largest component increases over time, indicating an increased potential for knowledge diffusion in the network.

Figure 4.3: Structural properties of co-inventor networks in wind power and photovoltaics.

4.4.1.3 Operationalization

For the econometric analysis we use two network measures as dependent variables. The size of the network is given by the number of nodes, i.e. the number of distinct inventors, which indicates the intensity and variety of inventive activity in the respective fields. Since the time series for WP and PV show an exponential trend, we use the first difference of network size, $\Delta Nodes$.

We use *Mean Degree*, calculated as the average number of collaboration partners, as a very simple and easy to interpret measure of network structure. Since it is independent of network size, it is superior to density and many other measures of network structure in the context of our study.

4.4.2 Policy variables

The operationalization of technology push (TP) and systemic instruments (SYS) is straightforward, since they are provided as monetary values (see Sections 4.3.1 and 4.3.2). We aggregate annual funding to three-year moving windows to account for the duration of the inventive process, with some projects taking more time to produce patentable output than others. We take first differences of the three-year moving windows to estimate the effect of changes in the funding policy.

To operationalize demand pull instruments (DP), we use the logarithm of annually installed capacity in Germany in MW per year. Since neither of the technologies analyzed was cost competitive with fossil fuel technologies during the observed time period, we assume that investments in installed capacity are only undertaken because of an effective demand pull instrument (Klaassen et al., 2005; Peters et al., 2012; Wangler, 2013; Dechezleprêtre and Glachant, 2014). Data on installed capacity is taken from Bergek and Jacobsson (2003) for the period before 1990 for WP and for PV from Jacobsson et al. (2004) and for 1990 onwards from BMWi (2015) for both technologies (see Fig. 4.4). This approach, however, does not differentiate between different possible causes for an increase in installed capacity.

4.4.3 Control variables

We control for other factors than policy measures that could influence inventive activity in RPGT. To account for a general increasing trend in patenting, we collect all patents filed at the German patent office and take the first differences ($\Delta Patents$). We also account for the overall, increasing trend in cooperation (Wuchty et al., 2007) by calculating mean *Team Size* for all German patents.[8] Furthermore, we use inflation adjusted changes in the crude oil price index ($\Delta Oilprice$) provided by the Federal Statistical Office of Germany (Destatis, 2014) to account for an induced innovation effect by increasing fuel prices (see Popp, 2002). We also control for the size of (potential) *Export Markets* and thereby also capture effects of foreign policies (Peters et al., 2012; Dechezleprêtre and Glachant, 2014; Costantini et al., 2017). To be precise, we take the logarithm of the global annual installations of WP in MW and the global annual production of PV in MW (Earth Policy Institute, 2014a,b) and subtract the respective new installed capacities in Germany.

[8] We use mean team size instead of mean degree since the latter is impossible to calculate due to the large number of German inventors and the related issues with name disambiguation. We also calculated the mean degree of a co-inventor network based on a random sample of 5% of all German patents. The correlation between the two is 0.99 so that we believe this is a viable proxy.

Table 4.1: Variables and descriptive statistics.

Variable	Description	RPGT	Min.	Median	Mean	Max.	SD	Obs.	Period
Δ *Nodes*	First differences of the number of distinct inventors in the network	WP	-32.00	15.00	46.10	271.00	80.70	29	1981-1983 until 2009-2011
		PV	-45.00	29.00	64.62	364.00	109.75	29	
Mean Degree	Average number of cooperations in the co-inventor network	WP	0.14	0.87	1.11	2.62	0.76	30	1980-1982 until 2009-2011
		PV	1.63	2.30	2.44	3.68	0.54	30	
TP+SYS	First differences of overall R&D funding	WP	-5.97	-0.45	0.23	10.58	4.06	31	1979-1981 until 2009-2011
		PV	-17.30	5.00	5.49	38.25	12.91	31	
TP	First differences of individual R&D funding	WP	-5.81	-0.80	-0.33	7.94	3.35	31	1979-1981 until 2009-2011
		PV	-15.90	1.24	1.63	19.38	10.01	31	
SYS	First differences of collaborative R&D funding	WP	-0.69	0.00	0.56	3.70	1.15	31	1979-1981 until 2009-2011
		PV	-7.47	1.85	3.86	28.86	8.84	31	
DP	Logarithm of annually installed capacity in MW	WP	0.00	6.06	4.58	8.08	3.20	35	1978 until 2012
		PV	0.00	1.10	2.88	8.94	3.27	35	
Export Market	Logarithm of annually installed capacity (WP)/ production (PV) outside Germany in MW	WP	0.00	6.67	6.55	10.66	2.92	35	1978 until 2012
		PV	1.25	4.34	5.03	10.30	2.44	35	
Δ *Oilprice*	First differences in oil price		-42.64	-0.79	1.60	27.84	14.74	31	1981 until 2011
Δ *Patents*	First differences in the overall number of patents in Germany		-52.68	-0.57	12.70	77.73	33.57	29	1981-1983 until 2009-2011
Team Size	Average number of inventors per patent in Germany		1.73	2.05	2.03	2.27	0.20	30	1980-1982 until 2009-2011

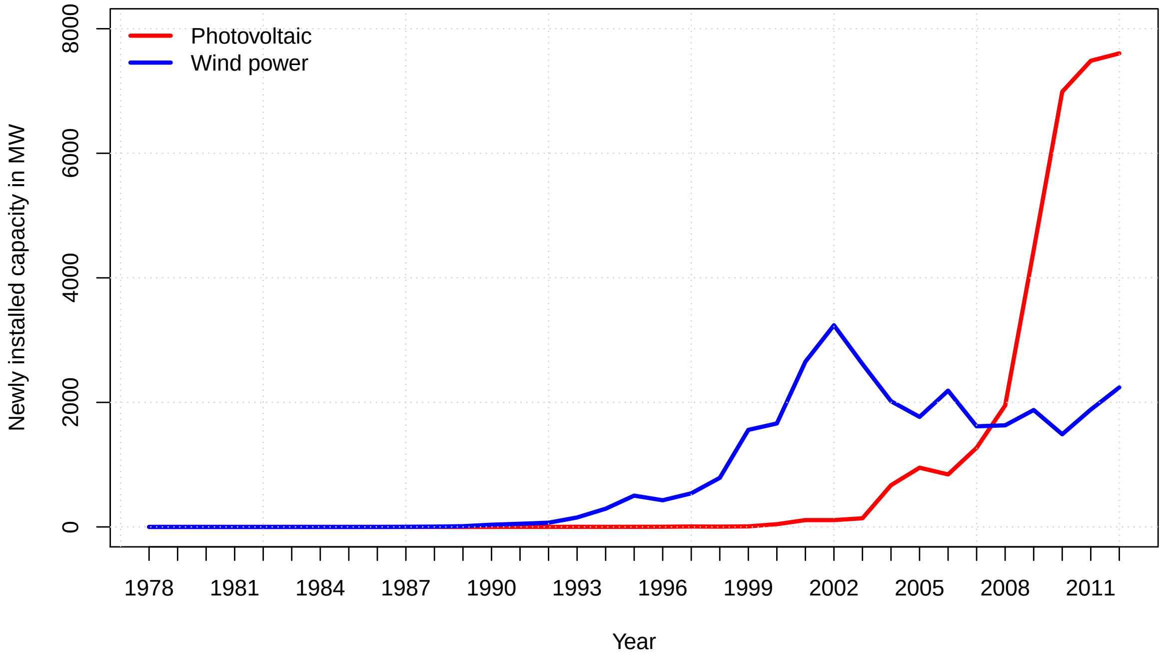


Figure 4.4: Annually installed capacity in wind power and photovoltaics in MW.
Data source: Bergek and Jacobsson (2003), Jacobsson et al. (2004) and BMWi (2015).

4.4.4 Econometric approach

4.4.4.1 Estimation strategy

We use OLS time series regressions to estimate the effect of the different policy instruments and their interaction on the size and structure of the network. We estimate ten different models to test the effect of the policy instruments on the two dependent variables in two technologies. The general functional form is as follows:

$$\left.\begin{array}{l}\Delta Nodes_t \\ MeanDegree_t\end{array}\right\} = \alpha + \boldsymbol{\beta}\ policies_{t-x} + \boldsymbol{\gamma}\ controls + \epsilon \tag{4.1}$$

We add variables to see their effect and apply different lags, denoted by $t-x$ (see Section 4.4.4.2 for a discussion of the lag structure). The first three models test whether funding in general affects inventive activity, *policies* is just the aggregate of *TP* and *SYS*, and *DP* is included with different lags to replicate the setup of previous studies (e.g. Johnstone et al., 2010; Peters et al., 2012; Nesta et al., 2014).

The fourth and all subsequent models use *TP* and *SYS* individually. In models 5 and 7, we again include *DP* with the respective lag structure. In models 6 and 8, we account for the export market instead of domestic demand. Due to problems of multicollinearity, we cannot include *DP* and *Export Market* in the same model.

We explicitly model the instrument mix in the last two models by including an interaction term between single instruments. The interaction term is supposed to grasp the type of consistency of the instrument mix. Model 9 introduces an interaction between *TP* and *DP*, while the last model employs an interaction between *DP* and *SYS*.

The correlation between the variables is not critical (see Appendix 4.7.1) except for *Team Size*, *DP* and *Export Market*, which can therefore not be used in the same models. Also, the variance inflation factors show no critical values, except for the interaction term in model 10.

According to the Breusch-Pagan test (Breusch and Pagan, 1979), we have heteroscedasticity in the error terms in most models. In addition, the Durban-Watson test (Fox, 2008) reveals autocorrelation in the error terms. To account for this, we use heteroscedasticity and autocorrelation consistent covariance matrices (HAC) (Newey and West, 1987; Andrews, 1991) to calculate standard errors.

Due to the time series nature of our variables, we apply a unit root test (Elliott et al., 1996) to test for non-stationarity. We cannot reject non-stationary in the dependent variables and *DP*. For the dependent variables, we provide alternative specifications that are stationary in Section 4.5.3. They show that non-stationarity does not bias our general results. While it would be possible to transform the *DP* variable in a way that is stationary (e.g. the growth rate of newly installed capacity), we would lose a lot of valuable information. Apart from that, we believe that the explosive growth in demand is what is particular about this instrument and is the basis for its effectiveness. Due to its very nature, it is not possible to model the effect of the *DP* variable as a one-time shock to the time series. However, this has to be considered while interpreting the results.

4.4.4.2 Lag structures

Analyzing the influence of a specific policy instrument on inventive activity requires considering time lags between the introduction of the instrument and the realization of an inventive output (see Hall et al., 1986, for a general discussion). Were this not the case, the policy instrument would rather influence the propensity to patent already existing inventions, instead of incentivizing inventive activity (Scherer, 1983).

Various lag structures have been proposed in the context of environmental innovations and RPGTs in particular. Brunnermeier and Cohen (2003) use no lag structure to estimate the effect of R&D expenditures on inventive output in environmental innovation, yet their results are robust to one and two years lags as well. Johnstone et al. (2010) also use no lags in their analysis. Peters et al. (2012) use one, three and five year lags for R&D spending, but abandon lags since their initial model provides the best fit. Wangler (2013) employs no lag for public R&D spending and a positive lag for installed capacity. A positive lag means that actors either anticipate future policies or have expectations regarding the future impact of existing policies and adjust their inventive activities accordingly. Böhringer et al. (2014) use a one year lag for R&D investments and no lag for installed capacity.

We decided to lag *TP* and *SYS* by one year. Most *DP* instruments were intensively discussed in the public before introduction (e.g. Hoppmann et al., 2014), so that the actors could anticipate policies well before their introduction and change their inventive behavior (*anticipation effect*). Therefore, for *DP*, we introduce a foresight of one year, which has also been used by Wangler (2013). In addition, a long term effect of a DP instrument, such as a FIT, would be generation of profits, which can be invested in inventive activity that shows success only some years later (*resource effect*).[9] Therefore, we assume four years to be a reasonable time span for new research projects to result in patentable output. For the interaction terms, we consider only the resource effect and lag *DP* by four years.[10] While thinking about optimal lag structures, one has to

[9] Nemet (2009) as well as Hoppmann et al. (2013) provide detailed evidence for the existence of both types of effects.

[10] We also considered interactions between *TP* and *DP* with the one year negative lag (anticipation), but overall, these models had a poorer fit.

consider that any specification of a lag structure is subject to noise. This is especially so in the case of inventive activities and somewhat accounted for by our reconstruction of networks with three-year moving windows. It is therefore unlikely that we find a single lag structure which clearly outperforms all other options. We provide robustness checks accounting for a series of lag structures in Section 4.5.3.

4.5 Results: policy impact on network size and structure

4.5.1 Size of the network

The size of the network is given by the number of nodes, which represent individual inventors and could be interpreted as the attractiveness of the research field.[11]

In the first three models for WP (Table 4.2), we observe that an increase in overall funding (*TP+SYS*) is associated with an increase in the number of nodes in the network. More effective DP policies, however, do not seem to be important for the stimulation of inventive activities, independent of the lag structure. The differential impact of the instrument mix on innovation in different technologies becomes clear by comparing the results for WP with those for PV (Table 4.3). Network size in PV is largely explained by effective *DP*, whereas we find almost no effect of funding. Comparing the two different lags shows that the *resource effect* provides a better model fit than the *anticipation effect*.

The individual effects of *TP* and *SYS* in model 4 are positive and significant in WP, while in PV only *SYS* increases network size. Also, the overall fit of the model is nearly zero for PV, indicating that R&D subsidies do not contribute significantly to the technological development. This confirms the hypotheses 1 and 3 for WP but not for PV. Including *DP* with different lags in models 5 and 7 shows similar coefficients as in models 2 and 3 but the *anticipation effect* for *DP* turns significant in WP. In PV, *TP* becomes significant, indicating that conventional R&D funding needs to be accompanied by *DP*. Here we can confirm the hypothesis 5 for PV but not for WP.

Comparing the models that differentiate between *TP* and *SYS* with the ones that do not shows that the model fit improves especially in WP but to a lesser extent in PV, which is due to the dominance of *DP* instruments in PV. In models 6 and 8, we account for the fact that firms in both industries are engaged on international markets and include the size of export markets. Again, the *anticipation effect* and the *resource effect* are strong predictors of network size in PV, but only the *anticipation effect* proves significant in WP. It is worth noting that including international demand instead of national demand (*DP*) leads to a better model fit in WP. In PV, comparing the models with *anticipation effect* (5 and 6), explanatory power is higher when we control for the *Export Market*. When it comes to the *resource effect* (models 7 and 8), the domestic market (*DP*) has a higher explanatory power than the *Export Market*.

The interaction of different instruments, especially between *TP* and *DP*, are used to evaluate the complementarity between the instruments, i.e. the consistency of the instrument mix. Acknowledging this interrelation between policies strongly improves the model fit in all cases analyzed. The interaction between *TP* and *DP* is significant for both technologies, which indicates that both policy instruments complement each other in attracting inventive activities, which is in line with hypothesis 7. We also find a significant positive effect of the interaction

[11] The results for changes in the number of patents instead of nodes are very similar. Respective results are available upon request.

between *DP* and *SYS* in model 10 in WP, while in PV, this effect is negative. This negative effect in PV could indicate that the combination of demand pull and systemic instruments mainly strengthens already existing actors and therefore makes entry into the industry more difficult.

4.5.2 Structure of the network

To analyze changes in the structure of the networks, we focus on the mean degree, which accounts for the intensity of collaboration. In this section, we test the effect of different policy instruments on the mean degree.

The first three models show in the case of WP (Table 4.4) and PV (Table 4.5) that both an increase of overall R&D funding (*TP+SYS*) and of *DP* increase the mean degree. From models 1 and 4, we can infer that changes in the network structures are not independent from the overall trend towards increased collaboration but controlling for this trend still leaves room for unexplained variation of the mean degree.

Models 4 to 8 differentiate between *TP* and *SYS*. As in the regressions in the previous section, this increases the explanatory power of our models only for WP but not for PV. The results for WP strongly support our hypotheses 2 and 4, since *SYS* is always positive and significant, while *TP* shows no influence on the mean degree. In PV, these relationships are not robust and strongly depend on the model specification. Overall, demand plays an important role in both technologies for stronger interaction in R&D. These findings are contrary to our expectations in 6, where we assumed that *DP* has no effect on network structure.

The joint effect of *SYS* and *DP* in model 10 is positive and significant for both technologies. This supports hypothesis 8, indicating that these instruments complement each other and form a consistent policy mix fostering collaboration in R&D. Concerning the interaction of *TP* and *DP* in model 9, we find no significant effect in WP but a significant negative one for PV. This result is somehow puzzling, but may indicate that an increase in *TP* provides companies with sufficient resources to perform R&D on their own, thereby reducing the incentive to engage in R&D collaboration.

4.5.3 Robustness checks

There might be concerns about endogeneity, especially reverse causality in the models explaining the size of the networks. It could be possible that policy makers react to an exogenous growth of the number of inventors by investing more into the specific technologies,[12] or that both phenomena are influenced by an unobserved variable that is exogenous to our model. We partly account for this issue by imposing a lag structure on our models, which implies a distinct direction of causality (Nesta et al., 2014). In addition, we check if any of our explanatory variables are correlated with the error term of our regressions, which could indicate endogeneity issues (Hayashi, 2000). This is not the case in any of our models. An instrumental variables approach has been put forward as a method to deal with possible endogeneity (Angrist et al., 1996; Brynjolfsson et al., 2009; Peters et al., 2012; Nesta et al., 2014). Peters et al. (2012) use the funding for one technology as an instrument for the other technology. However, due to the low number of observations, instrumental variable estimations are not reliable in our case (Crespo-Tenorio and Montgomery, 2013).

Concerning the imposed lag structure, we test the sensitivity of our results to different lags by estimating all possible lag combinations on the intervals [0, 3] for *TP* and *SYS* and [-1, 4]

[12] The reverse causality issue for mean degree is not that likely, since the cooperation intensity has only since recently been on the policy maker's agenda.

Table 4.2: OLS-regression results for $\Delta \textit{Nodes}$ wind power as dependent variable.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	54.736***	8.405	19.304	32.572***	-12.751	-94.680	6.017	-13.541	-25.186	14.563
	(13.012)	(28.261)	(18.528)	(11.711)	(26.028)	(58.940)	(20.045)	(35.632)	(18.438)	(13.691)
$(\mathrm{TP+SYS})_{t-1}$	19.437***	15.259**	14.030**							
	(5.105)	(5.883)	(6.106)							
TP_{t-1}				13.084***	9.040*	8.101**	9.387*	10.410**	-3.642	10.208**
				(4.228)	(4.713)	(3.877)	(4.729)	(4.200)	(3.025)	(3.893)
SYS_{t-1}				45.549***	41.183***	29.082**	37.966***	36.583***	38.120***	-17.656
				(9.704)	(11.228)	(13.472)	(13.391)	(12.705)	(11.944)	(12.936)
DP_{t+1}		8.820			8.670*					
		(5.458)			(4.503)					
DP_{t-4}			8.540				7.040		9.836**	2.869
			(5.425)				(4.919)		(3.746)	(3.508)
$\mathrm{DP}_{t-4} \times \mathrm{TP}_{t-1}$									3.168***	
									(0.792)	
$\mathrm{DP}_{t-4} \times \mathrm{SYS}_{t-1}$										9.839***
										(2.337)
$\Delta \mathrm{Oilprice}_{t-1}$	-0.033	-0.400	-0.544	-0.296	-0.654	-0.992	-0.686	-0.430	-0.370	-1.400**
	(0.707)	(0.578)	(0.559)	(0.972)	(0.867)	(0.619)	(0.819)	(0.917)	(0.686)	(0.642)
$\Delta \mathrm{Patents}_{t}$	-0.067	-0.391	-0.300	0.246	-0.076	0.064	0.016	0.133	0.388	0.168
	(0.278)	(0.398)	(0.373)	(0.251)	(0.308)	(0.287)	(0.324)	(0.236)	(0.385)	(0.237)
Export Market_{t+1}						17.740*				
						(8.949)				
Export Market_{t-4}								8.117		
								(5.742)		
Adj. R^2	0.627	0.662	0.674	0.697	0.735	0.771	0.727	0.720	0.809	0.822
Obs.	29	29	29	29	29	29	29	29	29	29
Max. VIF	1.134	1.942	2.095	1.742	1.942	2.696	2.157	2.224	4.313	9.970
F-Value	16.663	14.692	15.453	17.115	16.537	19.837	15.924	15.382	20.737	22.483
AIC	314.087	312.041	310.993	308.829	305.718	301.510	306.571	307.346	296.972	294.970

Robust standard errors (HAC) in parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level.

Table 4.3: OLS-regression results for $\Delta \mathit{Nodes}$ photovoltaics as dependent variable.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	33.258	-63.286**	-49.289**	19.979	-61.190*	-213.692***	-44.431*	-197.662***	-25.034*	-68.097***
	(23.620)	(30.442)	(22.496)	(32.867)	(32.659)	(59.256)	(21.624)	(66.072)	(12.127)	(19.628)
$(TP + SYS)_{t-1}$	4.644	4.627**	3.257***							
	(3.339)	(1.808)	(1.044)							
TP_{t-1}				4.255	4.888**	4.122**	3.480**	5.095*	1.501*	4.794***
				(2.824)	(2.323)	(1.858)	(1.298)	(2.515)	(0.831)	(1.349)
SYS_{t-1}				7.558***	2.664	0.029	0.678	1.786	1.960	7.818**
				(2.095)	(2.559)	(2.811)	(2.459)	(2.662)	(2.188)	(3.350)
DP_{t+1}		25.363***			27.162***					
		(6.950)			(8.993)					
DP_{t-4}			39.487***				42.552***		29.595***	49.017***
			(6.901)				(8.649)		(5.784)	(7.510)
$DP_{t-4} \times TP_{t-1}$									2.344***	
									(0.519)	
$DP_{t-4} \times SYS_{t-1}$										-1.303***
										(0.420)
$\Delta Oilprice_{t-1}$	1.168	-0.867	-1.101*	1.328	-1.119	-1.446**	-1.412*	-0.937	-0.742	-1.229
	(1.214)	(0.552)	(0.545)	(1.170)	(0.714)	(0.649)	(0.777)	(0.875)	(0.961)	(0.745)
$\Delta Patents_t$	0.936	1.589**	1.631***	1.301**	1.389*	1.043*	1.376***	1.070*	1.247***	1.872***
	(0.700)	(0.768)	(0.528)	(0.577)	(0.759)	(0.544)	(0.431)	(0.623)	(0.242)	(0.553)
Export $Market_{t+1}$						46.048***				
						(10.980)				
Export $Market_{t-4}$								54.108***		
								(17.020)		
Adj. R^2	0.046	0.575	0.725	0.045	0.572	0.677	0.737	0.518	0.826	0.796
Obs.	29	29	29	29	29	29	29	29	29	29
Max. VIF	2.064	2.146	2.138	2.444	2.445	2.698	2.579	2.580	2.683	7.131
F-Value	1.451	10.472	19.436	1.327	8.475	12.760	16.701	7.020	23.097	19.261
AIC	359.120	336.488	323.887	359.980	337.480	329.261	323.327	340.902	312.131	316.617

Robust standard errors (HAC) in parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level.

Table 4.4: OLS-regression results for *Mean Degree* wind power as dependent variable.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-4.411***	0.336***	0.405***	-3.754***	0.220	-1.071***	0.350***	0.192	0.335***	0.400***
	(0.725)	(0.026)	(0.025)	(0.768)	(0.197)	(0.186)	(0.091)	(0.263)	(0.091)	(0.080)
$(TP+SYS)_{t-1}$	0.065***	0.096**	0.061**							
	(0.023)	(0.036)	(0.027)							
TP_{t-1}				0.012	0.023	0.014	0.010	0.034	-0.007	0.014
				(0.020)	(0.028)	(0.014)	(0.018)	(0.036)	(0.017)	(0.014)
SYS_{t-1}				0.350***	0.437***	0.193***	0.336***	0.319***	0.317***	0.061
				(0.045)	(0.065)	(0.033)	(0.046)	(0.103)	(0.051)	(0.077)
DP_{t+1}		0.147***			0.131***					
		(0.024)			(0.034)					
DP_{t-4}			0.175***				0.149***		0.151***	0.131***
			(0.014)				(0.021)		(0.020)	(0.021)
$DP_{t-4} \times TP_{t-1}$									0.006	
									(0.005)	
$DP_{t-4} \times SYS_{t-1}$										0.046***
										(0.013)
$\Delta Oilprice_{t-1}$	0.000	0.002	0.000	0.002	0.004	0.000	0.002	0.008	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.002)	(0.004)	(0.007)	(0.003)	(0.003)
Team $Size_t$	2.729***			2.322***						
	(0.389)			(0.375)						
Export $Market_{t+1}$						0.284***				
						(0.026)				
Export $Market_{t-4}$								0.133***		
								(0.048)		
Adj. R^2	0.765	0.609	0.791	0.902	0.825	0.943	0.918	0.745	0.920	0.940
Obs.	30	30	30	30	30	30	30	30	30	30
Max. VIF	1.238	1.115	1.257	1.344	1.253	1.820	1.365	1.642	2.201	9.725
F-Value	32.443	16.071	37.475	67.669	35.172	121.080	82.087	22.175	68.116	91.142
AIC	30.803	46.040	27.339	5.395	22.769	-10.920	0.048	34.065	-0.115	-8.348

Robust standard errors (HAC) in parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level.

Table 4.5: OLS-regression results for *Mean Degree* photovoltaics as dependent variable.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	-1.617	1.941***	2.049***	-1.500	1.938***	1.300***	2.048***	1.378***	2.001***	2.075***
	(1.030)	(0.119)	(0.096)	(0.979)	(0.095)	(0.261)	(0.097)	(0.316)	(0.090)	(0.093)
$(TP+SYS)_{t-1}$	0.023***	0.013*	0.007							
	(0.007)	(0.006)	(0.006)							
TP_{t-1}				0.021**	0.013*	0.012	0.007	0.017*	0.013*	0.006
				(0.009)	(0.007)	(0.008)	(0.007)	(0.009)	(0.007)	(0.007)
SYS_{t-1}				0.026***	0.011	0.007	0.005	0.014**	0.000	-0.009
				(0.006)	(0.008)	(0.007)	(0.008)	(0.007)	(0.006)	(0.012)
DP_{t+1}		0.130***			0.132***					
		(0.023)			(0.020)					
DP_{t-4}			0.183***				0.186***		0.225***	0.171***
			(0.031)				(0.034)		(0.033)	(0.029)
$DP_{t-4} \times TP_{t-1}$									-0.007***	
									(0.002)	
$DP_{t-4} \times SYS_{t-1}$										0.003*
										(0.002)
$\Delta Oilprice_{t-1}$	0.004	0.003	0.003	0.004	0.002	0.003	0.002	0.006	0.001	0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)
Team $Size_t$	1.947***			1.886***						
	(0.490)			(0.463)						
Export $Market_{t+1}$						0.197***				
						(0.040)				
Export $Market_{t-4}$								0.231***		
								(0.063)		
Adj. R^2	0.667	0.786	0.807	0.657	0.779	0.758	0.800	0.663	0.829	0.809
Obs.	30	30	30	30	30	30	30	30	30	30
Max. VIF	1.070	1.078	1.164	1.252	1.343	1.422	1.435	1.334	2.441	4.568
F-Value	20.339	36.604	41.391	14.866	26.552	23.679	29.997	15.253	29.179	25.614
AIC	20.476	7.120	4.105	22.193	8.978	11.728	5.982	21.647	2.001	5.327

Robust standard errors (HAC) in parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level.

for *DP* (see Appendix 4.7.2). In general, the estimated coefficients imply that our results would also hold for most other tested lag structures even though they do not always provide the best model fit.

With respect to the data's time series nature, non-stationarity might be an issue. All variables except *Mean Degree* and *Team Size* enter our regressions as first differences.[13] Our dependent variables are non-stationarity and we create alternative, stationary dependent variables to investigate whether the non-stationarity biases our results: for $\Delta Nodes$, we divide the number of inventors in each technology by the overall number of German inventors and take the first difference. This represents change in the share of inventors in this technology in all German inventors and captures the changing attractiveness of the respective technology relative to all technologies. We divide the *Mean Degree* by the *Team Size* of all German patents to capture the propensity to cooperate in WP and PV relative to all technologies in Germany.

We re-estimate models 5 and 7 with our altered dependent variables. Models 5 and 7 were chosen because these models include all our explanatory variables with no interactions.[14] Table 4.6 shows that the results change very little, only in model 5 for *Relative Mean Degree* in PV is the *TP* variable insignificant and, for both models, the overall model fit is drastically reduced. However, since the new dependent variables do not have exactly the same meaning as the original ones, we consider these small deviations unproblematic. These results indicate that the non-stationarity of our dependent variable does not bias our general findings.

Table 4.6: OLS-regression robustness results with new dependent variables.

	ΔShare of Inventors				Relative Mean Degree			
	Wind power		Photovoltaics		Wind power		Photovoltaics	
	Model 5	Model 7	Model 5	Model 7	Model 5	Model 7	Model 5	Model 7
Intercept	-0.002	0.000	-0.003	-0.002	0.206**	0.239***	-0.054*	-0.038
	(0.002)	(0.002)	(0.002)	(0.001)	(0.079)	(0.044)	(0.032)	(0.026)
TP_{t-1}	0.000*	0.000*	0.000**	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SYS_{t-1}	0.000***	0.000***	0.000	0.000	0.000***	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
DP_{t+1}	0.001***		0.002***		0.039***		0.016**	
	(0.000)		(0.001)		(0.013)		(0.007)	
DP_{t-4}		0.001		0.004***		0.046***		0.020**
		(0.000)		(0.001)		(0.009)		(0.009)
$\Delta Oilprice_{t-1}$	0.000	0.000	0.000	0.000	0.001	0.000	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.001)	(0.001)
Adj. R^2	0.799	0.784	0.550	0.693	0.791	0.869	0.156	0.122
Obs.	29	29	29	29	30	30	30	30
Max. VIF	1.697	1.814	1.427	1.525	1.253	1.365	1.427	1.525
F-Value	28.853	26.454	9.550	16.781	28.490	48.991	2.291	1.974
AIC	-236.157	-234.088	-197.466	-208.540	-32.906	-46.821	-48.472	-47.341

Δ*share of inventors* is the first difference of the ratio between the number of inventors in each technology and the overall number of German inventors. *Relative Mean Degree* is the ratio of *Mean Degree* in the respective technology and *Team Size* in Germany.
Robust standard errors (HAC) in parenthesis. Sig. at *** 0.01, ** 0.05, * 0.1 level.

[13] Recall that *DP* is operationalized as the log of annual installments, which is the first difference of cumulative installments.

[14] We do not include Δ*Patents* and *Team Size* in these regressions. Both are control variables meant to account for the general development in Germany, which are part of the dependent variables.

4.6 Discussion and conclusions

This study attempts to shed light on the influence of the German policy mix with its constituting instruments and their consistency on the size and the structure of co-inventor networks in wind power (WP) and photovoltaics (PV) in Germany. We go beyond previous and related studies by focusing explicitly on co-inventor networks and not merely on the number of patents (e.g Johnstone et al., 2010; Wangler, 2013; Böhringer et al., 2014; Nesta et al., 2014). Such networks of knowledge transfer and learning have been identified as important drivers of innovation (Dosi, 1988; Powell et al., 1996; Ahuja, 2000). Several theoretical as well as empirical studies suggest a positive influence of increased interaction on innovation performance (Powell and Grodal, 2005; Fritsch and Graf, 2011; Phelps et al., 2012). Our main contribution in this respect is to analyze the effects of policy on interaction within co-inventor networks. For this purpose, we refer to the existing literature on technology push and demand pull policies, and extend the analysis by accounting for systemic instruments, specifically designed to foster cooperation and knowledge transfer. In addition, we provide insights regarding the consistency of the policy mix, by looking at the interaction of these policy instruments (Rogge and Reichardt, 2016). While most related studies are based on a panel of several countries, we focus solely on Germany. The reason for this choice of study design lies in the availability of more fine grained funding data that allows for the identification of the systemic instrument.

Despite this different approach, our general results are in line with previous studies on policy effects of push and pull instruments in RPGT. As in Johnstone et al. (2010); Wangler (2013) and Böhringer et al. (2014), we find positive effects of technology push on innovation activities (contrary to the findings by Nesta et al., 2014). Similar to Wangler (2013) and Peters et al. (2012) and partly in line with Johnstone et al. (2010), we show that demand pull policies play an important role in facilitating inventive activity. However, the effect is technology dependent, and seems to be very influential in PV but less pronounced in WP (also in line with Johnstone et al., 2010).

In particular, we find that the network size, i.e. the number of actors active in the technology, is positively affected by technology push and systemic instruments in WP, whereas in PV it is only technology push which shows an effect. Demand pull instruments, such as the EEG, have a strong positive effect in PV in creating resources for inventive activity (*resource effect*), but also by allowing the actors to anticipate policy effects, e.g. in terms of upcoming market opportunities for their products. In the case of WP, this *anticipation effect* seems to be relatively more important. This phenomenon has also been discussed by Nemet (2009) and Hoppmann et al. (2013) and seems to be a relevant force for technological development. Considering the international context, export market dynamics are closely correlated with domestic demand in Germany. Such an apparently aligned behavior might be a response to international CO_2 reduction targets or result from international policy learning. In line with Peters et al. (2012) and Dechezleprêtre and Glachant (2014) these export market dynamics also play a role in WP and PV, where actors anticipate market opportunities abroad and increase their inventive activities. In the case of PV, our results indicate a resource effect via export markets.

Our hypothesis regarding the influence of systemic instruments on the structure of the networks finds support only in the case of WP, whereas in PV, the results are inconclusive. As expected, technology push policies do not increase cooperation in WP at all, while for PV, the effect is ambiguous. Concerning the effect of demand pull instruments on collaboration, we find a strong positive influence in both technologies. This is quite surprising, since demand pull policies are not designed to support collaboration. One possible explanation could be the presence of an increased number of potential cooperation partners with complementary knowledge and capabilities. In a similar vein, the increase in market size might allow for more specialization, thereby increasing the benefits of cooperation when combining different sets of knowledge (Cantner and Meder, 2007).

Concerning the policy mix, we find that push and pull instruments work hand in hand in increasing network size, while pull and systemic instruments together spur cooperation. These results indicate the necessity of market demand to reap the full potential of technology push and systemic instruments. Our findings indicate strong consistency of the analyzed instruments in the policy mix. However, we also find some inconsistencies. Pull and systemic instruments interact in a way that seems detrimental to network size in PV. Apparently, this combination of instruments favors existing actors rather than attracting new ones. In a similar fashion, a combination of push and pull instruments works against collaboration in PV and rather favors individual research activities. Therefore, our results question the relevance of technology push to enhance cooperation. Since this instrument does not aim at fostering cooperation, but rather provides sufficient resources to conduct R&D without cooperation, this seems quite plausible. Apparently, we look at two, at least partly conflicting measures of system performance, since it might be difficult to sustain the level of average cooperation intensity in times of fast network growth. There might well be a tradeoff between policy goals that shows in the above mentioned inconsistencies, which is not necessarily to be judged negative (Quitzow, 2015).

Based on our empirical findings, we can derive several suggestions for policy: First, implementing a mix of policies goes beyond a single instrument in fostering innovation, at least in infant technologies. Second, demand inducing policies should be designed to create resources for inventive actors to enlarge their research activities, but also provide stable perspectives regarding future market opportunities. Third, cooperation activity should be supported by specific instruments and existing instruments should be evaluated concerning their effect on cooperation – some policies affect cooperation, even though it is not their objective. Fourth, all these policies form a mix that ought to be consistent in providing incentives to engage in R&D and especially collaborative activities as well as in supporting market creation. However, our results are technology specific. These differences may be related to the technologies' state of development, their relative competitiveness, market dynamics and differences concerning the nature of these technologies, which need to be considered when implementing a certain policy instrument within a policy mix (Huenteler et al., 2016b).

From a research perspective, we contribute the following insights: First, we bring together the literature on innovation networks and policy support in the context of environmental innovation. This helps to understand better the relationship between policy instruments and their effect on invention networks and the knowledge transfer in these networks. Second, we can show that certain policies do not only increase inventive activity, but also alter the underlying network structure. The effects of policies on network structure are still poorly understood and we provide first insights as to the types of policies that actually have an effect. Third, we demonstrate that public R&D funding can have different effects if it contains systemic components that successfully support network formation. Finally, with respect to the policy mix for innovation, we provide a simple approach to operationalize aspects of its consistency, which gives insights about how different policy instruments interact.

However, this study leaves room for improvement and extension. We consider only the situation in Germany; extending the scope of the analysis for a panel of countries and/or a broader set of technologies may lead to further insights on the effect of the different policy instruments and their interaction. Unfortunately, more fine grained data that would allow us to identify funding as technology push or systemic is, to our knowledge, not readily available for other countries. Concerning the systemic instruments, institutional funding to public research institutes and universities is not included in our analysis, neither are non-monetary policy instruments such as changes in patent law, the education system, grid access or other market design instruments, which need to be taken into account to understand fully the effect of systemic instruments.

Moreover, the role of potential export markets could be explored in more detail by accounting for interdependencies between national RPGT policies. Also, the consistency of the policy mix needs further empirical investigation. Here, more empirical applications in different countries and technologies are required to generalize our findings. From a methodological point of view, using instrumental variables would be desirable, which would be possible with a panel of countries.

4.7 Appendix

4.7.1 Correlation tables

Table 4.7: Correlations wind power.

	ΔNodes	Mean Degree	TP + SYS	TP	SYS	DP	Export Market	ΔOilprice	ΔPatents	Team Size
ΔNodes	—	0.820***	0.818***	0.737***	0.781***	0.537***	0.808***	0.266	-0.285	0.646***
Mean Degree	0.000	—	0.753***	0.639***	0.825***	0.701***	0.939***	0.369**	-0.244	0.841***
TP + SYS	0.000	0.000	—	0.982***	0.455***	-0.003	-0.095	0.345**	-0.360*	0.633***
TP	0.000	0.000	0.000	—	0.276	-0.083	-0.235	0.325*	-0.284	0.611***
SYS	0.000	0.000	0.006	0.108	—	0.370**	0.618***	0.229	-0.448**	0.505***
DP	0.003	0.000	0.987	0.637	0.028	—	0.839***	0.189	0.251	0.960***
Export Market	0.000	0.000	0.586	0.174	0.000	0.000	—	0.097	-0.158	0.909***
ΔOilprice	0.163	0.045	0.046	0.061	0.193	0.285	0.584	—	0.057	0.402**
ΔPatents	0.134	0.202	0.055	0.135	0.015	0.189	0.412	0.769	—	0.025
Team Size	0.000	0.000	0.000	0.000	0.004	0.000	0.000	0.028	0.897	—

Upper triangle: Pearson correlation coefficient, lower triangle: p-values. Sig. at *** 0.01, ** 0.05, * 0.1 level.

Table 4.8: Correlations photovoltaics.

	ΔNodes	Mean Degree	TP + SYS	TP	SYS	DP	Export Market	ΔOilprice	ΔPatents	Team Size
ΔNodes	—	0.633***	0.450**	0.185	0.451**	0.711***	0.740***	0.216	-0.056	0.539***
Mean Degree	0.000	—	0.510***	0.170	0.555***	0.878***	0.847***	0.358*	-0.441**	0.666***
TP + SYS	0.014	0.004	—	0.731***	0.625***	0.349**	0.326*	0.169	-0.706***	0.018
TP	0.335	0.369	0.000	—	-0.075	-0.064	-0.127	0.170	-0.467**	-0.213
SYS	0.014	0.001	0.000	0.669	—	0.584***	0.622***	0.053	-0.520***	0.267
DP	0.000	0.000	0.040	0.715	0.000	—	0.956***	0.287	-0.274	0.900***
Export Market	0.000	0.000	0.056	0.466	0.000	0.000	—	0.247	-0.254	0.876***
ΔOilprice	0.260	0.052	0.340	0.335	0.765	0.100	0.159	—	0.057	0.402**
ΔPatents	0.772	0.017	0.000	0.011	0.004	0.150	0.183	0.769	—	0.025
Team Size	0.003	0.000	0.924	0.258	0.154	0.000	0.000	0.028	0.897	—

Upper triangle: Pearson correlation coefficient, lower triangle: p-values. Sig. at *** 0.01, ** 0.05, * 0.1 level.

4.7.2 Lag structure

Fig. 4.5 shows for all four dependent variables overall model fit (AIC) and the effect of the respective policy instrument depending on different lag structures. For any given lag of the respective policy instrument, we perform regressions with all possible lag variations of the other instruments, thereby modifying the benchmark model 5 (Tables 4.2-4.5). Positive coefficients are displayed with a '+', negative ones with a '-' and those insignificant with a '◯' (the significance threshold is a p-value $\leq 10\%$). For example, in the case of $\Delta Nodes$ in WP, we see that TP is almost always positive for lags of 0 and 1, regardless of the lags of the other variables. However, TP is always insignificant for lags of 2 or 3. Furthermore, the model fit seems to be slightly better for lag of 0 according to the AIC.

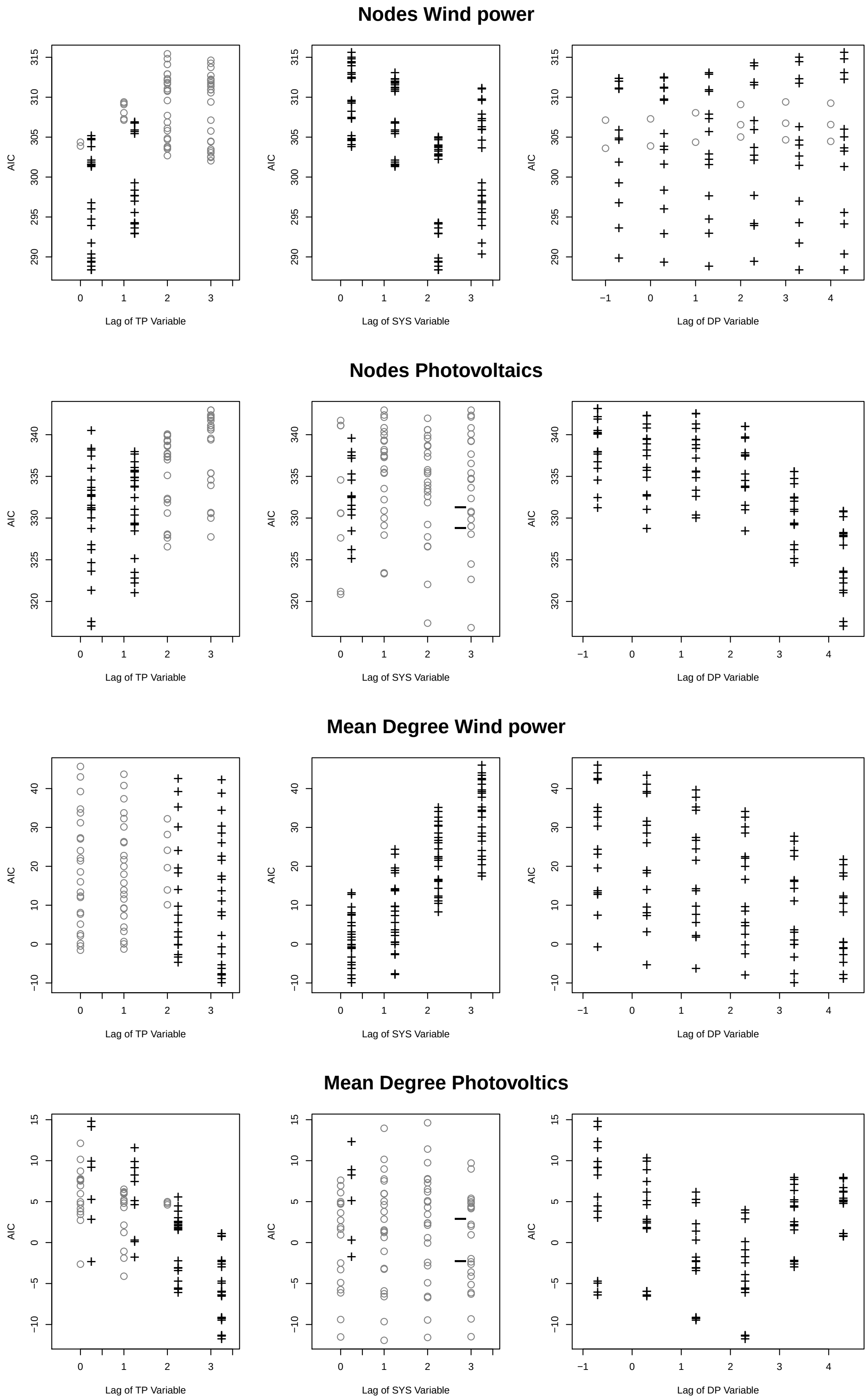


Figure 4.5: Sensitivity analysis of lag structures as variations of regression model 5.

Chapter 5

International research networks: Determinants of country embeddedness

Co-authored with Holger Graf

5.1 Introduction

The generation and diffusion of knowledge is a collective process and an increasingly global phenomenon. Collaboration among scientists and researchers has steadily increased during the last decades and leads to more valuable output than individual research (Wuchty et al., 2007; Adams, 2013). While geographically proximate partners are typically preferred, it is especially collaboration with distant partners, which allows access to diverse sets of knowledge with positive effects on performance (Bathelt et al., 2004; Cantner and Rake, 2014; Herstad et al., 2014). Collaboration with international partners leads to embeddedness in the global knowledge network. Here, embeddedness "refers to the process by which social relations shape economic action" (Uzzi, 1996, p. 674), and "research on embeddedness [...] advances our understanding of how social structure affects economic life" (Uzzi, 1997, p. 48). Being embedded in a network can therefore be understood as the position within a network in terms of connections to other actors (Wanzenböck et al., 2014, 2015). As such, embeddedness in the global knowledge network provides better access to knowledge with positive effects on inventive and innovative performance (Powell et al., 1999) and should therefore be considered as a policy objective.

Acknowledgements: This chapter was written as part of the research project GRETCHEN (The impact of the German policy mix on technological and structural change in renewable power generation technologies, www.project-gretchen.de), which is funded by the German Ministry of Education and Research (BMBF) within its funding priority "Economics of Climate Change" under the funding label Econ-C-026. We gratefully acknowledge this support. We would like to thank the GRETCHEN team members and especially Karoline Rogge for valuable discussions. Previous versions of the chapter were presented at the Doctoral CGDE-Workshop 2015 in Halle, the 2015 European Meeting on Applied Evolutionary Economics in Maastricht, the XII. Buchenbach-Workshop 2015 in Buchenbach, the Jahrestagung des Evolutorischen Ausschusses des Vereins für Socialpolitik 2015 in Bremen, the 5th Governance of a Complex World conference 2016 in Valencia, as a poster at the 16th International Joseph A. Schumpeter Society Conference 2016 in Montreal and at the The 2nd EAEPE RA [X] 'Networks' Workshop 2016 in Bochum. We are grateful for discussions by and with Muhammad Ali, Uwe Cantner, Robin Cowan, Dirk Fornahl, Johannes Herrmann, Frieder Kropfhäußer, Bastian Rake, and Friedrich Thießen, as well as three anonymous reviewers.

With the rising importance of international research communities, countries strive to be integrated in global knowledge networks to access external knowledge and thereby secure technological and economic progress (Adams, 2012). While the importance of access to international knowledge flows has been emphasized for a long time (Bush, 1945), only in the past decades, policy put an emphasis on fostering access to and integration into global knowledge networks. Prominent examples include the establishment of an European Research Area, support of scientist mobility (via several programs, e.g. Marie Skłodowska-Curie, Fulbright, Erasmus+), and distinct national strategies or policies to engage in international collaboration (see Park and Leydesdorff, 2010; Kwon et al., 2012, for the example of South Korea).

In this paper, we analyze the determinants of countries' embeddedness in the global photovoltaics (PV) knowledge network. We argue that the position of a country in this network is determined by two driving forces: First, by the structure and functionality of its innovation system (Nelson, 1993; Lundvall, 1992; Carlsson and Stankiewicz, 1991) and second, by active policy intervention to support research and development. With respect to the innovation system, we focus particularly on the interaction structure as a determinant of knowledge diffusion within the research system (OECD, 1997; Cowan and Jonard, 2004; Schilling and Phelps, 2007; Cantner and Graf, 2011; Herstad et al., 2014). This argument is related to the links between micro, meso, and macro levels of economic analysis (Dopfer et al., 2004). Here, the structure of national networks, i.e. the functionality of the research system and its set-up, determines international collaboration and embeddedness. With respect to policy intervention, we account for a variety of instruments that constitute the policy mix for renewable energies (Flanagan et al., 2011; Rogge and Reichardt, 2016). As such, we explore whether policy can create an environment conducive to international collaboration and increased embeddedness within the international research network.

Our empirical study is based on co-authorship information on scientific publications. This allows us to exploit the multimodal structure in publication data and link the national research network structure to the position of a country in the international research network. Scientific publications are an established tool for the measurement of knowledge generation or to track characteristics of the innovation process and collaboration intensity (Katz and Martin, 1997; Glänzel and Schubert, 2005). We focus on PV because it is a highly dynamic technology, which received strong governmental support and tackles a global problem by mitigating climate change. While there is a growing literature evaluating the effect of policies on innovation and diffusion in PV (e.g. Watanabe et al., 2000; Johnstone et al., 2010; Peters et al., 2012; Polzin et al., 2015; Cantner et al., 2016), there are to our knowledge no studies dealing with the influence of different policy measures on the embeddedness in international research network in general and not for PV in particular.[1] We derive hypotheses about the effect of national network structures and policy interventions on countries' embeddedness and test them by OLS-panel regressions for a large sample of countries with scientific publications in the period from 1980 until 2015.

In line with Huang et al. (2013) or Du et al. (2014), we observe a steady increase in collaboration within the global PV research network. While a small group of countries remains central throughout all years, some countries catch up whereas others lose relative positions in the network. With respect to the determinants of embeddedness, we find positive effects of overall cohesion and connectedness of the national research system. Among OECD countries, the effect is not that pronounced because they all have well established and internationally embedded research systems (Choi, 2012). Countries with a decentralized research network are internationally more embedded, indicating that diffusion oriented national research systems are more open towards external knowledge flows. With respect to the instruments of the policy

[1] Several bibliometric studies focus on PV publications from different perspectives (Dong et al., 2012; Huang et al., 2013; Du et al., 2014; Cho et al., 2015; Popp, 2016a,b) but not with respect to the determinants of international collaboration or embeddedness.

mix, demand side instruments seem to be important for research and collaboration in PV, as has been shown elsewhere for inventive activity (Johnstone et al., 2010; Peters et al., 2012) and collaboration in Chapter 2 (in the following referred to as Cantner et al., 2016). In particular, public procurement, proxied by the cumulative number of satellites, shows up as a robust predictor of embeddedness. This result fits well with the more general argument that governmental demand can increase research activity (Geroski, 1990; Edler and Georghiou, 2007; Aschhoff and Sofka, 2009; Guerzoni and Raiteri, 2015). With respect to direct R&D subsidies, we find ambiguous results. They seem only to encourage collaboration with already well embedded actors. The general commitment to mitigate climate change induces higher connectivity only for OECD countries.

Our research contributes in several ways to the literature. We propose a novel approach to measure the functionality of a research system and show its influence on system performance, i.e. the relationship between meso structure and macro performance. Furthermore, we provide insights on how the determinants of embeddedness depend on its operationalization. Our results show that instruments of innovation policy not only increase research activities, but have effects on international collaboration and embeddedness. Lastly, we add public procurement to the already established instrument mix for renewable energies.

In the following Section 5.2, we review the related literature and derive hypotheses. In Section 5.3, we first describe the publication data and then the international as well as the national collaboration networks. In Section 5.4, we present the econometric study where we estimate the effects of the national network structure and different policies on the embeddedness of countries. We discuss our results and conclude in Section 5.5.

5.2 Literature review and research objectives

5.2.1 Networks of scientific collaboration

Knowledge generation is a cumulative and interactive process in which the relations between actors are key for knowledge exchange and diffusion (Dosi, 1988; Powell et al., 1996; Ahuja, 2000). The continuous increase in collaboration during the last decades has – amongst others – been attributed to an increasing specialization and division of labor because of the cumulative and dispersed nature of knowledge (Jones, 2009). There is vast empirical evidence that collaborative research leads to more valuable output than individual research (e.g. Adams et al., 2005; Wuchty et al., 2007; Adams, 2013). However, researchers who collaborate, as documented e.g. by co-authorship, do not just add their individual expertise for a joint output but also exchange information and learn from each other (Breschi and Lissoni, 2004).

Not only the intensity of collaboration has increased in science, but also the geographical distance between co-authors. By drawing on 21 million publications across all fields of science, Waltman et al. (2011) show that the average collaboration distance per publication has increased from 334 kilometers in 1980 to 1553 in 2009. For Europe, Hoekman et al. (2010) find a diminishing effect of geographical proximity on co-publishing with territorial borders becoming less relevant. The reasons for this trend are manifold. The decline in travel cost, improvements in communication technologies and the rise of English as the common language in science have been put forward (Waltman et al., 2011). The globalisation of science is also driven by an increase in migrant scientists who typically have larger international research networks (Scellato et al., 2015).

The aggregate structure of collaboration is analyzed in what we refer to as knowledge networks. Co-authorship networks, where authors are treated as nodes connected by joint pub-

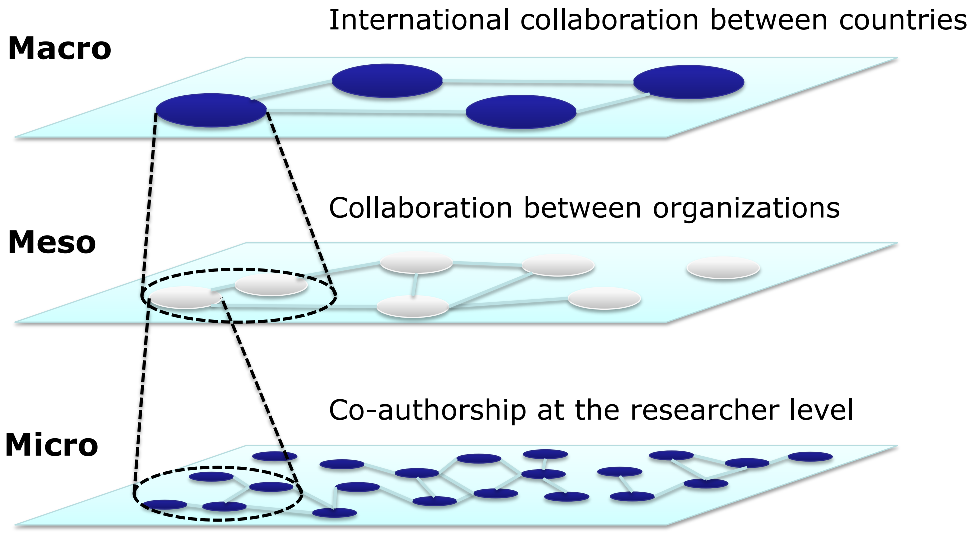


Figure 5.1: The multimodal network structure.

lications are a prime example for such knowledge networks (Glänzel and Schubert, 2005). In one research stream, knowledge networks are analyzed to identify universal structures, such as small world properties, or to test hypotheses regarding processes of network formation, such as preferential attachment or homophily (Newman, 2001; Barabasi et al., 2002). Besides their structural properties, networks are also of interest because they provide information about the position of individual nodes among a group of actors. Central positions might indicate importance or power in a network by controlling information flows between otherwise unrelated actors (Freeman, 1979). Some positions within the knowledge network might give an advantage for accessing novel, external knowledge. Given that external knowledge is a highly valuable input for processes of invention and innovation, a second research stream is concerned with the questions regarding the influence of network positions on performance. Based on various types of knowledge networks, this field of research produced substantial empirical evidence showing that direct but also indirect connections matter for innovation performance (for reviews see Ozman, 2009; Cantner and Graf, 2011; Phelps et al., 2012; Hidalgo, 2016).

5.2.2 Networks as multimodal structures

While interaction and learning takes place among individuals, networks are analyzed at more aggregated levels to study interaction between groups of actors, such as organizations, industries, regions, or countries (Glänzel and Schubert, 2005). A critical assumption for such an aggregation is that knowledge and information are transmitted within those larger entities. At the organizational level, one is interested in collaborations between organizations (affiliations of the researchers) while knowledge flows within these organizations are assumed to be existent but usually not explicitly taken into account (Adams et al., 2005; Cantner and Graf, 2006; Guan et al., 2015a). Aggregation can also account for the geographical dimension as in studies on international collaboration, shedding light on knowledge flows between different regions (Wanzenböck et al., 2014, 2015) or countries (Owen-Smith et al., 2002; Wagner and Leydesdorff, 2005a; Cantner and Rake, 2014).

Figure 5.1 displays the different levels or modes of networks that are used in the present study. Raw publication data is on the micro level and provides information about co-authorship between individuals. Information about the affiliation of researchers is used for aggregation on the meso level. These networks between organizations on the country level provide insights on the structure of national research and innovation systems. By using information on the home country of organizations, global networks represent the macro level of international collaboration. The position of countries within these networks provides valuable information about international embeddedness in terms of participation in scientific communities and the potential to access global knowledge flows.

The relationships and interactions between different levels of aggregation have recently been empirically tested. The underlying assumption of such analyses is that the network structures at different levels of aggregation influence each other (Gupta et al., 2007). For example, Guan et al. (2015b) analyze the influence of countries' positions in the global innovation network on the performance of actors in city level networks. In a similar vein, Paruchuri (2010) shows that inventor performance is influenced by the positions in intra- and interfirm networks.

5.2.3 Linking national research networks and global embeddedness

In the following, we derive hypotheses regarding the relation between the meso structures and macro embeddedness. Research networks on the national level can be thought of representing countries' research systems where different types of actors, such as universities, research institutes, companies, or governmental agencies interact in various ways. Collaboration on this level is determined by incentives, norms, or specific cultures towards collaboration which might differ between research fields and/or technologies, but also between countries (Lundvall, 1992; Malerba, 2002; Wuchty et al., 2007). While the cultural and technological determinants are typically beyond the reach of policy measures, there are several ways in which policy can shape the interaction structure by means of incentives, norms, and regulations (Smits and Kuhlmann, 2004). As such, the structure of the national research network is the result of a long term process driven by path dependencies and guided by political influence.

In theory, the choice to collaborate should only be based on scholarly ground, however, this is typically not the case. Scholars are biased towards collaboration with partners that speak the same language or are proximate with respect to geographical or institutional dimensions (Boschma, 2005; Hoekman et al., 2008). Choices are also influenced by norms, habits, and routines. In an institutional environment where collaboration is the norm and past experience tells that collaboration is beneficial, the probability to collaborate can be expected to be higher than in one that rewards and/or exemplifies individualism. Therefore, if a country is characterized by a high level of collaboration on the national level, we expect the likelihood to cooperate on the international level to be higher as well.

Hypothesis 9. *The intensity of national collaboration positively affects countries' international embeddedness.*

The mission vs. diffusion dichotomy in science and innovation policy can help us understand the relationship between international embeddedness and centralization (or concentration) of the national research system. According to Ergas (1987), countries can promote a technology either for reasons of national sovereignty and international competitiveness (mission) or to deal with market failures (diffusion). Countries that pursue mission oriented strategies are typically characterized by few strong actors (national champions) (Ergas, 1987). If the strategic goal is to advance knowledge mainly within the country, there is a quite natural reluctance to share knowledge internationally. If, on the other hand, the policy goal is to solve a global problem, the international diffusion of knowledge should be most welcome. In that context, Owen-Smith et al. (2002) argue, that the decentralized organization of public research in the U.S. was relevant for their central position within the international life sciences knowledge network. Therefore, we expect countries with a centralized research system to be less open to international collaboration and less embedded in the international research network.

Hypothesis 10. *Centralization of the national research network negatively affects countries' international embeddedness.*

Functioning research systems are characterized by the ability to generate knowledge spillovers (Carlsson and Stankiewicz, 1991; Hekkert et al., 2007). A prerequisite for knowledge diffusion and spillovers is the connectivity of the network as captured for example by the share of actors in the largest component (Fleming and Frenken, 2007). We expect that in such integrative systems, internal as well as external openness go hand in hand due to a general, learned capability of collaboration and networking (Bathelt et al., 2004; Graf, 2011). Therefore, we propose that highly connected national research systems are more prone to international collaboration than fragmented ones.

Hypothesis 11. *Connectivity within the national research system positively affects countries' international embeddedness.*

5.2.4 Policy influence on international embeddedness

PV is considered an environmentally friendly technology, which generates electricity without emitting CO_2 or other harmful substances. However, it was only until recently that PV became cost competitive with conventional electricity generating technologies. Therefore, governments intervene to foster R&D in PV to increase efficiency and to decrease production costs. In general, there are several approaches to support research activity and technological development within the broader policy mix (Flanagan et al., 2011; Rogge and Reichardt, 2016). The main instruments relate to demand pull or technology push policies (Mowery and Rosenberg, 1979). There is a growing theoretical and empirical literature in innovation and environmental economics which tries to understand how these policy interventions affect innovative output, especially in environmentally friendly technologies (see Jaffe et al., 2002; Kemp and Pontoglio, 2011; Groba and Breitschopf, 2013, for reviews). In the case of scientific research and collaboration, evaluations of such interventions are scarce and focuses on direct funding only.[2] In the following, we derive hypotheses regarding the influence of different policies towards renewable energies and PV in particular on the international embeddedness of countries in the global research network.

Technology push instruments are motivated by positive externalities or technological spillovers which lead to underinvestment in R&D. R&D subsidies are a classic example of such policies as they foster research activities by public and private actors (Arrow, 1962b; OECD, 1997). Several studies show that R&D subsidies increase inventive activity (Watanabe et al., 2000; Johnstone et al., 2010; Peters et al., 2012; Wangler, 2013) and networking (Cantner et al., 2016) in PV research. Concerning effects of technology push instruments on publications in general, Crespi and Geuna (2008) find that on the macro level expenditures on higher education research and development increase research output, while Popp (2016a) shows that direct funding increases research output in energy research, especially in solar energy, but with a considerable time lag. Concerning the effect of such policies on collaboration and network structures, there is only limited evidence for the collaboration intensity at the micro (researcher) level. Based on survey data, Bozeman and Corley (2004) and Lee and Bozeman (2005) find that the availability of grants leads to larger researcher teams and more collaboration. In a similar vein, Ubfal and Maffioli (2011) find that Argentinian researchers who received a grant are better integrated in the scientific community. Adams et al. (2005) find that federally funded R&D increases the number of papers, team size per publication, as well as international cooperation for US universities.

Hypothesis 12. *International embeddedness of countries increases with the amount of funding towards research and development.*

[2] However, several studies focus on the micro (researcher) or meso (institute) level and find usually a positive effect of funding on publication output (see Ebadi and Schiffauerova, 2013, for a review).

Demand pull policies increase demand by creating (niche) markets for new or infant technologies (Kemp et al., 1998; Nill and Kemp, 2009). Thereby, they attract companies to engage in production and benefit from economies of scale and learning-by-doing effects. If firms are profitable, they generate internal funds to conduct research and inventive activities which also contribute to the advancement of a technology. Investment subsidies, quota systems, or feed-in-tariffs are typical examples for such policies. In the case of PV, countries implemented different approaches to support commercialization of PV, which in most cases also increased inventive activity (Johnstone et al., 2010; Peters et al., 2012; Wangler, 2013) and research collaboration (Cantner et al., 2016). Public procurement is another form of demand pull policy which has shown positive effects on R&D activities (Geroski, 1990; Edler and Georghiou, 2007; Guerzoni and Raiteri, 2015). In the case of public procurement, governments create demand for societal needs and acts as a lead user by asking for sophisticated products with clearly defined characteristics. In the case of PV, the government was the first customer for PV cells to power satellites and space applications (Oliver and Jackson, 1999; Petroni et al., 2010; West, 2014), which can be considered public procurement. Since PV cells for aerospace needed to be as efficient as possible, research was conducted to fulfill advanced requirements and provide efficiency improvements until today.

Hypothesis 13. *International embeddedness of countries increases with the amount of effective demand pull policies.*

Besides these targeted instruments, the Kyoto Protocol can also be considered as a policy instrument, which should encourage research and development in PV. Ratifying the Kyoto Protocol shows commitment towards emission reduction and, especially for the Annex B countries, it has binding targets (UNFCC, 1997). Since one way to achieve these targets is PV, countries might increase their research effort and engage in international collaboration after ratifying the Protocol. Some studies show indeed that the ratification of the Kyoto Protocol fosters inventive activity for PV (Johnstone et al., 2010) and renewable energies in general (Nesta et al., 2014). Furthermore, the Kyoto Protocol contains instruments which foster international collaboration and knowledge transfer (Dechezleprêtre et al., 2008). These instruments, namely the clean development mechanism and joint implementation, increase international collaboration and form networks of knowledge transfer by itself (Kang and Park, 2013), which can lead to scientific collaboration between countries as well.

Hypothesis 14. *International embeddedness of countries is larger after ratifying the Kyoto Protocol.*

5.3 Scientific collaboration networks

5.3.1 Data: photovoltaic publications

Publications are frequently used to measure output and collaboration at early stages of the research and innovation process. We collect data on PV publications from Thomson Reuters Web of Science Core Collection.[3] The sample consists in total of 106,836 publications from 1946–2015 written by authors from 146 countries covering various scientific fields. Figure 5.2a depicts the number of publications over time. An exponential growth in the number of publications which indicates the increased pervasiveness of PV research during the last decades is evident.

[3] The query used is photovoltai* or solar cell* in the title, abstract and keywords section on August 22^{nd} 2016. Since we focus our research on PV only, we decided to be conservative and refrain from using more general search terms, such as “solar*” to minimize false positives at the cost of higher coverage. Only articles, proceedings papers, reviews or book chapters are considered. More than 98% of the publications are in English.

Table 5.1: Number of publications and international collaboration by country 1980–2015.

Country	Publications	Share	International collaboration per publication
China	21,380	16.7%	1.266
USA	18,790	14.6%	1.451
Japan	9,196	7.2%	1.329
South Korea	8,985	7.0%	1.319
Germany	8,648	6.7%	1.662
India	5,728	4.5%	1.344
Taiwan	4,787	3.7%	1.214
United Kingdom	4,688	3.7%	1.837
France	3,851	3.0%	1.828
Spain	3,447	2.7%	1.739
Rest of World	38,843	30.3%	—
Total	**128,343**	**100,0%**	**1.256**

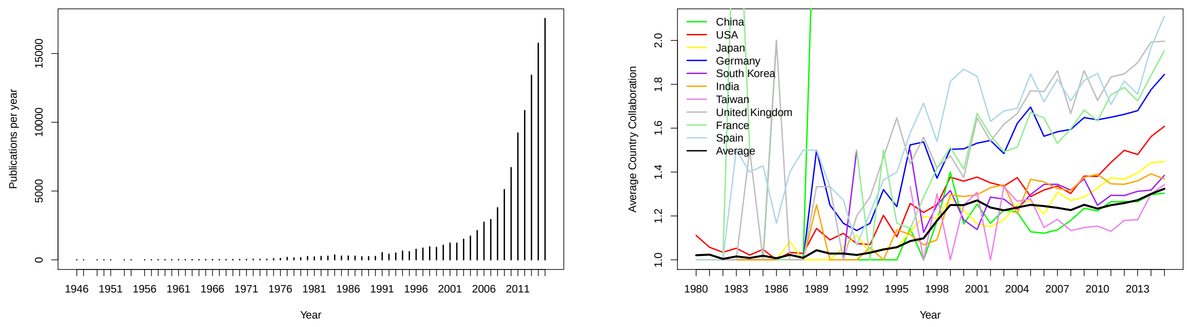
In the following analysis, we restrict the sample to the years from 1980 until 2015 since there are only few publications before 1980. Furthermore, policy makers started to put more emphasis on PV research as a response to the oil crises in the 1970s and research took off globally. In the sample from 1980 to 2015, 105,809 publications are included. We use information on affiliations as provided by Web of Science to assign papers to organizations and countries. Most publications are from China, the USA, and Japan (see Table 5.1) but also European countries are among the top publishing countries.[4]

Concerning international collaboration, i.e. publications of co-authors with affiliations located in different countries, there are on average 1.26 different countries involved in each publication. European countries, especially the United Kingdom, France, and Spain are more frequently involved in international collaboration than Asian countries, especially Taiwan and China which are less collaborating internationally. Concerning the development over time, depicted in Figure 5.2b, there is a steep increase around 1996, which is most likely related to our original data source. The information on author affiliations in the Web of Science is more reliable from 1996 onwards. Keeping this potential problem in mind but in line with Adams et al. (2005), we observe an increasing trend in international collaboration with some notable differences between countries. Asian countries, especially Taiwan and China, do not collaborate extensively internationally and stay roughly at the same level. European countries frequently engage in international collaborations and increase their international activity over time. This increase for the European countries could be related to the common labor market and the EU-Framework programmes, which require pan-European collaboration.

5.3.2 International research network

Before analyzing the determinants of embeddedness, we have to understand the structure and dynamics of scientific collaboration between countries. We employ methods of social network

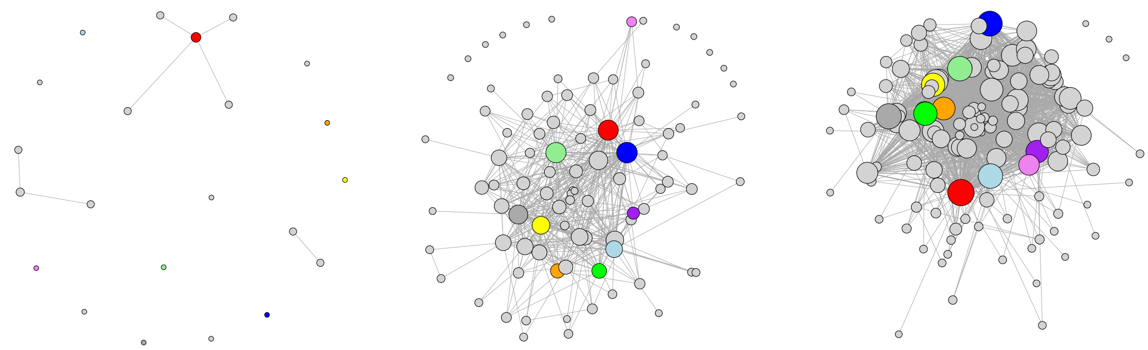
[4] Since the main focus of this paper is on collaboration, we do not calculate publication shares in case of international collaborations. Therefore the total number of publications per country does not match the total number of publications. Furthermore, we do not control for the quality of publications since our focus is on collaboration patterns and restricting the sample to some top journals would not represent the whole collaboration network. We also do not limit the scope of papers to specific research fields, since technological and social progress are interlinked.



(a) Annual photovoltaics publications. **(b)** No. of countries per publication.

Figure 5.2: Photovoltaics publications and international collaboration.

analysis (see Wassermann and Faust, 1994) to elaborate on the countries' collaboration pattern and embeddedness in the international research network. To analyze the networks over time, we use three-year moving windows. Thereby we account for persistence and decay of collaboration, since the date of publication is just a point in time, while the actual collaboration existed before and maybe persisted after the publication (Fleming et al., 2007; Schilling and Phelps, 2007).[5] We reconstruct undirected international research networks using publications from 1980 until 2015, i.e. the first network covers the period 1980 to 1982 and the last network covers 2013 to 2015 leading to 34 overlapping observation periods. Figure 5.3 displays three of these reconstructed international networks and illustrates how the network changes in terms of size and connectedness.



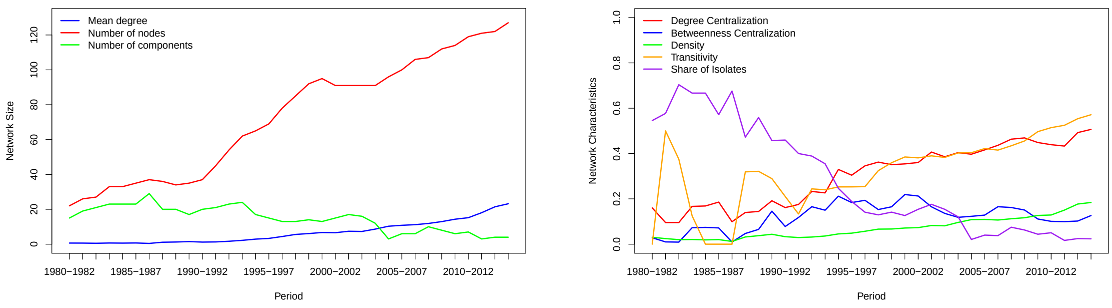
(a) Period 1980–1982. **(b)** Period 2003–2005. **(c)** Period 2013–2015.

Figure 5.3: International research network for three periods.

Figure note: Node size is a function of the node's degree. Colored nodes refer to the countries presented in Figure 5.6.

We calculate several indicators to describe the development of the international collaboration network over time (see Figure 5.4). The number of nodes (i.e. countries), which indicates the size of the network, increases steadily (see Figure 5.4a). The mean degree measures the average number of connections per node, i.e. the number of distinct co-authoring countries. Here, we see

5 There is no consensus among network researchers regarding the correct length of the window. Some assume only the publication year (Wagner and Leydesdorff, 2005b), others three (Li et al., 2014a), five (Li et al., 2013), or seven years (Fleming and Marx, 2006), and some do not account for a link decay at all (Breschi and Catalini, 2010). While this decision certainly influences the level of network metrics, it does not affect the direction of change. Therefore, it is up to the researcher to balance the trade-off between networks of higher density and connectedness on the one side and more observations over time on the other.



(a) Network size. **(b)** Network characteristics.

Figure 5.4: Evolution of the international research network.

a steady increase, indicating that on average countries become increasingly embedded within the global network. The declining number of components also shows that the countries are getting increasingly interconnected and hardly any country performs research without international collaboration by the end of our observation period. This can also be seen in the share of isolates, countries which are not connected to another country, which diminishes drastically (see Figure 5.4b).

Concerning the importance of different countries in the network, we use the concept of network centralization. These measures are less concerned with the overall connectedness but rather with the specific structure of relations and relative positions of nodes. We use two centralization measures to account for the concentration of linkages on few nodes (degree centralization) and the dependence on nodes that connect many other nodes (betweenness centralization) proposed by Freeman (1979). Both measures are equal to 1 in a star network, in which all nodes are connected to one central node but not among each other, and take a value of 0 for networks without prominent positions, such as a ring or a complete graph. In Figure 5.4b, we present degree and betweenness centralization for the network. Degree centralization increases constantly over time, indicating that there are some countries that are way more interconnected than the average. The development of betweenness centralization shows that the concentration of knowledge flows increases during the early periods but diminishes throughout the last periods. Additionally, transitivity indicates the likelihood that adjacent nodes of a node are connected. For the global network, we see that except for the early phase transitivity increases constantly. Apparently, countries increasingly form densely connected clusters. Network density, which is the share of all present connections in all possible connections, increases despite network growth, indicating an over-proportional increase in linkage formation.

Regarding countries' positions within the global network, we focus on three measures of embeddedness. Degree, flow betweenness, and k-core are different concepts of centrality and embeddedness, all related to the number of connections. Degree is a simple count of the number of connections irrespective of their intensity, while flow betweenness considers the intensity but also the relative position within the whole network (Freeman et al., 1991). The k-core of a graph is the maximal subgraph in which every node has at least degree k (Seidman, 1983). Higher values indicate membership in an increasingly cohesive subgroup which forms the network core.

Figure 5.5 and Table 5.2 show a simple example to point out the differences between the three concepts. Nodes A and B in the example have the same degree, both are connected to four other nodes. But if we consider flow betweenness, we see that node B is much more central than A. B is better connected to its neighboring nodes than A, which puts B in a better position in the network to access external knowledge. However, it has to be noted that degree is limited by the number of nodes in the network, while flow betweenness is more or less unrestricted. This measure not only accounts for the number of collaboration partners (A still has more access to

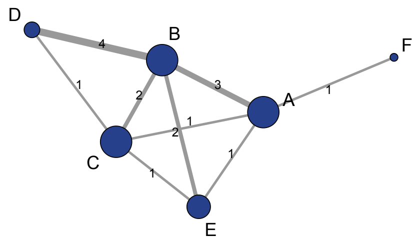


Figure 5.5: Example network.

Table 5.2: Example data.

Node	Degree	Flow Betweenness	K-Core
A	4	18	3
B	4	36	3
C	4	12	3
D	2	4	2
E	3	10	3
F	1	0	1

knowledge than the other nodes) but also for the quality of cooperation partners. The k-core tells us if a node is member of the network core or rather of its periphery. Here, we see that nodes A, B, C, and E form the core in which every node has a degree of at least three, while D and F are in a more peripheral position.

Figure 5.6 depicts the development of publications and the three measures of embeddedness for the top ten countries over time. The number of publications is highest for the USA until 2010, when China takes over the lead. In general, there is a strong increase in the number of publications from Asian countries. Besides China, also South Korea, India, and Taiwan catch up. Japan is among the most publishing countries since early on, but is eventually outmatched by China, South Korea, and most recently by India. The same holds true for Germany.

With respect to measures of embeddedness, degree shows an interesting development (the maximum for degree is limited by the size of the network, see Figure 5.4a). Surprisingly, Spain has the highest degree in some of the early periods but is again overtaken by the USA, which together with Germany has most connections over time. Both are connected to about 70% and 60% respectively of all countries in the last period. Furthermore, the USA and European countries have a higher degree than Asian countries for most of the time, and especially Taiwan is lagging behind. A similar pattern can be observed for flow betweenness, where the USA and Germany have the highest values. However, in the last periods, China catches up and ranges among the top three countries. This indicates that China, even though it has a lower degree than the presented European countries, is well embedded in terms of access to knowledge flows. However, again, Taiwan is least embedded among the top ten countries, surpassed by India and Japan. The k-core shows no surprising development. Over time all high publishing countries join the core group within the network. There is very little variation over time and besides Taiwan, all ten countries quickly connect to the central core.

So far, we exemplified general trends of network development by looking at the top ten publishing countries. To analyze the underlying dynamics for all countries, we compare their relative position in the network over time. We rank all countries according to their degree in period 2003–2005 and compare this ranking with the periods 2008–2010 and 2013–2015. This gives us a Salter-Curve like representation of the dynamics in the network (see Figure 5.7). We see that at the top of the ranking the changes are marginal, while there is quite some turbulence in the middle. Among the top actors, especially Mexico is loosing its position, while most of the other countries hold their positions. Qatar, the United Arab Emirates, Serbia, and Malaysia are the countries which improve the most. Some other Arab countries improve their position as well. The top 15 as well as the 15 countries with the largest movement in the ranking are shown in Appendix 5.6.1.

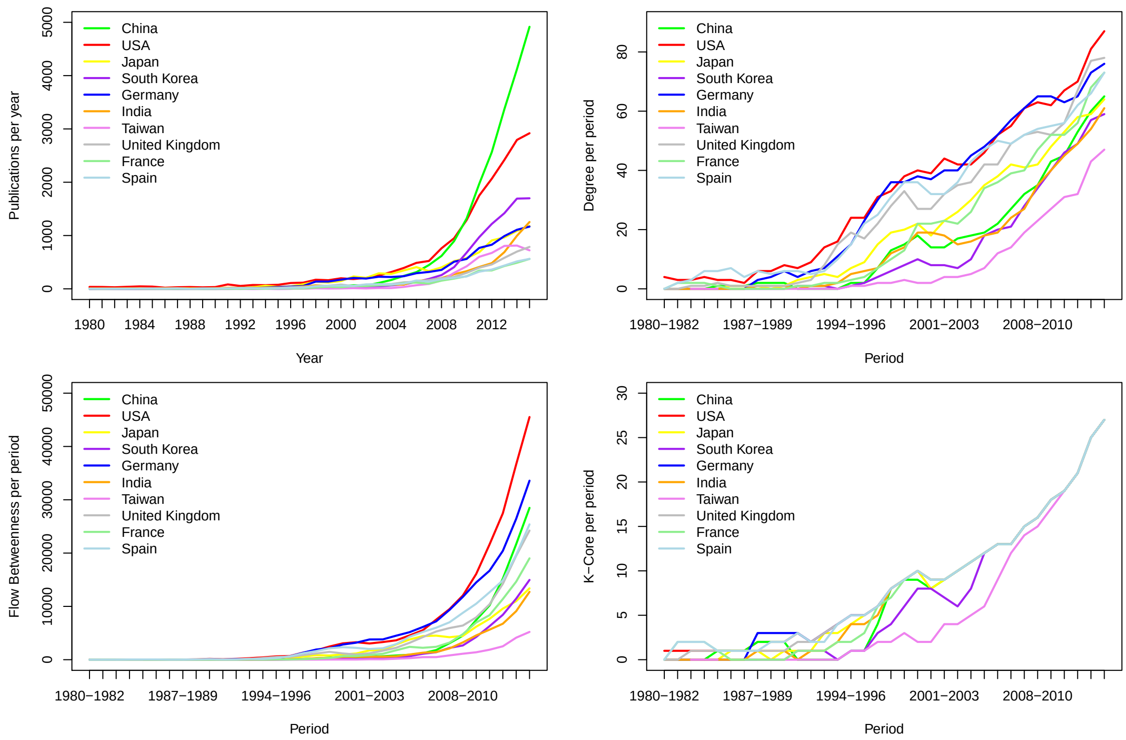


Figure 5.6: Publications and network measures for top ten publishing countries.

5.3.3 National research networks

In the following, we focus on the structure of interaction within each country. Information on author affiliations allows us to reconstruct national research networks. Here, nodes represent different organizations, such as universities, research institutes, or companies and edges represent joint publications of researchers with different affiliations.[6] We reconstruct national research networks for all countries in our sample. Again, we present network measures for the top ten publishing countries in Figure 5.8 to illustrate the general patterns of research activity and network development.

We observe an exponential increase in network size, indicating that more organizations emerge and engage in PV research. But there are notable differences between countries. While China and India experienced vast growth especially in the latest periods, other countries, most notably the United Kingdom, show hardly any increase in the number of actors. Concerning the connections among these actors in the research system, mean strength (degree, weighted by the intensity of the connection) is increasing in all countries. Especially actors in Taiwan and South Korea are very well connected. This is remarkable, since they are not that well connected internationally, as shown above (Table 5.1 and Figure 5.6). Another interesting case is India, which shows a very large increase in the number of nodes, but not with respect to mean strength, which indicates that there might be some deficits in domestic collaboration. In general, Asian countries seem to have a higher degree of internal interaction than European countries in the last periods.

Further indicators add to our understanding of the development of structural differences between national research networks. Degree centralization accounts for the concentration of links

[6] Since we are interested in the structure of national research systems (and use its structural properties to explain global network positions, i.e. international collaboration in Section 5.4), we exclude cooperation partners in foreign countries. Furthermore, since the affiliation data is quite noisy, we consider only the organization name and neglect information about departments or other subsidiary information.

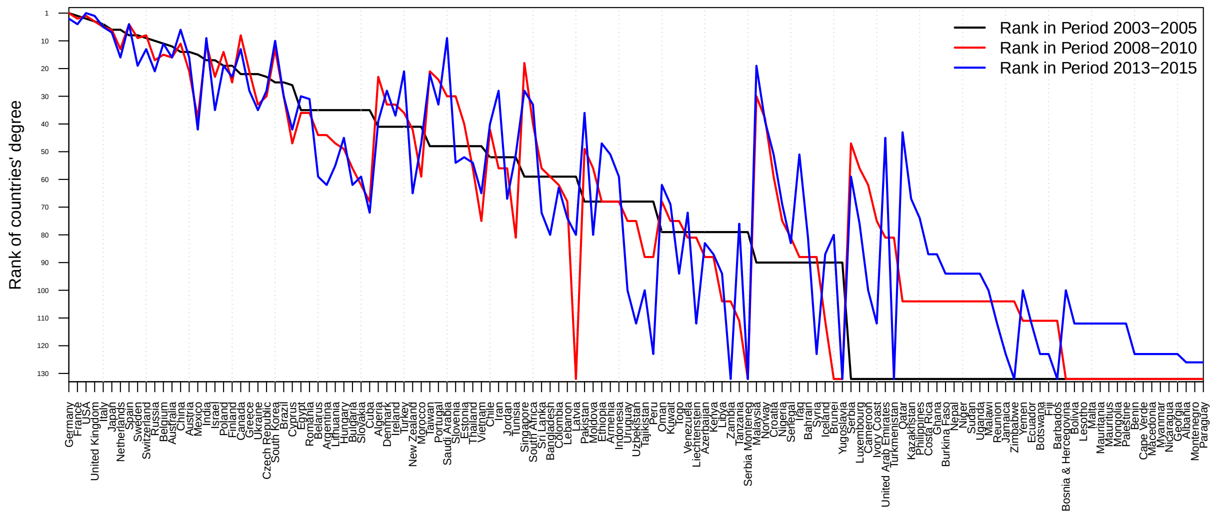


Figure 5.7: Rank changes of the degree of countries.

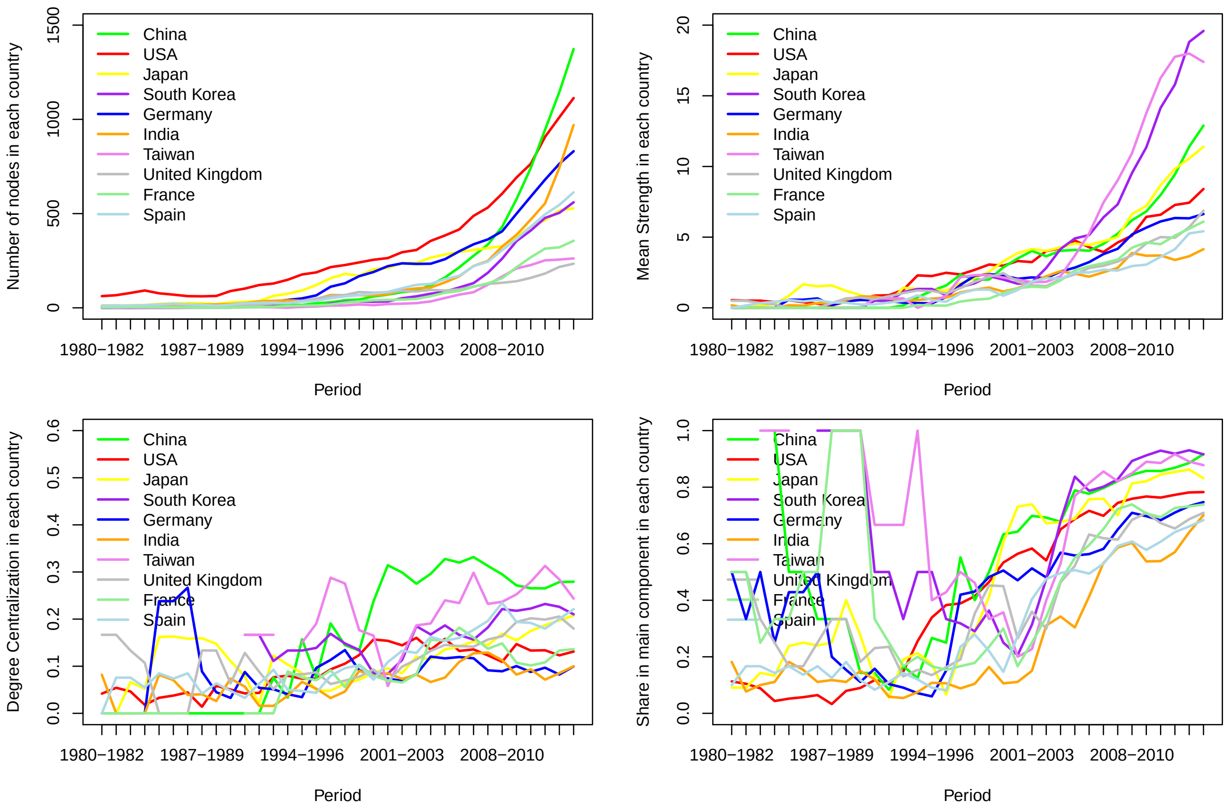


Figure 5.8: Properties of the national research networks for top ten publishing countries.

in the network. There is no clear trend but we observe quite some variation between countries. Especially Taiwan, China, and South Korea appear to have a more centralized research systems in PV than e.g. Germany, India, the USA, or France. The share of actors in the main component is another indicator for the structure of the network and accounts for its connectivity. It takes the size of the largest component over the size of the network.[7] This measure increases in all

[7] The share of actors in the main component is sensitive for small networks and can lead to extreme values as seen in the first periods.

countries from the mid 1990s onwards indicating that the networks become less fragmented over time with the potential for knowledge flows between an increasing number of national actors.

5.4 Explaining embeddedness in the international research network

5.4.1 Variables

To test our hypotheses on the influence on embeddedness, we use four sets of variables: dependent variables to describe international embeddedness of countries in the global PV research network and independent variables characterizing the national networks, national policies related to PV and climate change, as well as controls. We conduct the analysis for the period 1980–2015, a robustness check for the sub-period 1997–2015 is discussed in Section 5.4.4. Since we use three-year moving windows for international and national network measures, a period serves as an observation and the starting year of the period refers to the year of observation. So the first period 1980–1982 is the observation for 1980 and the second period, 1981–1983 is the observation for 1981. Summary statistics of the variables are presented in Table 5.3. The correlations between variables are documented in Appendix 5.6.3.

Dependent Variables – International embeddedness

The three dependent variables *degree*, *flow-betweenness*, and *k-core* (as discussed in Section 5.3.2) measure countries' international embeddedness and access to knowledge flows. The three network variables emphasize different aspects of international embeddedness, i.e. how well a country is connected to other countries and how important a country is in terms of knowledge transfer between other countries.

National network variables

We use three properties of the national research networks as explanatory variables to account for the characteristics of the respective innovation systems (see Section 5.3.3). *Mean strength* measures the intensity of interaction, *degree centralization* indicates the concentration of linkages, i.e. the importance of 'national champions', and the *share in main component* accounts for the overall potential of knowledge flows inside the country.

Policy variables

Several variables are used to operationalize national policies towards PV in particular and climate change mitigation in general. To account for technology push policies towards PV research, we use *PV R&D expenditures* by the government in Mio US$ (IEA, 2016). However, this information is only available for some OECD countries and not for all years. Whenever only a few years of observation for a country are missing, we interpolate R&D data and add a dummy to control for a possible effect of interpolation (*PV R&D Exp. interp. Dummy*). Furthermore, we use the logarithm of annually *installed PV capacity* in MW (IEA, 2016), as a proxy for demand pull policies. Since PV is only recently price competitive, any installation must have been somehow subsidized by the government. This measure is frequently used in the literature because it accounts for the effectiveness of a variety of demand inducing policy instruments (Peters et al., 2012; Wangler, 2013; Cantner et al., 2016). Additionally, we use data on satellites to proxy

Table 5.3: Variable descriptive statistics, 1980–1982 until 2013–2015.

	Min.	**Median**	**Mean**	**Max.**	**SD**	**Obs.**
Dependent variables						
Degree_t	0.000	7.500	13.887	87.000	15.591	1540
$\text{Flow Betweenness}_t$	0.000	189.000	1210.045	45521.000	3305.788	1540
K-Core_t	0.000	6.000	8.115	27.000	7.097	1540
Publication_t	1.000	9.000	59.379	3371.000	202.121	1413
National network variables						
$\text{Mean Strength}_{t-3}$	0.000	0.800	1.258	16.264	1.613	1540
$\text{Degree Centralization}_{t-3}$	0.000	0.109	0.117	0.667	0.110	1540
$\text{Share in Main Component}_{t-3}$	0.033	0.429	0.436	1.000	0.221	1540
National policy variables						
$\text{Kyoto Ratification}_{t-1}$	0.000	1.000	0.508	1.000	0.500	1540
$\text{Cum. Number of Satellites}_{t-1}$	0.000	1.000	84.232	3412.000	429.341	1540
$\text{Installed PV Capacity}_{t-1}$	0.000	0.336	1.562	9.138	2.241	437
$\text{PV R\&D Exp.}_{t-1}$	0.000	8.754	27.928	395.660	47.136	437
PV R&D Exp. interp. Dummy_{t-1}	0.000	0.000	0.071	1.000	0.257	437
Controls						
$\text{GDP per Capita}_{t-1}$	428.150	17173.502	20053.469	164136.454	16325.668	1540
$\text{EU Membership}_{t-1}$	0.000	0.000	0.281	1.000	0.450	1540

public procurement in PV, since satellites were the first major application of PV and require until today the highest efficiency, which is achieved by constant research activity (Oliver and Jackson, 1999; Petroni et al., 2010; West, 2014). We use the *cumulated number of satellites* deployed over time[8] to proxy the effort and commitment of a country towards the aerospace sector. *Kyoto Ratification* is a dummy variable which takes a value of 1 in each year in which a country has ratified the Kyoto Protocol and 0 otherwise. It serves as an indicator for countries' commitment towards emission reduction.

Control Variables

We use the *GDP per Capita* provided by the Penn World Table (Feenstra et al., 2015) to account for countries' general state of development. Furthermore, we expect that the common EU research area fosters collaboration between European research partners (Defazio et al., 2009) and control for *EU Membership*.

5.4.2 Estimation strategy

We conduct our analysis using unbalanced OLS-panel regressions controlling for country and time fixed effects to account for the differences between countries but also for time effects such as general economic circumstances. Since we are interested in the causal effect of the policies, we lag the national network variables by three years and policy variables by one year. This allows to estimate the effect of these variables on the position within the network of the following three years.[9] To account for heteroscedasticity, we report robust standard errors. Indexing countries by i and time by t, the generic regression model is the following:

[8] The data was collected from `http://satellitedebris.net/Database/LaunchHistoryView.php` on May 2^{nd} 2015.

[9] As explained in Section 5.3.2, networks are reconstructed for overlapping three-year moving windows. A lag of three years leads to no overlap between different networks.

$$\text{Embeddedness}_{it} = \boldsymbol{\beta_1}\text{Network Structure}_{it-3} + \boldsymbol{\beta_2}\text{Policy}_{it-1} + \boldsymbol{\beta_3}\text{Controls}_{it-1} + \text{FE}_i + \text{FE}_t + \varepsilon$$

For each of the three measures of embeddedness (1-3), we estimate three models (a-c). Model a includes 99 countries for which network and policy variables are available. Models b and c include only the 18 OECD countries for which *installed PV capacity* and *PV R&D expenditures* are available.[10] Model b estimates model a for the smaller OECD sample to see if differences in coefficients between models a and c are due to the inclusion of additional variables or because of the smaller sample.

5.4.3 Results

With three dependent variables and three specifications, we end up with nine regression models to analyze the effects of national network structure and policy intervention (Table 5.4). In the following, we discuss the results for the three different measures of embeddedness separately followed by an overall summary of the results.

Degree: The factors influencing international embeddedness as measured by a country's *degree* are estimated in models 1a-c. In model 1a, the three national network measures show significant effects in the expected direction. With respect to the policy variables, there is an effect from procurement proxied by the *cumulated number of satellites* but not by the *Kyoto Ratification*, which accounts for an overall commitment to mitigate climate change. If the sample is reduced to the 18 OECD countries, there is a significant effect of the *Kyoto Ratification* but *mean strength* does not play a role. After including additional policy variables in model 1c, the effect of *share in main component* is not significant anymore. With respect to the additional policy variables, *installed PV capacity* positively influences embeddedness while, surprisingly, *PV R&D expenditures* have a significant negative effect.

Flow Betweenness: *Flow betweenness* is analyzed in models 2a-c. In model 2a the results are similar to model 1a for *degree*, with differences only in the controls. If the number of countries is reduced to the OECD sample in model 2b, *mean strength* is again no longer significant. The additional policy variables in model 2c result in a loss of significance of the national network measures as well. As above, *installed PV capacity* is positive, and contrary to *degree*, *PV R&D expenditures* have a positive significant effect.

K-Core: In the case of *k-core*, model 3a reveals that only national collaboration in terms of *mean strength* and *degree centralization* have a significant influence on membership in a higher level core of the global knowledge network. The models 3b and 3c show opposite signs for *cumulated number of satellites* and *installed PV capacity* and non of the other variables are significant. The reason lies in the properties of this measure of embeddedness. Since the central core of the network is composed of many, highly interrelated countries (35 countries by the end of our observation period), nearly all 18 OECD countries included in the two models enter the core at some point, so that there is very little variation in the dependent variable (see Figure 5.6). As such, this measure of embeddedness does not discriminate between the most central countries as much as *degree* and *flow betweenness*. This is also indicated by the small adj. R^2, which is about an order of magnitude smaller than in most of the other regressions. We therefore abstain from interpreting the models 2b and 2c in the following.

[10] These OECD countries are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, South Korea, Spain, Sweden, Switzerland, Turkey, and the USA.

Summary: Overall, international embeddedness in the global research network is strongly influenced by the structure of the national research network as well as by national policies. As hypothesized for *mean strength* in H 9, intense collaboration within the national research network increases international embeddedness. However, this holds only true for models that include the large set of countries, regardless of how embeddedness is measured. For the models which cover only 18 OECD countries, this relationship does not hold. Centralization of the national research system is detrimental for embeddedness and H 10 gains support in all models with the large country sample and also for *degree* and partly for *flow betweenness* in the OECD sample. This indicates that countries with centralized PV research activity and focus on 'national champions' are on average less embedded in the international network. Concerning the functioning of the national research system, H 11 assumes that connectedness as measured by *share in main component* has a positive effect on embeddedness. This argument finds support in the *degree* model as well as in the *flow betweenness* for the large sample of countries and partly in *degree* and *flow betweenness* for the OECD sample. In general, the national network structure seems to be a good predictor of international embeddedness, especially if a larger population of countries is considered and in the absence of additional policy variables.

With respect to the influence of governmental intervention, H 12 assumes that direct R&D subsidies increase embeddedness. However, our results are inconclusive. There is a negative effect if embeddedness is measured by *degree* and a positive effect on *flow betweenness.* Apparently, research funds are not used to establish new connections per se, but to establish or intensify connections to well embedded countries. In line with H 13, demand side policies have a very robust positive effect on embeddedness. This holds for demand side policies as proxied by *installed PV capacity* and also for public procurement as proxied by the *cumulated number of satellites.* Hypothesis 14 assumes that the *Kyoto Ratification* induces activities to foster renewable energies, which might show in an increased embeddedness in the global PV research network. However, this hypothesis is only supported in the *degree* models for the 18 OECD countries. This might be explained by the differential binding effect of the Kyoto Protocol. In the whole sample, many developing or less developed countries signed the Kyoto Protocol without having to commit to emission reductions, whereas for the 18 OECD countries it unfolds its binding effect. While, overall, governmental interventions influence international embeddedness, the instruments differ in their effects. Market creation by means of demand side policies seems more effective for international embeddedness than the provision of research funds or a general commitment to mitigate climate change.

5.4.4 Robustness tests

We conduct two robustness tests for the econometric analysis. First, we deal with the less reliable publication data in early years by analyzing a subset for later periods only. Second, we use the number of *publications* as a measure for the overall research output. Publications are the underlying data for the networks so that it serves as a benchmark for the regressions on international embeddedness.

As mentioned in section 5.3.1, the way Web of Science stores affiliation data changed around 1996. Furthermore, with the disbandment of the Soviet Union, several countries left the sample and new ones emerged. To account for such effects beyond the already present time fixed effects, we perform regressions with a subsample of the data covering the periods 1997–1999 to 2013–2015. The results as well as the correlations and descriptive statistics are presented in Tables 5.8, 5.10, and 5.11 in the Appendix. The regression results for this shorter but more reliable period are quite stable and there are only marginal differences to the results presented above. There are only two changes worth discussing: In Model 1c the *share in main component* becomes significant and in Model 2c *degree centralization* as well. Both differences strengthen

Table 5.4: OLS-panel regression results for country embeddedness, periods 1980–1982 until 2013–2015.

	Degree			Flow Betwenness			K-Core		
	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
Mean Strength$_{t-3}$	2.186***	0.379	0.562	642.310**	360.226	388.130	0.744***	-0.030	-0.044
	(0.541)	(0.541)	(0.522)	(270.417)	(484.992)	(427.864)	(0.171)	(0.123)	(0.130)
Degree Centralization$_{t-3}$	-18.509***	-16.209***	-10.336**	-6372.334***	-10153.781*	-6027.097	-2.425*	1.873	0.920
	(2.919)	(5.300)	(4.392)	(1655.650)	(5216.224)	(3805.733)	(1.256)	(1.435)	(1.373)
Share in Main Component$_{t-3}$	10.010***	9.517***	5.315	2651.762***	3042.337*	157.752	0.680	-0.512	0.178
	(2.436)	(2.436)	(3.763)	(926.439)	(1682.146)	(1838.029)	(0.793)	(0.631)	(0.751)
Kyoto Ratification$_{t-1}$	0.618	2.715***	2.741**	-347.436	-578.118	-4.880	-0.024	-0.701	-0.782
	(1.033)	(0.914)	(1.375)	(533.444)	(1299.025)	(766.470)	(0.327)	(0.600)	(0.543)
Cum. Number of Satellites$_{t-1}$	0.019***	0.016***	0.016***	14.098***	13.336***	14.168***	0.000	-0.002*	-0.002**
	(0.004)	(0.003)	(0.003)	(2.352)	(2.480)	(2.003)	(0.002)	(0.001)	(0.001)
Installed PV Capacity$_{t-1}$			1.284**			882.222***			-0.209**
			(0.581)			(313.398)			(0.089)
PV R&D Exp.$_{t-1}$			-0.018*			15.605**			0.000
			(0.010)			(6.336)			(0.001)
PV R&D Exp. interp. Dummy$_{t-1}$			-0.575			-294.517			-0.142
			(1.444)			(1149.031)			(0.146)
GDP per Capita$_{t-1}$	0.000**	0.000	0.000	0.029	-0.128	-0.093	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.035)	(0.123)	(0.085)	(0.000)	(0.000)	(0.000)
EU Membership$_{t-1}$	-0.990	0.551	0.714	-1071.045***	619.309	1129.039**	0.625	-0.114	-0.183
	(1.635)	(2.199)	(1.941)	(394.676)	(841.276)	(537.511)	(0.716)	(0.540)	(0.498)
Country fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.305	0.148	0.230	0.252	0.229	0.345	0.059	-0.005	0.030
n	99	18	18	99	18	18	99	18	18
T	34	34	34	34	34	34	34	34	34
N	1540	437	437	1540	437	437	1540	437	437
df	1401	379	376	1401	379	376	1401	379	376

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

our argument with respect to the importance of the national network structure. Since the networks in early periods are very small and sparse they are a less reliable indicator of research system structure.

Our measures of embeddedness are based on the co-authorship of scientific publications. As such, countries can only be embedded in the international research network if they publish research articles. We therefore perform the same regressions as above on the number of publications[11] to find out whether the effects of policies differ between embeddedness and research output (see Table 5.5). Without any difference, embeddedness would merely be a side-effect of increased output. Overall, the results do not differ much. Characteristics of the research system, especially *mean strength* and *degree centralization*, as well as the technology push and demand pull policies influence both, embeddedness and output. However, there are also some noteworthy differences which make us confident that certain policies and system characteristics are relatively more important for embeddedness than for publication output. The functionality of the research system as measured by the *share in main component* seems irrelevant for the number of publications but not for embeddedness. *Kyoto Ratification* increases the number of international partners but has no influence on the number of publications. This indicates that acknowledging greenhouse gas emissions as a global societal problem induces international collaboration.

5.5 Discussion and conclusion

In the present study we analyzed the global research network in PV based on an original dataset of scientific publications to describe its evolution between 1980 and 2015 and to identify the determinants of a country's embeddedness in the international research network. Regarding the determinants of embeddedness, we derived a set of hypotheses on the influence of characteristics of the national research system and instruments of the policy mix for renewable energy and tested them for a large sample of countries.

With respect to the evolution of structural properties of the global PV research network, we observe that research output and the resulting network of international research collaboration are constantly growing. This highlights the global awareness regarding renewable energies and PV in particular as possibilities to mitigate climate change, but also with respect to existing market opportunity worth exploiting (Oliver and Jackson, 1999; Zheng and Kammen, 2014). Especially Asian countries catch up and overtake European countries in terms of research output, indicating that the increase in PV production during recent years (Zheng and Kammen, 2014) goes hand in hand with increased research activities. We also observe an increase in collaboration over time, which is not specific to PV but a general trend in research and innovation activities (Wuchty et al., 2007; Adams, 2012). However, there are some notable differences between countries. While European countries collaborate quite frequently with international partners, Asian countries conduct most of their research domestically. This might be related to cultural differences, geographic proximity, or national strategies (Luukkonen et al., 1992). There is not only a surge in research output, but also in terms of the number of actors, which indicates that an increasing number of countries engage in PV research. The reasons should be found in environmental awareness as well as improved market opportunities and industrial policies (Stern, 2007; Mazzucato, 2013).

Countries which engage in PV research are quickly embedded in the global research network and the number of connections per actor increases steadily. Thereby the network becomes

[11] Since we use this specification to check the robustness of our results, rather than to measure research performance, we abstract from using citation-weighted publication shares, or similar, more sophisticated measures of scientific performance.

Table 5.5: OLS-panel regression results for country publications, years 1980–2013.

	Publication		
	Model 4a	Model 4b	Model 4c
Mean Strength$_{t-3}$	71.778***	33.643	34.000**
	(18.964)	(21.388)	(16.872)
Degree Centralization$_{t-3}$	-400.025***	-493.474***	-347.866***
	(76.716)	(164.580)	(102.799)
Share in Main Component$_{t-3}$	50.452	95.843	-11.818
	(36.195)	(94.653)	(95.295)
Kyoto Ratification$_{t-1}$	-31.847	-82.040	-49.425
	(29.124)	(82.440)	(45.677)
Cum. Number of Satellites$_{t-1}$	0.947***	0.901***	0.962***
	(0.191)	(0.105)	(0.054)
Installed PV Capacity$_{t-1}$			30.850**
			(14.065)
PV R&D Exp.$_{t-1}$			1.253***
			(0.277)
PV R&D Exp. interp. Dummy$_{t-1}$			-51.828
			(59.005)
GDP per Capita$_{t-1}$	-0.002	-0.009	-0.007
	(0.002)	(0.006)	(0.005)
EU Membership$_{t-1}$	-56.518***	-0.247	7.973
	(20.382)	(35.980)	(23.693)
Country fixed effects	yes	yes	yes
Time fixed effects	yes	yes	yes
Adj. R^2	0.307	0.415	0.521
n	97	18	18
T	34	34	34
N	1413	421	421
df	1276	363	360

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

increasingly connected, suggesting that the global system functions well and allows for knowledge diffusion. However, there seems to be an ongoing centralization process, such that some countries form a highly interconnected core. The network periphery is characterized by a substantial degree of turbulence. Some countries, such as Mexico, Russia, and the Netherlands move towards the network periphery, despite a doubling of their number of connections. Others improved their relative position in the network, especially countries in the MENA region due to strategic decisions taken by their governments (Griffiths, 2013). Also Malaysia, which only recently engaged in PV research due to overall political commitment, moved among the top countries (Muhammad-Sukki et al., 2012). The increase in centrality of some Asian countries, especially China, Taiwan, South Korea, and India, is fairly moderate. Even though they nowadays publish most of the research in PV they are not among the most central countries. As such, by giving priority to national partnerships, they do not fully exploit their knowledge sourcing potentials.

In the regressions, embeddedness is measured by three concepts of network centrality which emphasize different aspects of knowledge access. The number of collaborating countries, as measured by degree, as well as the relative position and intensity of collaboration, as measured by flow betweenness, lead to coherent results, generally in line with our predictions. Membership in a highly connected core, as measured by k-core, shows to be a less convincing measure of embeddedness. To explore the determinants of international embeddedness, we employ two sets of country characteristics.

With the first set of factors we enter an emerging research field by relating country level network characteristics – the meso level – to macro level embeddedness (Dopfer et al., 2004; Gupta et al., 2007). While there are some studies concerned with the effects of network structure on performance (e.g. Verspagen and Duysters, 2004; Uzzi et al., 2007; Fritsch and Graf, 2011), only few studies relate different levels of networks in a research or innovation context (Gupta et al., 2007; Paruchuri, 2010; Guan et al., 2015b). We argue that the structure of national networks should be interpreted as characteristics of the national research system that are also subject to decisions taken by policy makers (Carlsson and Stankiewicz, 1991; Lundvall, 1992; Smits and Kuhlmann, 2004; Hekkert et al., 2007). The results are – at least partly – sensitive to the centrality concept used to measure embeddedness. Cohesion and connectedness of the national network positively influence international embeddedness. However, the effects are not that pronounced for OECD countries which are in general internationally well embedded and all have well established and functioning research systems (Choi, 2012). Centralization of the national network, i.e. a focus on 'national champions', shows to be detrimental for embeddedness. This implies that diffusion oriented research systems in which actors are well connected, diverse, and decentralized are supportive of international embeddedness. However, the establishment of an institutional systems conducive for such structures is certainly influenced by policy intervention and strategic decisions of governments (Ergas, 1987). Overall, our empirical results show that country level network structures are highly relevant for international embeddedness.

The second set of factors is comprised of national policies towards PV and climate change in general. Thereby, we add to the broad literature that analyzes effects of policy on environmentally friendly innovation (e.g. Popp, 2002; Newell, 2010; Kemp and Pontoglio, 2011; Acemoglu et al., 2012) and the more recently upcoming literature on the policy mix for innovation (Flanagan et al., 2011; Rogge and Reichardt, 2016). Our results indicate that policy instruments have a differential effect on international embeddedness. R&D expenditures for PV are the most direct way to support research activity (Adams et al., 2005; Popp, 2016a) and international cooperation (Adams et al., 2005; Ebadi and Schiffauerova, 2013). Our results for R&D expenditures are mixed and sensitive to measure of embeddedness. They show a negative effect on the embeddedness in terms of degree, but have a positive effect if the relative position of countries in the network is considered. This implies that R&D expenditures are used to establish or intensify connections to well embedded countries rather than to establish connections to previously unrelated countries. In addition, there might be an indirect effect of R&D expenditures on international embeddedness. Since R&D grants have been found to increase collaboration within the country (Adams et al., 2005; Cantner et al., 2016) they help to establish a structure of the national research network which is conducive to international collaboration. Demand pull policies are a very robust predictor of international embeddedness. Even though they are not designed to foster international R&D and collaboration, they apparently provide incentives and create an environment that strengthens international research activities. In addition to market creating demand pull instruments, such as quotas or feed-in-tariffs, we also analyzed the effects of public procurement, which is highly relevant for innovative activity (Edler and Georghiou, 2007; Guerzoni and Raiteri, 2015). In our case, since we use the cumulative number of satellites to proxy procurement, this type of policy should be more relevant in the early years of the technology than during the last decades. However, procurement shows to be a very strong predictor of performance and international embeddedness not only in the long period 1980–2015 but also for the period 1997–2015. This hints at long term first-mover advantages and since spacecraft development is frequently conducted in multinational projects, it might well explain its effects on international embeddedness (Moloney et al., 2014). The commitment to mitigate climate change indicated by ratifying the Kyoto Protocol seems only to increase the number of international cooperations for the sample of OECD countries. This seems reasonable, since these countries have binding reduction targets whereas in the whole sample many countries do not need to reduce their emissions. Overall, policy instruments have an effect on international embeddedness and knowledge exchange, which has so far been neglected from discussions about an effective policy mix (Flanagan et al., 2011; Rogge and Reichardt, 2016).

Based on these results, we recommend policy makers to consider the following propositions. First, the general setup of the national research system should be higher on the policy maker's agenda to secure integration in international research communities and to embed a country in such networks. There has been discussions about systemic instruments which support functions of a research system (Smits and Kuhlmann, 2004; Hekkert et al., 2007; Wieczorek and Hekkert, 2012). These instruments can be used to create a diffusion oriented research system and embed countries in international networks. This seems to be especially relevant for non-OECD countries, which are developing their research capacity. Steering the research system into a diffusion oriented would increase the collaboration with international researchers. Second, policy instruments which are supposed to increase research activity also increase collaboration and international embeddedness. These partially unintended effects should be taken into consideration by policy makers and fostered to increase the effect of instruments. A striking example are the EU-Framework programs, which encourage international collaboration and increase access to global knowledge flows. In a same vein, a well-tailored mix of different instruments should be implemented to not only increase research performance, but also support access to international knowledge flows. Thereby the policy support should include (pre-)commercial support as well as classical R&D support.

This chapter contributes to several streams of research. First, a novel approach to measure the functionality of a research system is proposed and used to understand how the design of the research system influences global connectivity. While we treat the drivers of the national research network setup as a black box, we encourage further research to understand how this is shaped, for example deliberately by systemic instruments (Smits and Kuhlmann, 2004; Wieczorek and Hekkert, 2012; Cantner et al., 2016). Second, by making use of the multi-level structure of publication data in our analysis, we contribute to the emerging stream of research on multi-level networks (Gupta et al., 2007). We show that the meso level influences structures on the macro level, as proposed in theoretical discussions (Dopfer et al., 2004). Third, we provide novel insights how actor's embeddedness in a network is influenced. We operationalize embeddedness in three different ways and use several possible determinants, which extend the determinants that have been used previously (Wanzenböck et al., 2014, 2015). Lastly, with respect to the effect of different innovation policy instruments, we show that these instruments not only increase research activity, but also positively affect international collaboration and embeddedness. This dimension is so far neglected in the discussion of the effect of different policy instruments. Thereby we add public procurement to the already established set of instruments and extend the discussion about the composition of the instrument mix for renewable energies (Flanagan et al., 2011; Rogge and Reichardt, 2016).

As with any research, this chapter is not without limitations and some of them might affect the interpretation of our results more than others. Publication data is far from perfect to measure collaboration: the intensity of collaboration is not accounted for, collaboration might not be properly reflected in co-authorship, or affiliation information is incomplete (for further issues with publication data, see Katz and Martin, 1997; Laudel, 2002; Glänzel and Schubert, 2005). Unfortunately, our analysis suffers from incomplete data, especially concerning R&D expenditures and demand pull instruments. These policy indicators are only available for a small – and certainly not random – subset of countries. Increasing the scope of data coverage would increase the reliability of our results. Finally, since we focus on a highly specific technology in which policy plays an important role, we expect that especially our estimates on national policies are sensitive to the technology which limits generalizability.

In future research it would be important to understand how the different policies interact within the broader policy mix to affect network structures. This would require to take a deeper look at the policy strategies and goals as well as the consistency and stringency of the mix (Rogge and Reichardt, 2016). Another issue regards the interplay between meso structure and macro embeddedness. Here, we assumed that this is a one-directional relationship where the meso influences the macro. However, there might well be a reverse link so that macro embeddedness influences the way linkages on the meso level are formed. A thorough analysis of these feedbacks and interdependencies remains another challenge for future inquiry.

5.6 Appendix

5.6.1 Ranking of countries

Table 5.6: Rank of the degree of the top 15 countries.

	Rank 2003-05	Degree 2003-05	Degree 2008-10	Degree 2013-15	Δ Rank 03-05–08-10	Δ Rank 03-05–13-15	Rank 2013-15
Germany	1	45	65	76	0	-2	3
France	2	43	54	73	-1	-3	5
USA	3	42	63	87	1	2	1
United Kingdom	4	36	53	78	0	2	2
Italy	5	34	44	68	-1	-1	6
Japan	7	30	42	64	0	-1	8
The Netherlands	7	30	34	54	-7	-10	17
Spain	9	26	47	73	4	4	5
Sweden	9	26	36	50	-1	-11	20
Switzerland	10	24	39	55	1	-4	14
Russia	11	22	25	49	-7	-11	22
Belgium	12	21	31	56	-4	0	12
Australia	13	19	27	54	-4	-4	17
China	15	18	35	65	3	8	7
Austria	15	18	23	54	-7	-2	17

Table 5.7: Rank of the degree of the 15 most increasing countries.

	Rank 2003-05	Degree 2003-05	Degree 2008-10	Degree 2013-15	Δ Rank 03-05–08-10	Δ Rank 03-05–13-15	Rank 2013-15
Qatar	133	na	1	28	28	89	44
United Arab Emirates	133	na	3	27	51	87	46
Serbia	133	na	10	19	85	73	60
Malaysia	91	0	18	50	60	71	20
Kazakhstan	133	na	1	15	28	65	68
Philippines	133	na	1	11	28	58	75
Luxembourg	133	na	8	10	76	56	77
Norway	91	0	15	32	52	51	40
Costa Rica	133	na	1	5	28	45	88
Ghana	133	na	1	5	28	45	88
Croatia	91	0	7	25	31	39	52
Saudi Arabia	49	5	18	61	18	39	10
Iraq	91	0	2	25	2	39	52
Burkina Faso	133	na	1	4	28	38	95
Nepal	133	na	1	4	28	38	95

5.6.2 Descriptives small dataset

Table 5.8: Descriptive statistics of the periods 1997–1999 until 2013–2015.

	Min.	Median	Mean	Max.	SD	Obs.
Dependent variables						
Degree$_t$	0.000	11.000	16.535	87.000	16.219	1231
Flow Betweenness$_t$	0.000	336.000	1498.846	45521.000	3640.156	1231
K-Core$_t$	0.000	9.000	9.717	27.000	7.035	1231
National network variables						
Mean Strength$_{t-3}$	0.000	1.000	1.490	16.264	1.716	1231
Degree Centralization$_{t-3}$	0.000	0.133	0.134	0.667	0.113	1231
Share in Main Component$_{t-3}$	0.060	0.475	0.462	1.000	0.218	1231
National policy variables						
Kyoto Ratification$_{t-1}$	0.000	1.000	0.636	1.000	0.481	1231
Cum. Number of Satellites$_{t-1}$	0.000	0.000	76.253	3412.000	426.535	1231
Installed PV Capacity$_{t-1}$	0.000	1.423	2.331	9.138	2.442	284
PV R&D Exp.$_{t-1}$	0.000	8.239	24.297	395.660	43.405	284
PV R&D Exp. interp. Dummy$_{t-1}$	0.000	0.000	0.092	1.000	0.289	284
Controls						
GDP per Capita$_{t-1}$	428.150	15585.486	20702.082	164136.454	17460.171	1231
EU Membership$_{t-1}$	0.000	0.000	0.265	1.000	0.441	1231

5.6.3 Correlation tables

Table 5.9: Correlation table for the periods 1980–1982 until 2013–2015.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Degree_t	1.000													
2	$\text{Flow Betweenness}_t$	0.782	1.000												
3	K-Core_t	0.873	0.580	1.000											
4	Publication_t	0.598	0.824	0.425	1.000										
5	$\text{Mean Strength}_{t-3}$	0.707	0.576	0.663	0.599	1.000									
6	$\text{Degree Centralization}_{t-3}$	0.352	0.178	0.447	0.149	0.566	1.000								
7	$\text{Share in Main Component}_{t-3}$	0.206	0.242	0.190	0.279	0.503	0.435	1.000							
8	$\text{Kyoto Ratification}_{t-1}$	0.385	0.210	0.543	0.103	0.296	0.300	0.227	1.000						
9	$\text{Cum. Number of Satellites}_{t-1}$	0.196	0.180	0.094	0.178	0.094	0.105	-0.034	-0.088	1.000					
10	$\text{Installed PV Capacity}_{t-1}$	0.834	0.758	0.744	0.675	0.666	0.269	0.530	0.528	0.124	1.000				
11	$\text{PV R\&D Exp.}_{t-1}$	0.214	0.356	0.010	0.503	0.198	-0.111	0.002	-0.130	0.635	0.254	1.000			
12	$\text{PV R\&D Exp. interp. Dummy}_{t-1}$	0.131	0.089	0.106	0.093	0.143	0.073	0.132	0.025	0.161	0.096	-0.019	1.000		
13	$\text{GDP per Capita}_{t-1}$	0.446	0.280	0.405	0.180	0.311	0.150	0.045	0.128	0.067	0.380	0.125	0.107	1.000	
14	$\text{EU Membership}_{t-1}$	0.298	0.144	0.234	-0.004	0.139	0.121	0.010	0.069	-0.110	-0.002	-0.254	-0.012	0.324	1.000

Table 5.10: Correlation table for the periods 1997–1999 until 2013–2015.

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Degree_t	1.000												
2	$\text{Flow Betweenness}_t$	0.787	1.000											
3	K-Core_t	0.859	0.573	1.000										
4	$\text{Mean Strength}_{t-3}$	0.682	0.561	0.628	1.000									
5	$\text{Degree Centralization}_{t-3}$	0.288	0.139	0.378	0.530	1.000								
6	$\text{Share in Main Component}_{t-3}$	0.178	0.235	0.122	0.515	0.446	1.000							
7	$\text{Kyoto Ratification}_{t-1}$	0.265	0.143	0.411	0.184	0.186	0.141	1.000						
8	$\text{Cum. Number of Satellites}_{t-1}$	0.229	0.210	0.126	0.119	0.142	0.021	-0.091	1.000					
9	$\text{Installed PV Capacity}_{t-1}$	0.810	0.724	0.676	0.561	0.050	0.466	0.363	0.182	1.000				
10	$\text{PV R\&D Exp.}_{t-1}$	0.485	0.559	0.183	0.381	-0.121	0.258	-0.114	0.668	0.466	1.000			
11	$\text{PV R\&D Exp. interp. Dummy}_{t-1}$	0.094	0.062	0.046	0.118	0.062	0.094	-0.050	0.229	0.054	0.030	1.000		
12	$\text{GDP per Capita}_{t-1}$	0.451	0.281	0.422	0.307	0.123	0.077	0.106	0.051	0.202	0.208	0.088	1.000	
13	$\text{EU Membership}_{t-1}$	0.379	0.180	0.335	0.186	0.151	0.067	0.140	-0.095	-0.026	-0.258	-0.032	0.339	1.000

5.6.4 Regression results for the periods 1997–1999 until 2013–2015

Table 5.11: OLS-panel regression results for country embeddedness, periods 1997–1999 until 2013–2015.

	Degree			Flow Betwenness			K-Core		
	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3a	Model 3b	Model 3c
Mean Strength$_{t-3}$	2.183***	-0.066	0.117	667.201***	288.217	451.481	0.726***	-0.051	-0.132
	(0.416)	(0.322)	(0.308)	(256.654)	(410.184)	(419.523)	(0.152)	(0.157)	(0.168)
Degree Centralization$_{t-3}$	-14.106***	-12.199***	-10.821**	-5142.913***	-11189.149**	-9478.380**	-2.923**	1.691	0.984
	(2.566)	(4.432)	(4.437)	(1463.247)	(5421.651)	(4630.801)	(1.300)	(1.468)	(1.314)
Share in Main Component$_{t-3}$	6.440***	8.402***	6.439**	1977.474**	3423.751**	1604.725	0.205	-0.352	0.538
	(1.979)	(2.629)	(2.655)	(821.927)	(1645.123)	(1646.171)	(0.766)	(0.769)	(0.920)
Kyoto Ratification$_{t-1}$	-0.064	1.656*	1.669*	-211.367	1335.970	1299.211	-0.139	-0.956	-0.956*
	(0.766)	(0.898)	(1.001)	(380.121)	(1034.839)	(1093.581)	(0.380)	(0.584)	(0.543)
Cum. Number of Satellites$_{t-1}$	0.028***	0.013***	0.012**	44.798***	48.245***	41.705***	0.002	-0.004**	-0.002**
	(0.011)	(0.004)	(0.005)	(12.501)	(3.217)	(4.060)	(0.003)	(0.002)	(0.001)
Installed PV Capacity$_{t-1}$			0.620**			525.582*			-0.271**
			(0.263)			(273.996)			(0.110)
PV R&D Exp.$_{t-1}$			-0.012***			15.812**			0.000
			(0.004)			(6.843)			(0.001)
PV R&D Exp. interp. Dummy$_{t-1}$			0.237			-416.041			-0.032
			(1.253)			(1573.139)			(0.223)
GDP per Capita$_{t-1}$	0.000	0.000	0.000	0.002	-0.115	-0.086	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.034)	(0.100)	(0.083)	(0.000)	(0.000)	(0.000)
EU Membership$_{t-1}$	-1.881			-1020.279***			0.425		
	(1.877)			(333.918)			(0.843)		
Country fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj. R^2	0.216	-0.002	0.028	0.293	0.348	0.388	0.013	0.013	0.066
n	99	18	18	99	18	18	99	18	18
T	17	17	17	17	17	17	17	17	17
N	1231	284	284	1231	284	284	1231	284	284
df	1109	244	241	1109	244	241	1109	244	241

Robust standard errors in parentheses. Sig. at *** 0.01, ** 0.05, * 0.1 level.

Chapter 6

Flexibility in the selection of patent counts: Implications for p-hacking and policy recommendations

Co-authored with Stephan B. Bruns

6.1 Introduction

Patent counts have a long tradition in economics as a measure of inventive and innovative activity and to elaborate on technological change. Specifically, patent counts are used to understand drivers of innovative activities, how innovative activities in turn influence economic activities and, more generally, to analyze knowledge-technology relationships including the evolution of technologies (see Pavitt, 1985; Basberg, 1987; Griliches, 1990; Nagaoka et al., 2010; Hall and Harhoff, 2012, for surveys of the literature). However, there is little consensus on how relevant patents can be identified and which quality dimension of patents should be considered. In this study, we explore how the flexibility in the selection of patent counts transmits to uncertainty in econometric estimates of policy effects.

Patent counts are frequently used to evaluate policies designed to foster inventive and innovative activities.[1] Based on the induced innovation concept (Hicks, 1932; Acemoglu, 2002), different kinds of policy instruments can be implemented to induce such activities. These instruments can be distinguished in technology push and demand pull instruments (Bush, 1945; Schmookler, 1966; Mowery and Rosenberg, 1979). The effects of these policy instruments on patent counts have been studied especially for environmentally friendly technologies. Recent

Acknowledgments: We are grateful to Nick Johnstone for providing us data and estimation code for Johnstone et al. (2010) and to Volker Hoffmann and Michael Peters for providing us data on the policy variables of Peters et al. (2012). Previous drafts of the chapter were presented at the OECD IP Statistics for Decision Makers Conference 2015 in Vienna, at the Ruhr-Universtiy Bochum, the 10th European Meeting on Applied Evolutionary Economics in Strasbourg and the ZEW Mannheim Energy Conference 2017. We are grateful for discussions by and with Rudi Bekkers, Uwe Cantner, Holger Graf, Maximilian Göthner, Dietmar Harhoff, Christian Pigorsch, Muhammad Faraz Riaz, Karoline Rogge.

[1] Inventive and innovative activities describe different parts of the innovation process. While inventive activity refers to the discovery or creation of new knowledge, which results, for example, in a patent, the innovation brings this discovery to the market. In the following we refer to inventive activity if it is related to patented output and to innovation if the process is considered.

contributions are, for example, Aghion et al. (2016) who use patent counts to show that higher tax-inclusive fuel-prices spur inventive activities in the clean auto industry. Calel and Dechezleprêtre (2016) use patent counts to analyze if the European Union Emissions Trading System induces inventions in low-carbon technologies.

With respect to climate change, solar energy technologies are of particular importance mirrored by extensive and differentiated policy support that these technologies received to induce inventive and innovative activities. Solar energy technologies can be divided into photovoltaics (PV) and concentrated solar power (CSP). There are two seminal contributions to this literature that are at the center of our analysis. Johnstone et al. (2010) uses patent counts for solar energy technologies (PV and CSP combined) and tests how different policy instruments affect inventive activities. Peters et al. (2012) explicitly test if domestic or foreign technology push or demand pull policies influence inventive activities in photovoltaics.[2]

While Griliches (1990) urgently warns about the possible misuse of patent data, there is no systematic analysis how the flexibility in the selection of patent counts can influence econometric analysis.[3] The patent selection process can be divided into two parts: The search strategy and the quality dimension of patents. The search strategy refers to how patents are selected based on their content. Here, several approaches are possible. The most frequent ones use either a classification system or use keywords to search for in the patent documents. Thereby the classifications or keywords target a specific technology, which is an important part of the search strategy. The quality of patents refers to the skewed distribution of patent value and the large number of patents with low novelty contents (e.g. Harhoff et al., 2003). Several approaches are possible to attain a minimum level of patent quality for economic analysis (e.g. Harhoff et al., 2003; Squicciarini et al., 2013). We focus in the following on the most prominent and basic approach that distinguishes patents into six quality groups based on their filing and granting procedure (i.e. priority filings, granted patents, claimed priorities, PCT filings, transnational filings, and triadic filings). As different combinations of search strategies and quality dimensions of patents may appear plausible in analyzing policy effects, uncertainty in estimated policy effects is likely to be introduced.

This uncertainty in estimated policy effects may ease to engage in what was recently coined *p*-hacking (Simonsohn et al., 2014). Hacking the *p*-value refers to uncertainty in model selection which can be used to select models that 'work', that is, they provide estimates that fulfill the research's prior and usually support a hypothesis, while those models that did not 'work' remain unreported (Bruns and Ioannidis, 2016). Hacking the *p*-value is eased if flexibility in patent selection approaches transmits to a wide range of estimated policy effects from which statistically significant and hypothesis-confirming estimates can be selected. Presumably, only a small share of researchers is willing to engage in a deliberate search for estimates that 'work'. But researchers face substantial uncertainty which patent selection approach is best to proxy inventive activity in a specific technology or industry and, thus, it is natural to explore the results for multiple patent selection approaches. It becomes *p*-hacking if the researcher is influenced by

[2] With respect to renewable energy technologies in general, Johnstone et al. (2010) also analyzes other types of renewable energy technologies. Several follow up studies exist to further understand policy effects on patent counts. For example, Dechezleprêtre and Glachant (2014) study the effect of domestic and foreign demand pull policies for wind power, Nesta et al. (2014) investigate the effect of polices and competition for renewable energies in general and Costantini et al. (2015b) analyze the effects of technology push and demand pull policies on biofuel patents.

[3] There is a debate in the literature how relevant patents can be selected. Several recommendations exist concerning the search strategy and the quality dimension of patents. However, there is neither a consensus nor a systematic evaluation how the selection approach of patents influences the econometric results. So far, only Colombelli et al. (2015) point out the possibility of a bias due to different selection approaches, while de Rassenfosse et al. (2014) show how focusing only on filings from one patent office can bias econometric results.

motivated reasoning (Kunda, 1990) and only reports the estimated policy effects that ‘work’ as (s)he believes them to be the best proxies after seeing the estimates.

Empirical evidence suggests that such selective reporting is widespread in empirical economics. Brodeur et al. (2016) use more than 50,000 estimates extracted from the American Economic Review, Quarterly Journal Economics and Journal of Political Economy to demonstrate that 10-20% of the marginally significant *p*-values are inflated, that is, non-significant *p*-values are inflated to become marginally significant p-values. Ioannidis et al. (2017) show that many studies in economics suffer from low power and point estimates are overstated to obtain statistical significance.

The large flexibility in the selection of patent counts and the possibility of *p*-hacking has several implications for policy makers, who use econometric studies to design or justify policy interventions. *p*-hacking may lead to statistically significant policy effects, although a genuine policy effects is absent, or it may overstate the effect of a policy intervention potentially resulting in misallocation. Since patent data is frequently used to assess policy interventions that aim to increase inventive activity, a careful assessment is needed how the selection of patent counts can influence such policy evaluations.

The contribution of this article is threefold. First, we analyze to what extend patent counts of various patent selection approaches vary by using solar energy technologies as an example. We identified 51 different search strategies for solar energy technologies in the literature. These different search strategies aim to be generic in capturing the inventive activity in the different solar energy technologies (PV, CSP, or both). We show how patent counts obtained by these 51 search strategies differ in magnitude, overlap and country coverage. Second, we analyze to what extend the flexibility in the selection of patent counts transmits to variation of econometric estimates of policy effects with direct implications for *p*-hacking and evidence-based policy. To this end, we use as best-practice research designs the two main studies that analyze policy effects on inventive activity in solar energy technologies: Johnstone et al. (2010) and Peters et al. (2012). In these best-practice research designs, patent counts are used as dependent variables and various policy variables are considered as explanatory variables. We estimate both best-practice research designs for all 306 types of patent counts (51 search strategies and for six patent quality dimensions each). We characterize the distribution for each estimated policy effect by using extreme-bounds analysis (Leamer, 1983; Levine and Renelt, 1992), the share of positive estimates, and vibration plots that relate the size of the estimated coefficient to statistical significance (Patel et al., 2015). Third, we analyze which characteristics of the patent selection approaches determine the sizes of estimated policy effects using meta-regressions (Stanley and Jarrell, 1989).

The magnitudes of patent counts obtained by the 51 different search strategies for solar energy patents show severe differences. The overlap of the selected patents across the search strategies varies at the technological level, especially between PV and CSP, while the country coverage is nearly uniform across search strategies. The different patent quality dimensions seem to only affect the magnitude of patent counts, while relative patent counts across search strategies tend to be robust. The sensitivity analysis reveals that the different selection approaches result in substantial uncertainty regarding the sign, size, and statistical significance of many estimated policy effects for the two best-practice research designs. We obtain for nearly all policy variables positive as well as negative estimates that are statistically significant. When we consider subsets of the selection approaches based on quality considerations such as journal impact factor, citations of the underlying study, or correction for outliers, then for some of the policy effects the uncertainty is reduced. In fact, our analysis reveals that the core findings of the two studies that are used as best-practice research designs can be supported in terms of the signs of the core estimated policy effects. Moreover, our results reveal that characteristics of the search strategies are key determinants of the sizes of estimated policy effects.

Our results demonstrate the need for more sensitivity analysis and a careful motivation and documentation of why a specific search strategy and patent quality dimension is chosen. This will help to improve reliability and credibility of econometric evaluations of policy instruments that aim to foster inventive activities and is an essential step towards evidence-based policy.

The chapter proceeds by describing the two main elements of patent selection approaches. Section 6.3 describes and analyzes the 51 different selection approaches that we identified from the literature. Section 6.4 presents our empirical strategy and the results of our assessment regarding uncertainty in estimated policy effects and the determinants of policy effect sizes. Section 6.5 discusses our results and the last Section concludes.

6.2 Selection of patent counts

6.2.1 Search strategies for technology specific patents

Patent selection approaches consist of two elements: the search strategy that aims to be generic for a given technology and the patent quality dimension that describes the value of the patent in terms of technological or economic value.

The search strategy defines how the relevant patents for a specific technology or product can be selected from patent databases that are managed by various patent offices. Patent offices manage their databases to fulfill their needs – to search for prior art and to clarify the relevance and novelty of the patents they examine.[4] The patent search for specific technologies, products, or processes for economic analysis is possible by several strategies. The common strategies to select patents are based on patent classification systems, keywords, or their combination (Eisenschitz and Crane, 1986; Dirnberger, 2011; Xie and Miyazaki, 2013).[5] However, each strategy has several advantages and disadvantages which need to be considered when selecting patent counts.

A patent office uses a classification system to support the examination process and classifies patents according to underlying technological principles (Jaffe and Trajtenberg, 2002). Common classification systems are the International Patent Classification (IPC) managed by the World Intellectual Property Organisation (WIPO) or the recently introduced Cooperative Patent Classification System (CPC).[6] Classification systems are not designed to distinguish specific products or fulfil the economist's needs. This causes problems analyzing specific technologies, products, or processes which combine different technological principles. For the use of classification systems to search for patents, the respective classifications which describe the specific product or process need to be identified. Here, some issues emerge, since a technological principle can be used for different products or describes different phenomena (Vijvers, 1990; Costantini et al., 2015a).[7] Using classifications might include patents which are not related to the product or process under consideration. This can be referred to as a type I error. Additionally, it is also possible that a

[4] Besides the databases managed by patent offices there are several commercial databases specialized in patent search (Palangkaraya, 2010).

[5] Besides these strategies, there are several other ways, for example, classification co-occurrences, use of a predefined set of patents to train an algorithm to identify specific keywords, or use of citations from a specific set to retrieve previous patents (Benson and Magee, 2013; Abbas et al., 2014).

[6] There are further classification systems introduced by patent offices, see Held et al. (2011) or Wolter (2012) for comparisons.

[7] For example, the principle of light absorption is characteristic for PV; but also digital cameras or other products refer to this technological principle.

product or process combines different technological principles and if these classifications are not considered, relevant patents are missing. This can be referred to as a type II error.[8]

Keywords are frequently used to search for patents as well. If a product or technology can be described by a set of technology specific unique keywords, this approach can deliver reliable results. Several issues exist, since keywords can be used in various technologies or products not related to the technology under consideration, resulting in a type I error.[9] Furthermore, a type II error occurs if patent documents are written in a way to avoid specific keywords to keep the invention hidden from competitors. Language differences between patent offices can also reduce the number of selected patents if the keywords do not account for multiple languages or different terminologies used in different countries (Montecchi et al., 2013). In addition, patent databases are not always complete so that missing titles, abstracts, or other content do not allow searching in all relevant patents. The combination of classifications and keywords can reduce type I errors, but cannot avoid type II errors.

6.2.2 Patent filing procedures as indicator of patent quality

The second element of patent selection approaches is the quality dimension. Patents contain codified knowledge, which should be new, non-obvious and applicable. However, the economic and technological value or quality of this knowledge is hard to determine (Griliches, 1990). Several studies tried to estimate the values or qualities of patents (e.g. Schankerman and Pakes, 1986; Harhoff et al., 2003) and usually find a skewed distribution with a few very valuable patents and many patents with no or little economic value or technological novelty. There are several indicators which can be used to assess patent quality (Squicciarini et al., 2013). One basic indicator is the patent office in which the patent is filed and if it is granted. Since filing in specific or multiple patent offices is expensive, a patent of higher quality or economic value will go through specific filing routes. This is especially relevant if patent counts are used for international comparisons of inventive activities, where heterogeneity in patent offices can bias results and, thus, patents should be counted on a comparable quality basis (Lanjouw et al., 1998; Dernis et al., 2001; van Pottelsberghe de la Potterie, 2011). In the following, we discuss the six different demarcations of patents that are used in this study and their potentials to infer on the qualities and international comparability of inventive outputs.

The baseline to count patents is to consider all **priority filings** (first filings) filed at national patent offices. Several shortcomings are attributed to this approach. There are differences between the national patent offices, which can influence the propensity to patent, such as application fees and procedures. Due to this, patents can be quite heterogeneous in terms of quality if different costs to file a patent exist (Atal and Bar, 2010; van Pottelsberghe de la Potterie, 2011; de Rassenfosse and van Pottelsberghe de la Potterie, 2011, 2013).[10]

Granted patents meet some basic quality criteria, since they successfully underwent examination at a national patent office. The criteria to grant a patent, however, differ between

[8] Other problems relate to the classification system, such as changes over time or that patent examiner misclassify a patent or assign too many or too less classes to a patent.

[9] For example, silicon is one of the widely-used materials in PV cells, but it is also used in other semiconductor devices. Furthermore, the product or process can be a non-crucial part of an invention and would be considered as well. In the case of PV, it could be that an electronic device uses a PV cell as power source, even though the invention does not contribute to the PV development at all.

[10] Furthermore, this approach follows the implicit assumption that all the patents, which are applied at a certain national office are invented in the respective country. However, this is not always the case and a geographical bias exists, such that especially many applications filed at the United States Patent and Trademark Office are invented in neighboring countries (Griliches, 1990; Harhoff et al., 2009; OECD, 2009). To reduce such bias in international comparisons, patents can be attributed to countries based on the inventor's residence (de Rassenfosse et al., 2013).

countries, which is reflected in the granting rates (Ordover, 1991), variation in the examination procedures (Lemley and Sampat, 2012), and granting decisions that are not equal across patent offices (Palangkaraya et al., 2011; de Rassenfosse et al., 2016). See also (Eckert and Langinier, 2014) for further issues related to the granting processes and international comparability.

Claimed priorities refer to patents which have one or several secondary filings at other patent offices claiming a priority filing under the Paris Convention (OECD, 2009). The applicant will only consider an application in a second or more jurisdictions if the patent has the potential to generate revenues to cover these additional costs (OECD, 2009; Haščič and Migotto, 2015). This results in a patent family with members from at least two patent offices. The size of the patent family is a frequently used indicator of patent value (Putnam, 1996; Lanjouw et al., 1998; Harhoff et al., 2003).

PCT filings are applications under the Patent Cooperation Treaty (PCT) which allows filing a unified application at designated national offices. PCT was introduced in 1970, but it took some time until the procedure was widely accepted and especially in early years only a few applications were filed (OECD, 2009). PCT applications can be of higher value than applications at only the national patent office and allow better international comparability (Grupp and Schmoch, 1999; Guellec and van Pottelsberghe de la Potterie, 2000).

Transnational filings comprise patents either filed via a PCT procedure or filed at the European Patent Office (EPO) (Frietsch and Schmoch, 2010). Both ways of application can impose higher costs on the applicant than national applications and this reduces low-quality applications. They also allow for international comparisons.

Triadic filings are patents with family members filed at the Japan Patent Office (JPO) and the EPO and granted at the United States Patent and Trademark Office (USPTO) (Grupp, 1996; Dernis et al., 2001).[11] These patents are considered of high value due to the imposed costs of filing in these three jurisdictions (Dernis and Khan, 2004; OECD, 2009). They are frequently used for international comparisons, since they have no home country bias (Criscuolo, 2006).

6.3 Selections of patent counts for solar energy technologies

There is a growing interest in the development of solar energy technologies. Numerous studies use patent data to understand how solar energy technologies develop over time, which determinants influence their developments and especially how policy effects influence the innovation process. Such studies use patent counts or derive further indicators based on patent counts, but they differ in the search strategy used to select the respective patent data.[12]

Solar energy technologies can be divided into two very different technologies. Photovoltaics (PV) uses a photovoltaic cell for a direct conversion of sunlight into electricity. Concentrated solar power (CSP) uses a thermodynamic cycle where a collector stores thermal energy in an absorber to utilize the heat for (residential) heating or to use a heat engine to convert heat into electric energy, usually by steam power. Although PV and CSP are often referred to as solar energy technologies, both technologies differ in their applicability, scalability and costs (Peters et al., 2011). The underlying technological principles differ significantly and this results in differences in the innovation process. The patent search needs to consider these technological differences, especially if patent counts are used for country comparisons, since some countries

[11] There is a discussion about relaxing this strong definition and include national patent offices in Europe or Asia as well (Sternitzke, 2009).

[12] However; there are two frequently used search strategies. The WIPO provides a so called “Green Inventory” which states a list of IPCs for PV and CSP. Furthermore, the CPC has distinct classes for PV and CSP (Veefkind et al., 2012).

focus on CSP, others on PV, or on both technologies. This translates also to policy evaluations, since countries can implement policies which are not technological neutral.

We performed a literature search and identified 51 distinct search strategies that are used to select solar energy technology patents (see Table 6.1 and Appendix 6.7.1).[13]

These selection approaches differ with respect to the search strategy employed (classifications, keywords, or both) and the solar energy technology considered (PV, CSP, or solar). Search strategies intend to be generic for a given technology as documented by several search strategies being used in multiple studies (see Appendix 6.7.1). In Table 6.1 we present the search strategies found in the literature disaggregated by the search strategies employed and technologies considered.

Table 6.1: Number of search strategies used in the literature.

	PV	solar	CSP	Total
Classifications	7	12	6	25
Keywords	11	3	2	16
Both	9	0	1	10
Total	27	15	9	51

We use the Worldwide Patent Statistical Database (PATSTAT) (EPO, 2014) to select patent counts based on the 51 search strategies. For each search strategy, we obtain patent counts for the six patent quality dimensions outlined in Section 6.2.2 (priority filings, granted patents, claimed priorities, transnational, PCT, as well as triadic filings).[14] We restrict the data to the period 1978-2005 and to 23 countries[15] to be consistent with the two studies that we use as benchmark research designs for our analysis (see Section 6.4.1). We present summary statistics for the overall patent counts of the different selection approaches in Table 6.2. Figure 6.1 depicts the number of priority filings for each search strategy. They are both based on patent counts aggregated over all 23 countries and the period 1978–2005.

Table 6.2: Summary statistics and correlations for 51 search strategies.

	No. of patents					Correlations					
	min	median	mean	max	sd	Priority	Granted	Claimed	Transnat.	PCT	Triadic
Priority	2,942	20,946	56,426	714,877	135,769.7	1					
Granted	1,714	7,511	20,695.6	266,964	50,625.6	0.9997	1				
Claimed	737	3,762	11,912.6	160,060	30,553	0.9991	0.9996	1			
Transnat.	440	2,377	5,837.7	64,619	12,530.9	0.9938	0.9944	0.9943	1		
PCT	290	1,411	3,210.3	34,083	6,629.4	0.9913	0.9926	0.9925	0.9994	1	
Triadic	110	1,109	3,393.6	42,822	8,237.3	0.9967	0.9973	0.9977	0.9983	0.9968	1

[13] We consider only search strategies which used classification (IPC or CPC), keywords or both. We did not consider strategies using classification or keyword co-occurrences (e.g. Liu et al., 2011; Choe et al., 2013), USPTO classifications (e.g. Popp, 1997; Huang et al., 2011; Benson and Magee, 2013; Dong et al., 2013; Guan and Yan, 2016), parts of the technologies (e.g. Tseng et al., 2011; Lizin et al., 2013; Chen and Pham, 2014) and in some cases strategies are not provided (e.g. Watanabe et al., 2001; Marinova and Balaguer, 2009; Breyer et al., 2013). Certainly, there are more search strategies used in the literature.

[14] We selected patents by first searching for the respected classifications and/or keywords in all patents in the database and then selected based on the patent's DOCDB Patent Family the priority patent. This approach allows us to capture patents where title or abstract are only available for family members. Patents are assigned to a country based on the patent office of the priority filing. Other approaches use the inventor's address, but not all patents contain this information. There are concerns that using the patent office as a proxy for location of inventive activity, however for our means it is sufficient, since a possible bias would be present across all selection approaches.

[15] These countries are: Australia, Austria, Belgium, Canada, Denmark, France, Finland, Germany, Greece, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Republic of Korea, Spain, Sweden, Switzerland, United Kingdom, and United States of America.

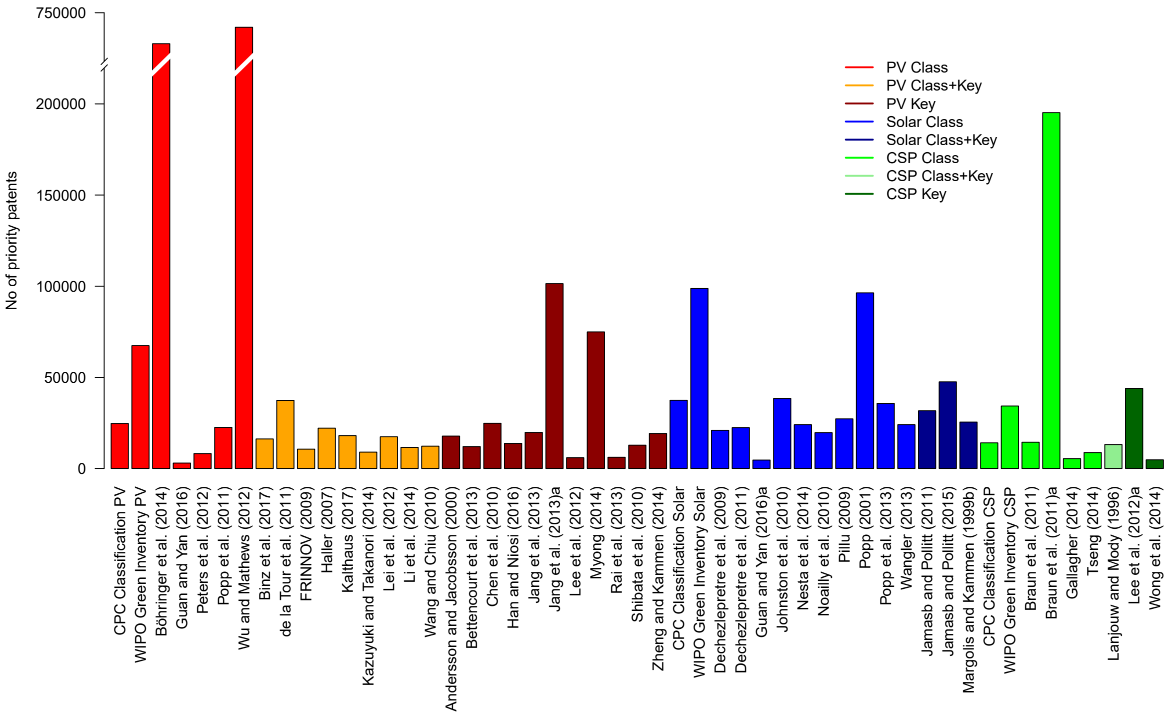


Figure 6.1: Patent counts for priority filings of the 51 search strategies.

Figure note: ‘Class’ refers to the use of IPC or CPC classifications and ‘Key’ refers to the use of keywords.

The summary statistics in Table 6.2 as well as Figure 6.1 illustrate huge differences between the search strategies. For priority filings, the maximum number of patents is 243 times larger than the minimum indicating severe flexibility in the number of patents that can be obtained by different search strategies. Particularly, search strategies that use classifications can result in extreme patent counts as indicated by both the maximum and minimum of patent counts stemming from search strategies based on classifications (Wu and Mathews (2012) and Guan and Yan (2016)). The number of patent counts selected varies substantially across different patent quality dimensions, but the numbers of patents across patent quality dimensions are almost correlated by one, indicating that while the total number of identified patents varies with patent quality the relative number of patents identified by a given search strategy remains constant (see Appendix 6.7.2 for triadic patents and the Supplementaries 6.8.1 for the other quality dimensions).

Moreover, the degree of overlap between the sets of identified patents for the various search strategies differ as shown in Figure 6.2. We measure overlap between two search strategies by the number of patents that are identified by both search strategies and then divide by the number of patents identified by the first search strategy. For example, the overlap of patents between a search strategy based on the CPCs for PV and a search strategy based on the WIPO Green Inventory for PV is 94% with respect to the total of patents in the CPCs for PV and only 34% with respect to the WIPO Green Inventory for PV. This indicates that a search strategy based on the WIPO Green Inventory for PV contains nearly all PV patents, which can be selected by the CPCs for PV, but the WIPO Green Inventory for PV contains a large portion of patents which are not considered in the CPCs for PV.

The geographical distribution of patents identified by the 51 different search strategies is depicted as the share of priority patents per country in Figure 6.3. Most patents are filed at the

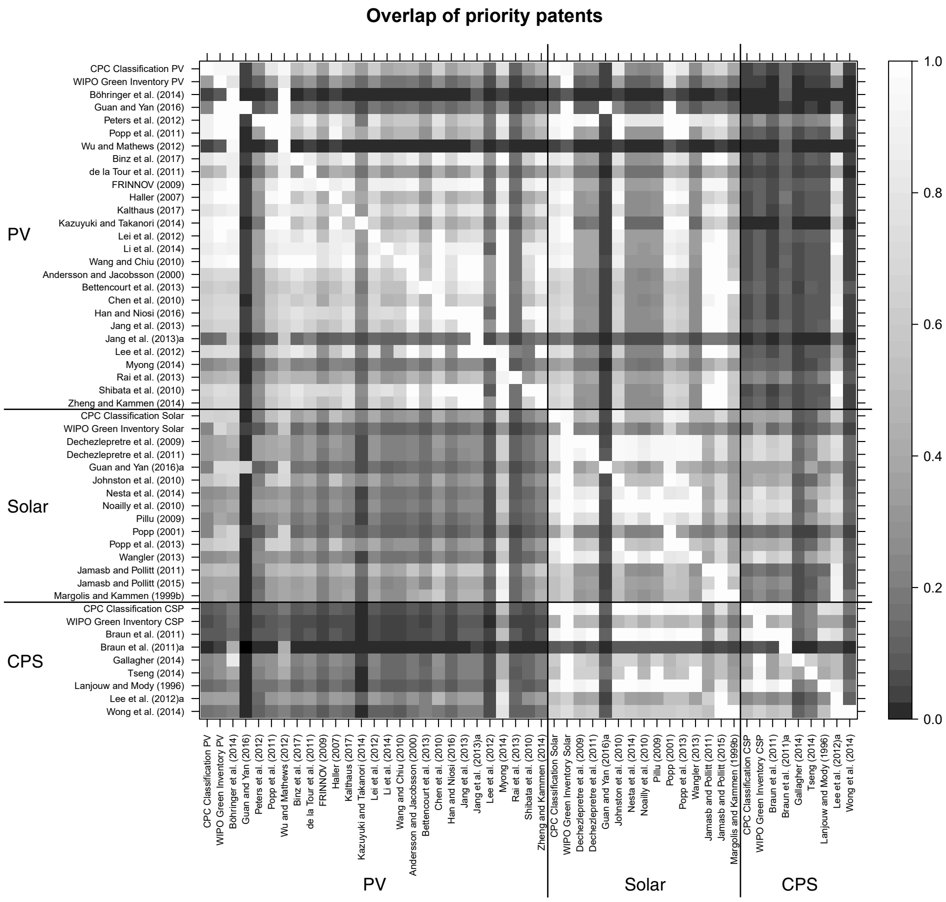


Figure 6.2: Overlap of priority filings between the 51 search strategies.

Figure note: Each horizontal line is calculated by $\frac{PatentsA \cap PatentsB}{PatentsA}$ where PatentsA refers to the search strategy on the horizontal axis and PatentsB to the different search strategies on the vertical axis. The lower the overlap between two search strategies, the darker the corresponding area.

Japan Patent Office across all search strategies (more than 65% on average). This high share is related partly to the filing procedure at the Japan Patent Office, which allowed only one claim per patent until 1988 (Sakakibara and Branstetter, 2001). Other countries with a considerable average share are the US (14%), Germany (10%), South Korea (3%), France (3%) and Great Britain (1%). However, if triadic patents are considered (see Figure 6.10 in Appendix 6.7.2), the US has the highest average share with 37% followed by Japan (27%), Germany (17%), France (6%), Great Britain (3%) and South Korea (2%). For the average share of all patent quality dimensions per country across the 51 selection approaches see Figure 6.11 in Appendix 6.7.2. Comparing average country shares between the solar energy technologies shows that the Japanese share is highest for PV and lowest for CSP search strategies, while for other countries the shares are either stable or increase slightly for solar and CSP. This pattern is persistent across patent quality dimensions.[16]

[16] The average share for Japanese priority patents is 70% for PV, 62% for Solar and 56% for CSP. In the case of triadic patents, the Japanese share is 29% for PV, 27% for Solar and 22% for CSP.

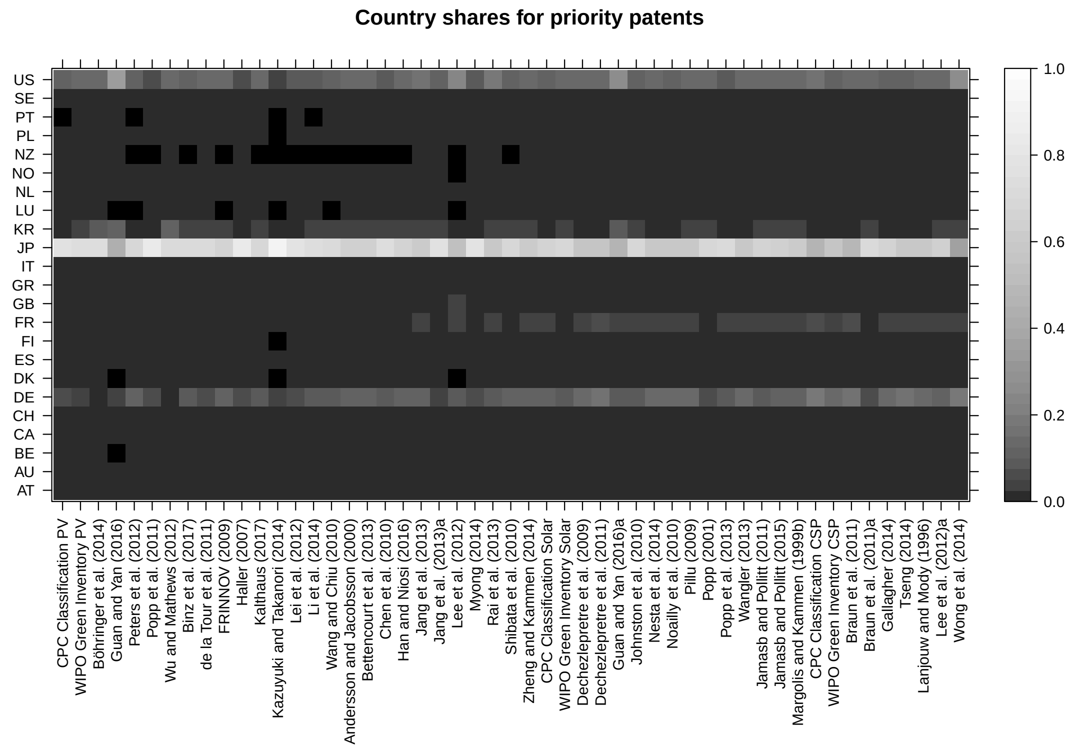


Figure 6.3: Share of countries for priority filings between the 51 search strategies.

Figure note: The horizontal axis refers to the 23 countries in our sample while the vertical axis depicts the different search strategies. The darker the area, the lower is the share of a country in the patent selection. Black represents no patent at all.

6.4 Assessing uncertainty in estimated policy effects

6.4.1 Benchmark research designs

We use the research designs of two leading studies in the field of policy evaluations of renewable energy policies as benchmark research designs for our analysis. These studies are Johnstone et al. (2010) and Peters et al. (2012) which are cited more than 700 and 100 times according to google scholar, respectively.[17] Both are key contributions to the analysis of policy effects on inventive activity, especially for the demand pull – technology push nexus. Patent counts are used in both studies to measure inventive output which is induced by different policy variables. We use these studies to systematically analyze the variation of estimates that can be obtained due to the large variety of patent selection approaches in terms of search strategy, patent quality dimension and different solar energy technologies.

Both studies use an unbalanced panel of countries and apply a negative binomial model with country fixed effects to estimate how patent counts are influenced by policy and other variables. Johnstone et al. (2010) consider 23 countries for the period 1978-2003 (N=418), while Peters et al. (2012) cover 15 countries for 1978-2005 (N=374). The search strategy of Johnstone et al.

[17] See Appendix 6.7.1.

(2010) uses several IPCs covering technical principles of PV and CSP. They consistently refer in their analysis to solar energy technologies. Peters et al. (2012) also use IPCs, but they focus explicitly on PV and are restrictive in their search strategy, including only a few classifications. With respect to the patent quality dimension, Johnstone et al. (2010) use patents filed at the EPO and assign the patents via the inventors' address to countries using fractional counts. Peters et al. (2012) consider three different quality dimensions, namely triadic filings[18], claimed priorities and all priority filings. For the first two, they assign patents to countries via the inventor's address without fractional counting. For the latter, they use the patent office of the priority filing.

In both studies, several policy variables are considered to test their effects on patent counts. Johnstone et al. (2010) use nine different policy variables; three continuous and six dummy variables. The continuous variables are R&D expenditures for solar energy technologies, feed-in tariff levels for solar energy, and renewable energy certificate (REC) targets for renewable energy in general. R&D expenditures serve as a technology push instrument while the other two can be seen as demand inducing mechanisms. The other six variables capture the introduction of several other instruments supporting renewable energies in general, which cannot be measured continuously (Kyoto protocol, investment incentives, tax measures, guaranteed price, voluntary programs, and obligations).

Peters et al. (2012) use six variables to capture demand pull and technology push instruments. They use R&D expenditures for PV to account for technology push. R&D expenditures are divided into three groups: domestic R&D expenditures, continental R&D expenditures and intercontinental R&D expenditures to capture domestic and foreign policy effects on domestic inventive activity. Annually installed PV capacity is used to proxy a demand pull effect. Again, annually installed capacity is divided into domestic, continental and intercontinental to estimate the effects of domestic and foreign demand pull policies.

For our analysis, we reproduce the econometric setups of both studies based on their original data. We are able to fully reproduce the analysis of Johnstone et al. (2010).[19] For Peters et al. (2012), we can reproduce the descriptive statistics of the explanatory variables but we do not have the patent data to reproduce their full analysis.[20]

6.4.2 Variation in econometric estimates

We assess the variation in estimated policy effects by estimating the regression models of Johnstone et al. (2010) and Peters et al. (2012) for all 306 patent selection approaches (51 search

[18] Peters et al. (2012) deviate from the OECD definition of triadic patents and follow Sternitzke (2009). They use "Patent families with publications in at least Germany or the European Patent Office, Japan or China, and the US" (Peters et al., 2012, P 1301, FN 8).

[19] The estimates in Johnstone et al. (2010) are obtained by using STATA. We can replicate the exact point estimates and model characteristics by using R. However, we cannot replicate the robust standard errors provided by STATA. We use "vcovHC = HC1" from the 'sandwich' package and the standard errors are very similar but tend to be larger. In three cases they are 10% larger and in only two cases the standard errors are smaller. This deviation of standard errors affects the inference by turning investments incentives and the dummy for Great Britain from significance at the 0.1 level to non-significance.

While replicating the study of Johnstone et al. (2010) we noticed that a dummy for New Zealand was missing in the estimated regression for solar patents. Adding this dummy and using R for the estimation leads to two changes for the policy variables. Tax measures turn from non-significant to negative significant and guaranteed price from significant to non-significant.

[20] We replicated this study with patent counts based on their search strategy and our point estimates are in the same ballpark. We cannot reproduce the exact patent data of Peters et al. (2012) since they deviate from the OECD triadic patent definition and use a different database (INPAFAMDB - International Patent Family Database) to obtain their patent counts.

strategies and for each search strategy six patent quality dimensions). The stylized regression to assess the variation in the econometric estimates is given by

$$Pat_{sq} = P_j \beta_{jsq} + C_j \gamma_{jsq} + \mu_j + \epsilon_{jsq} \tag{6.1}$$

where $s = 1, ..., 51$ is an index for search strategies and $q = 1, ..., 6$ is an index for patent quality dimensions. The research design of Johnstone et al. (2010) is denoted by $j = 1$ and the research design by Peters et al. (2012) is denoted by $j = 2$. The research design comprises the study specific policy variables, P_j, control variables, C_j, and country fixed effects, μ_j, including the study specific set of countries and the time horizon considered. The vector of interest is β_{jsq} that corresponds to the policy variables in P_j. We analyze how $\hat{\beta}_{jsq}$ varies if the dependent variable, Pat_{sq}, is varied where $\hat{\beta}_{jsq}$ is the estimate of β_{jsq}.[21]

We use two approaches to describe the variation in $\hat{\beta}_{jsq}$. First, we use Extreme-Bounds Analysis (EBA) that was originally suggested by Leamer (1983) to analyze the robustness of empirical findings with regards to varying assumptions in the estimation process, such as the variation of control variables. EBA has been prominently applied to the growth literature (Levine and Renelt, 1992; Sala-i Martin, 1997) but also to other fields (e.g. Moosa and Cardak, 2006; Wang, 2010). While EBA is usually applied to estimate the extreme bounds of some key explanatory variables when the set of control variables is varied, we use EBA to characterize the set of estimates that can be obtained due to the flexibility in the selection of patent counts, which is the dependent variable in the analysis. Let $\hat{\beta}^{(k)}_{jsq}$ denote the coefficient for the kth policy variable in $\hat{\beta}_{jsq}$. For each of the two research designs j, the lower extreme bound for $\hat{\beta}^{(k)}_{jsq}$ is defined as the smallest value of $\hat{\beta}^{(k)}_{jsq} - 2\sigma^{(k)}_{jsq}$ where $\sigma^{(k)}_{jsq}$ is the standard error of $\hat{\beta}^{(k)}_{jsq}$. The upper extreme bound for $\hat{\beta}^{(k)}_{jsq}$ is defined as the largest value of $\hat{\beta}^{(k)}_{jsq} + 2\sigma^{(k)}_{jsq}$. By subtracting and adding the standard error the range of obtainable estimates also includes the uncertainty introduced by sampling variability.

Moreover, we further characterize the variation in $\hat{\beta}^{(k)}_{jsq}$ by using the share of positive $\hat{\beta}^{(k)}_{jsq}$ that is given by $\frac{1}{sq}\sum_{s=1}^{51}\sum_{q=1}^{6} 1(\hat{\beta}^{(k)}_{jsq} > 0)$ where $1(\hat{\beta}^{(k)}_{jsq} > 0)$ is an indicator function that is 1 if $\hat{\beta}^{(k)}_{jsq} > 0$. This measure of variation is less conservative compared to the use of extreme bounds as it ignores uncertainty that is introduced by sampling variability.

Second, we visualize the variation in $\hat{\beta}^{(k)}_{jsq}$ by using vibration plots that relate the point estimate of $\beta^{(k)}_{jsq}$ to a transformation of its p-value (Patel et al., 2015; Bruns and Ioannidis, 2016). These vibration plots help to assess the potential for p-hacking by illustrating, for example, whether statistically significant positive and negative estimates can be obtained for the same policy effect.

As a robustness check, we use subsets of the search strategies as search strategies of weak quality may result in extreme estimates of β_{jsq}. The first subset addresses outliers according to the sum of priority patents that is identified by a given search strategy. As discussed in Section 6.3, some search strategies identify small sums of patents while other search strategies identify huge sums of patents. We remove search strategies based on trimming the distribution of total priority patens, that is, we remove search strategies that result in the 10% largest

[21] Note that search strategies usually aim to be generic for a given technology. In this case variation in $\hat{\beta}_{jsq}$ is mainly caused by measurement error while the true effect, β_{jsq}, may be the same for some s. For the sample sizes considered in the benchmark research designs, measurement error in combination with a preferential publication of statistically significant estimates can easily result in overstated effect sizes (Loken and Gelman, 2017). The quality dimension of patents can capture different aspects of inventive activity (e.g. national vs international). In this case, variation in $\hat{\beta}_{jsq}$ may be mainly caused by variation in the true effect, β_{jsq}.

and 10% smallest sum of priority patents. The second subset that we consider consists of search strategies that stem from studies with at least 20 citations according to google scholar.[22] As studies of high quality that were published recently may not have obtained more than 20 citations yet, we consider a third subset with search strategies from studies that are published in journals which have a Source Normalized Impact per Paper (SNIP) factor that is larger than 1.5. Source normalizations are essential as the search strategies are published in journals of various disciplines, such as economics, management and engineering.

6.4.3 Explaining the variation in econometric estimates

Finally, we identify determinants of the variation in $\hat{\beta}^{(k)}_{jsq}$ by using meta-regressions. This approach follows Stanley and Jarrell (1989) who suggested meta-regressions to identify the sources of variation in estimates. While meta-regressions are typically applied to synthesize estimates of multiple studies, we apply meta-regressions to the estimated policy effects obtained by the use of various dependent variables as outlined in Section 6.4.1. We estimate

$$\hat{\beta}^{(k)}_{jsq} = T\delta^{(k)}_{1j} + S\delta^{(k)}_{2j} + Q\delta^{(k)}_{3j} + log(PP_s)\delta^{(k)}_{4j} + \epsilon^{(k)}_{jsq} \tag{6.2}$$

where $\hat{\beta}^{(k)}_{jsq}$ denotes the vector of point estimates for policy variable k of research design j for all 306 patent selection approaches that results from $s = 1, ..., 51$ search strategies and $q = 1, ..., 6$ patent quality dimensions. T contains two dummy variables. The first is one if PV was used in search strategy s and zero otherwise. The second is one if CSP is used in search strategy s and zero otherwise. S also contains two dummy variables. The first is one if keywords are used in search strategy s and zero otherwise and the second is one if keywords in combination with classifications are used in search strategy s and zero otherwise. Q contains five dummy variables that are one if either granted, claimed, PCT, transnational, or triadic patents are used and zero otherwise. Hence, the baseline is the case where the search strategy is based on classifications for the technology solar using priority patents. We also include the log of the number of priority patents, $log(PP_s)$, of search strategy s to control for the breadth of the search strategy.

6.4.4 Results

6.4.4.1 Extreme-Bounds Analysis

The results of the EBA disaggregated by technology and patent quality for the research design of Johnstone et al. (2010) are presented in Table 6.3. For nearly all policy variables, the lower extreme-bounds are negative and the upper extreme-bounds are positive indicating substantial uncertainty regarding the signs of most estimated policy effects. However, the shares of positive estimates are large for many estimated policy effects and even become one in many cases for solar and CSP, where the number of patent selection approaches is smaller compared to PV. But policy effects that show a large share of positive estimates for some patent quality dimension also reveal small shares of positive estimates for other patent quality dimensions. For example, the variable R&D expenditures has a large share of its estimates positive for all priority patents and granted patents while this share is smaller particularly for triadic patents. These results can hint to the fact that R&D subsidies are granted nationally and international markets are not that relevant for the inventors. The results for granted patents are more puzzling, especially for the variable feed-in tariff levels, where the point estimate is nearly always negative for all three technologies, while for the other quality dimensions the point estimates are nearly always

[22] See Appendix 6.7.1 for the corresponding search strategies.

positive. Generally, results are similar across different technologies, particularly between solar and CSP, while substantial differences occur across patent quality dimensions.

Alternatively, if we disaggregate the results of the EBA by technology and search strategy (Table 6.8 in Appendix 6.7.3), the extreme bounds are never of the same signs and the share of positive point estimates is often similar across technologies and search strategies for a given policy variable. As will be revealed in the next section by the use of vibration plots, these findings occur as the estimates often cluster by the patent quality dimension resulting in more mixed findings when the results of the EBA are disaggregated by patent quality dimensions.

As robustness checks, we restrict the sample according to the three quality subsets and present the results disaggregated by technology and patent quality dimension (see Supplementaries 6.8.2). For the trimmed subset, the share of positive estimates is one in many cases and for several policy variables, the upper and lower bounds have the same signs, especially for solar and CSP. The subset based on citations shows a similar pattern, but in several cases the shares of positive estimates are lower, even though the number of search strategies is substantially smaller than in the trimmed subset. The subset based on the SNIP is comparable with the subset based on citations, but in several cases shares of positive estimates are even lower.

For Peters et al. (2012), the results of the EBA disaggregated by technology and patent quality dimension are shown in Table 6.4.[23] The extreme bounds are again of opposing signs in the vast majority of cases and the results across technologies are similar, particularly for solar and CSP, while PV shows in many cases higher shares of positive estimates. But the results are this time also similar across patent quality dimensions. Granted patents show only in a few cases opposing results compared to the other patent quality dimensions, especially for intercontinental capacity. Moreover, the policy variable domestic capacity tends to have a large shares of positive point estimates across all patent quality dimensions and the three technologies. For the policy variable domestic R&D funding, this is only true for PV while there is high variability in the share of positive point estimates in the case of solar and CSP. Patent quality dimensions, which are attributed to higher valued patents (PCT, transnational, triadic) show in most cases higher shares of positive point estimates than patent quality dimensions that are attributed to lower valued patents.

We again disaggregate the results of the EBA by search strategy and technology and the lower and extreme bounds are again never of the same signs indicating that the estimates cluster by patent quality dimension rather than by search strategy (Table 6.9 in Appendix 6.7.3).

The robustness checks show again that the trimmed subset increases the share of positive estimates and again in some cases the lower and upper extreme bound are always of the same signs (see Supplementaries 6.8.2). The other two subsets have in general more uncertainty with respect to the direction of the effect. But, in a few cases, they show lower and upper extreme bounds of the same signs which is not the case in the trimmed subset. However, there are considerably less search strategies in these subsets compared to the first one.

Overall, the EBA points to substantial uncertainties regarding the signs and sizes of most policy effects. The findings are particularly unstable across the different quality dimensions of patents, though this is less true for the research design of Peters et al. (2012).

6.4.4.2 Vibration plots

As an alternative presentation of the variation of econometric estimates, we use vibration plots that relate the size of the estimated coefficient to a transformation of its *p*-value. The vibration

[23] The estimation procedure in R does not converge for three models. All of these models use triadic patents. We excluded these three triadic patent counts from the analysis.

Table 6.3: Extreme-Bounds Analysis for the research design of Johnstone et al. (2010).

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-2.758	2.649	0.889	0.096	4.316	1	-0.886	4.451	0.852	-3.987	7.361	0.296	-1.753	3.177	0.333	-1.836	3.623	0.407
Feed-in tariff levels	-0.036	0.090	1	-0.079	0.072	0.037	-0.061	0.178	0.926	-0.039	0.592	1	-0.066	0.233	0.852	-0.096	0.580	0.815
REC targets	-0.148	0.746	0.963	-0.540	0.776	0.148	-0.233	0.566	0.778	-0.369	0.635	0.333	-0.322	0.593	0.370	-0.559	0.627	0.222
Kyoto protocol	-0.245	2.431	0.852	-0.904	1.726	0.148	-0.334	1.923	0.926	-0.683	3.456	0.852	-0.221	2.311	1	-0.395	2.027	0.963
Investment incentives	-2.058	0.691	0.704	-1.496	1.272	0.963	-0.525	0.748	0.815	-1.466	1.848	0.963	-1.028	1.220	0.963	-0.949	1.280	0.963
Tax measures	-0.282	1.811	0.926	-1.075	1.314	0.259	-0.475	0.967	0.889	-1.069	1.171	0.630	-0.441	1.021	0.889	-0.604	1.508	0.963
Guaranteed price	-0.734	4.617	0.963	-1.761	5.168	0.148	-1.116	4.301	0.963	-1.621	5.044	1	-1.605	4.801	0.889	-2.906	5.235	0.741
Voluntary programs	-0.430	1.295	0.556	-1.433	0.545	0	-0.496	0.951	0.852	-0.801	1.574	1	-0.456	1.436	0.926	-0.777	1.669	0.963
Obligations	-0.317	1.471	0.852	-0.218	1.556	1	-0.407	1.366	0.926	-0.101	2.106	1	-0.510	1.521	0.889	-0.777	1.442	0.704
Patent selections	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-0.661	2.721	1	1.662	6.174	1	-0.392	3.105	1	-1.241	5.138	1	-2.473	1.753	0.800	-1.952	2.020	0.733
Feed-in tariff levels	-0.034	0.048	1	-0.050	0.029	0	-0.038	0.059	1	-0.030	0.082	1	-0.031	0.062	1	-0.184	0.064	0.467
REC targets	-0.079	0.789	1	-0.345	0.672	0.600	-0.204	0.697	0.933	-0.263	0.472	0.667	-0.169	0.626	0.800	-0.502	0.723	0.733
Kyoto protocol	-0.023	1.637	1	-0.570	0.940	0.733	-0.004	1.748	1	-0.357	1.846	0.733	0.004	1.792	1	-0.080	1.736	1
Investment incentives	-1.071	0.265	0.133	-0.801	0.753	0.867	-0.885	0.286	0.067	-0.926	1.175	0.933	-0.988	0.600	0.933	-0.707	0.832	0.933
Tax measures	-0.493	0.645	1	-1.338	0.393	0.067	-1.024	0.408	0.333	-0.607	0.561	0.267	-0.915	0.433	0.267	-0.681	0.876	0.600
Guaranteed price	-0.450	1.769	0.400	-1.183	2.017	0.067	-0.463	1.959	1	-0.360	2.390	1	-0.278	2.257	1	-0.853	4.224	1
Voluntary programs	-0.182	0.831	1	-1.371	0.003	0	-0.311	0.741	1	-0.160	1.253	1	0.083	1.119	1	-0.029	1.291	1
Obligations	-0.530	0.543	0.267	-0.341	1.131	1	-0.207	1.304	1	-0.002	1.607	1	-0.185	1.379	1	-0.622	1.533	0.600
Patent selections	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-0.207	3.003	1	1.321	6.601	1	-1.014	2.440	1	-2.031	3.809	1	-3.377	2.426	0.667	-4.634	3.038	0.667
Feed-in tariff levels	-0.019	0.037	1	-0.046	0.022	0	-0.024	0.068	1	-0.021	0.099	1	-0.049	0.065	0.889	-0.241	0.111	0.556
REC targets	-0.237	0.482	0.778	-0.390	0.404	0.444	-0.361	0.548	0.778	-0.364	0.650	0.667	-0.312	0.535	0.778	-0.614	1.268	0.889
Kyoto protocol	-0.132	0.883	0.889	-0.653	0.426	0.444	-0.375	0.824	1	-0.926	0.781	0.333	-0.350	0.963	1	-0.781	1.279	0.889
Investment incentives	-0.663	0.299	0.111	-0.335	0.772	1	-0.860	0.339	0.111	-0.776	1.487	1	-0.536	0.738	0.556	-0.717	1.604	0.556
Tax measures	-0.535	0.680	0.889	-1.063	0.349	0.111	-0.729	0.503	0.444	-0.902	1.194	0.556	-0.736	0.692	0.667	-1.034	1.794	0.556
Guaranteed price	-0.822	0.425	0.333	-1.177	0.510	0	-1.115	0.793	0.778	-0.677	1.921	1	-0.966	1.252	0.889	-2.052	2.407	0.889
Voluntary programs	-0.115	0.651	1	-1.349	-0.133	0	-0.271	0.907	1	0.030	2.139	1	-0.029	1.176	1	-0.622	1.645	0.889
Obligations	-0.624	0.286	0.111	-0.318	0.862	1	-0.352	0.925	1	-0.449	1.057	1	-0.498	0.811	0.667	-1.431	1.099	0.333
Patent selections	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Table 6.4: Extreme-Bounds Analysis for the research design of Peters et al. (2012).

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.914	0.517	0.852	-0.222	1.294	1	-0.259	0.718	0.889	-0.231	0.999	0.926	-0.273	0.849	0.926	-0.255	0.825	0.923
Continental R&D funding	-0.405	0.396	0.519	-0.468	0.584	0.593	-0.289	0.384	0.148	-0.480	0.763	1	-0.160	0.500	0.926	-0.245	0.432	0.885
Intercont. R&D funding	-0.994	0.580	0.222	-1.197	0.591	0.148	-1.191	1.692	0.593	-4.022	5.487	0.556	-1.518	2.725	1	-0.571	2.240	1
Domestic capacity	-0.366	0.250	0.889	-0.311	0.600	1	-0.072	0.450	1	0.028	0.649	1	-0.133	0.433	0.926	-0.162	0.496	0.846
Continental capacity	-0.200	0.644	0.815	-0.273	0.448	0.704	-0.226	0.318	0.704	-0.313	0.440	1	-0.238	0.408	0.741	-0.273	0.445	0.808
Intercont. capacity	-0.093	0.971	0.963	-0.408	0.890	0.037	-0.046	0.732	1	-0.125	1.330	1	-0.138	0.759	0.926	-0.224	0.603	0.346
Patent selections	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	26	26	26
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.472	0.211	0.200	-0.158	0.598	1	-0.280	0.549	0.267	-0.144	0.484	1	-0.179	0.560	0.933	-0.076	0.679	1
Continental R&D funding	-0.598	0.169	0.067	-0.677	0.218	0.067	-0.663	0.349	0.067	-0.179	0.640	1	-0.517	0.409	0.133	-0.165	0.429	0.857
Intercont. R&D funding	-0.913	0.694	0.067	-1.183	0.395	0	-0.758	1.712	0.133	-1.304	3.677	0.600	-0.202	2.262	1	0.014	2.127	1
Domestic capacity	-0.187	0.268	0.933	0.002	0.701	1	0.007	0.481	1	0.052	0.482	1	-0.016	0.346	1	0.007	0.400	1
Continental capacity	-0.133	0.183	0.867	-0.260	0.187	0.8	-0.193	0.150	0.667	-0.220	0.258	0.933	-0.157	0.162	0.400	-0.144	0.324	0.857
Intercont. capacity	-0.080	0.680	1	-0.329	0.505	0.067	-0.080	0.527	1	-0.045	0.856	1	-0.029	0.545	1	-0.162	0.457	0.786
Patent selections	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	14	14	14
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.381	0.141	0	-0.193	0.626	1	-0.391	0.289	0.111	-0.308	0.765	0.667	-0.335	0.490	0.333	-0.375	0.573	0.5
Continental R&D funding	-0.676	0.067	0	-0.774	0.072	0	-0.796	0.273	0	-0.636	0.747	0.444	-0.891	0.311	0.222	-0.732	0.235	0.375
Intercont. R&D funding	-1.059	0.591	0.111	-1.439	0.327	0	-1.144	0.756	0.111	-0.910	1.912	0.444	-0.789	1.286	0.889	-0.780	1.110	0.875
Domestic capacity	-0.116	0.343	1	0.128	0.677	1	-0.061	0.361	1	-0.440	0.425	0.889	-0.176	0.309	1	-0.216	0.408	0.375
Continental capacity	-0.124	0.190	0.889	-0.160	0.192	0.778	-0.212	0.144	0.556	-0.181	0.215	1	-0.223	0.128	0.111	-0.260	0.341	0.5
Intercont. capacity	-0.093	0.273	1	-0.368	0.062	0	-0.096	0.350	1	-0.028	0.598	1	-0.026	0.400	1	-0.227	0.337	1
Patent selections	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	8	8	8

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

plots for Johnstone et al. (2010) are given in Figures 6.4 and 6.5. The first column shows vibration plots for the full results while the second column presents vibration plots for the subset of search strategies obtained by trimming the distribution of the sums of priority fillings. The third column represents the trimmed subset and only search strategies for solar patents as this is the technology that was used in the original analysis of Johnstone et al. (2010). This column can be interpreted as a robustness test of the initial study.

The vibrations plots demonstrate how the estimated policy effects tend to cluster by the patent quality dimensions. Particularly, granted patents tend to form clusters but also priority and claimed patents form clusters in some cases. For example, estimates for the coefficients of R&D expenditures form two clusters if patent counts with either priority or granted patents are used. Both clusters represent positive and statistically significant estimates, while the estimates obtained by using other quality dimensions center around zero and tend to be non-significant. For feed-in tariff levels, the estimates obtained by the use of granted patents form a cluster with negative estimates, while many of the estimates obtained by the use of PCT patents show substantially larger estimates compared to the estimates that are obtained by the use of other patent quality dimensions. Similar clustering is observable for guaranteed price and voluntary programs. Interestingly, there is a considerable share of positive significant estimates for higher quality patent counts (PCT, transnational, triadic) for REC targets and investment incentives, but these high shares of positive and statistically significant policy effects do not tend to occur for solar. With respect to the search strategies, visual inspection does not permit to identify systematic patterns but the analysis of the determinants of policy effect sizes in the next section will demonstrate that these systematic patterns exist.

The vibration plots based on the trimmed subset demonstrate that some of the more extreme estimates disappear indicating that outliers in terms of patent counts seem to result in somehow more extreme estimates of policy effects. If we further reduce the set of patent counts to search strategies for solar patents, negative estimates tend to disappear with granted patents being a notable exception. Ignoring granted patents, almost all of the estimates for the two key policy variables, that is, R&D expenditures and feed-in tariff levels, are positive indicating that the core results of Johnstone et al. (2010) are robust in terms of the signs of the policy effects. However, substantial uncertainty remains about the effect sizes. The estimates can be interpreted as semi-elasticities and, thus, flexibility in the selection of patent counts results in uncertainty about an increase of solar patents between -0.26% and +4.64% for an additional billion of R&D expenditures. For feed-in tariffs, the range of effects is –0.032% to +0.042% for an additional US cent/kWh of the feed-in tariff.

The vibration plots for Peters et al. (2012) are presented in Figures 6.6 and 6.7. For this research design, estimates based on the use of granted and PCT patents often form clusters. For example, for continental R&D funding estimates based on the use of PCT patents tend to be positive and substantially larger than estimates based on other patent quality dimensions, while estimates based on granted patents tend to be negative. With respect to the search strategy, systematic patterns are again hard to detect in the vibration plots, but they exist as analyzed in the next section.

The trimmed subset results again in some of the more extreme estimates to disappear. The focus on search strategies for PV, which is the technology analyzed in the original study, reveals that the estimates for the two key policy variables, that is, domestic R&D funding and domestic capacity, are almost exclusively positive indicating that the core results of Peters et al. (2012) are robust with respect to the signs of the effects as well. Similar to the research design of Johnstone et al. (2010), uncertainty regarding the effect sizes remains. The coefficients in Peters et al. (2012) can be directly interpreted as elasticities as the policy variables are considered in logs. The effect of increasing domestic R&D funding by 1% on the number of PV patents ranges

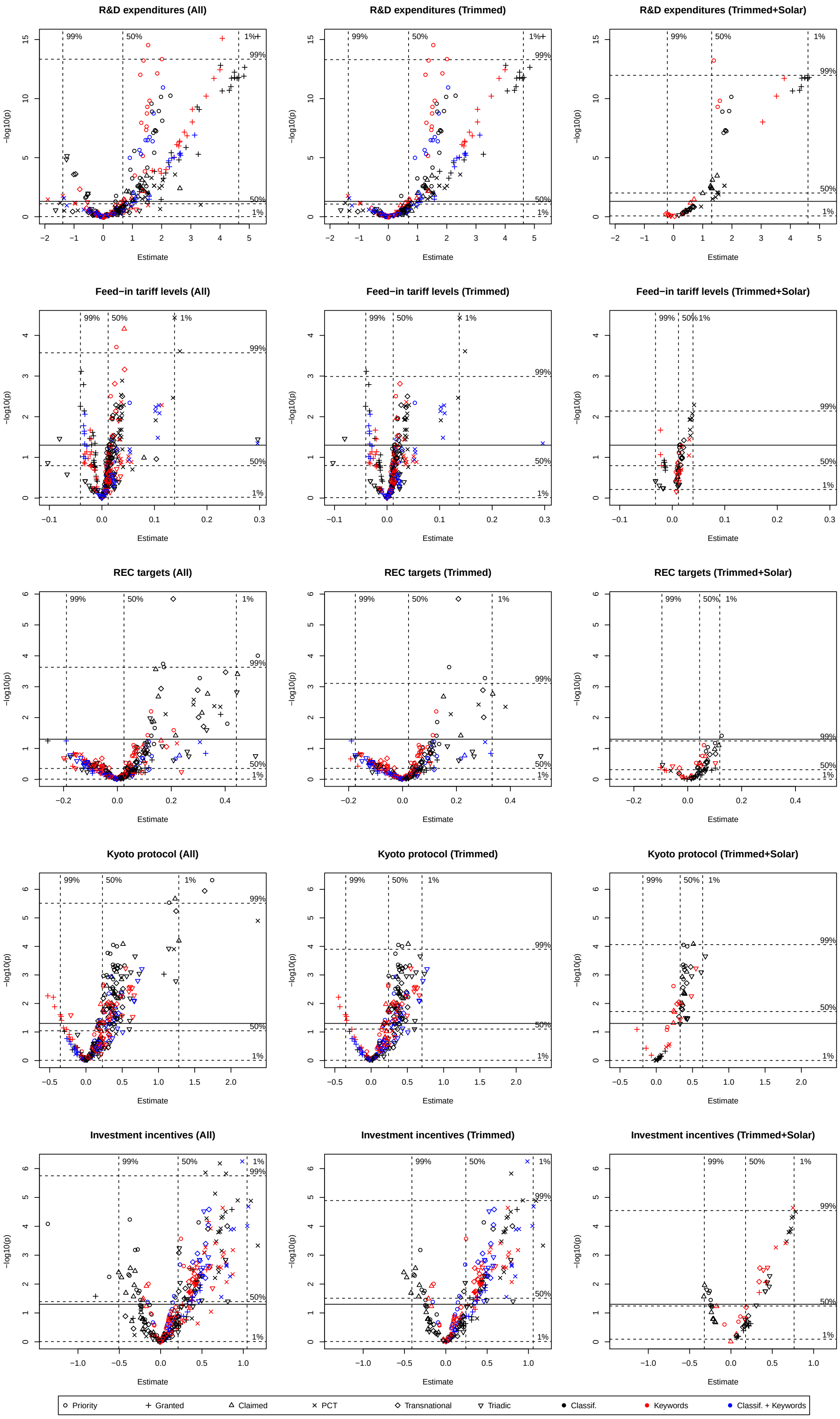


Figure 6.4: Vibration plots for the research design of Johnstone et al. (2010) (1/2).

Figure note: The y-axis displays $-log10(p - value)$. Thus, all estimates above the solid line are statistically significant at the $p = 0.05$ level. “All” covers 306 coefficients, “Trimmed” 234 coefficients and “Trimmed+Solar” 66 coefficients.

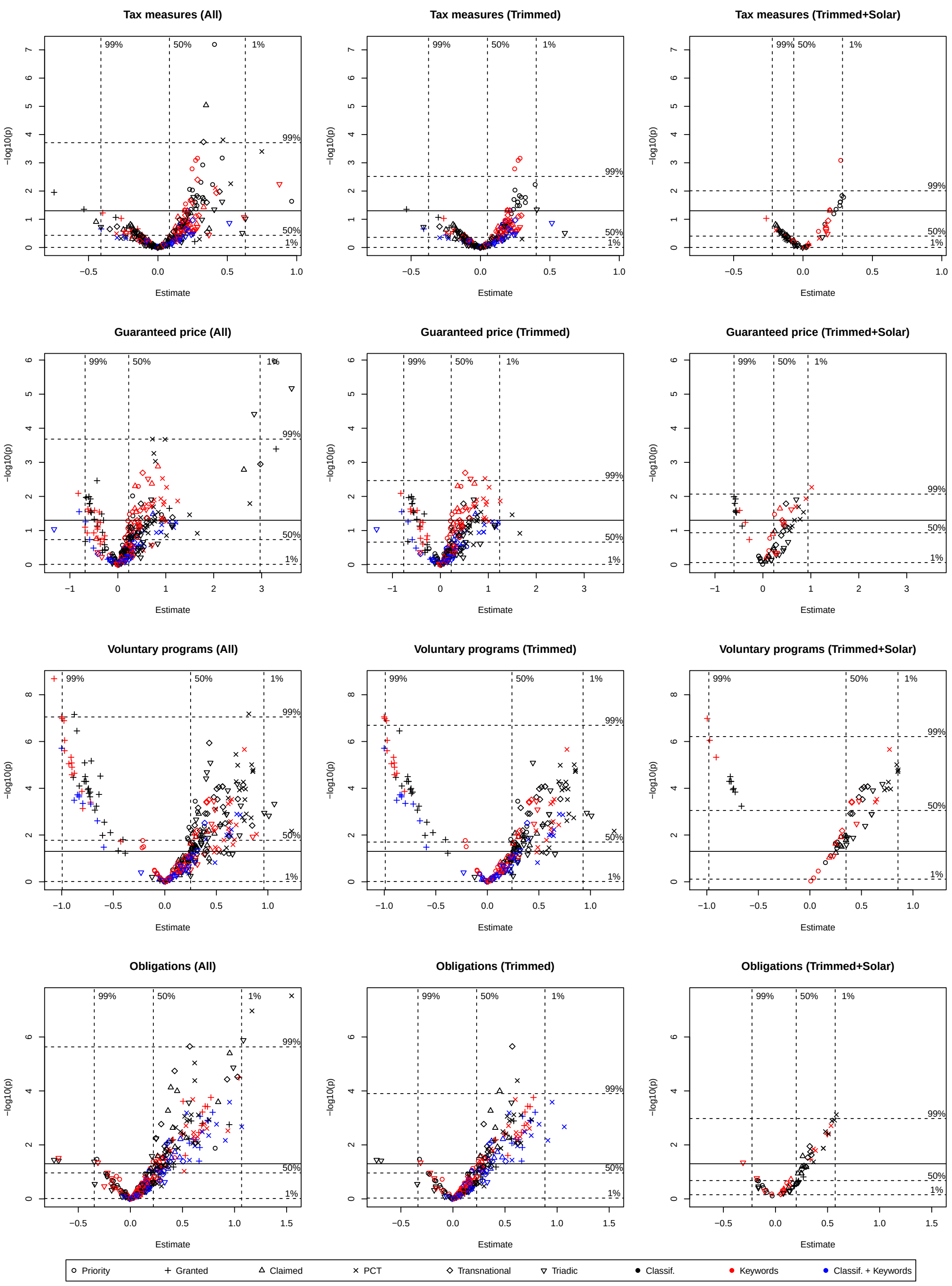


Figure 6.5: Vibration plots for the research design of Johnstone et al. (2010) (2/2).

Figure note: The y-axis displays $-log10(p - value)$. Thus, all estimates above the solid line are statistically significant at the $p = 0.05$ level. "All" covers 306 coefficients, "Trimmed" 234 coefficients and "Trimmed+Solar" 66 coefficients.

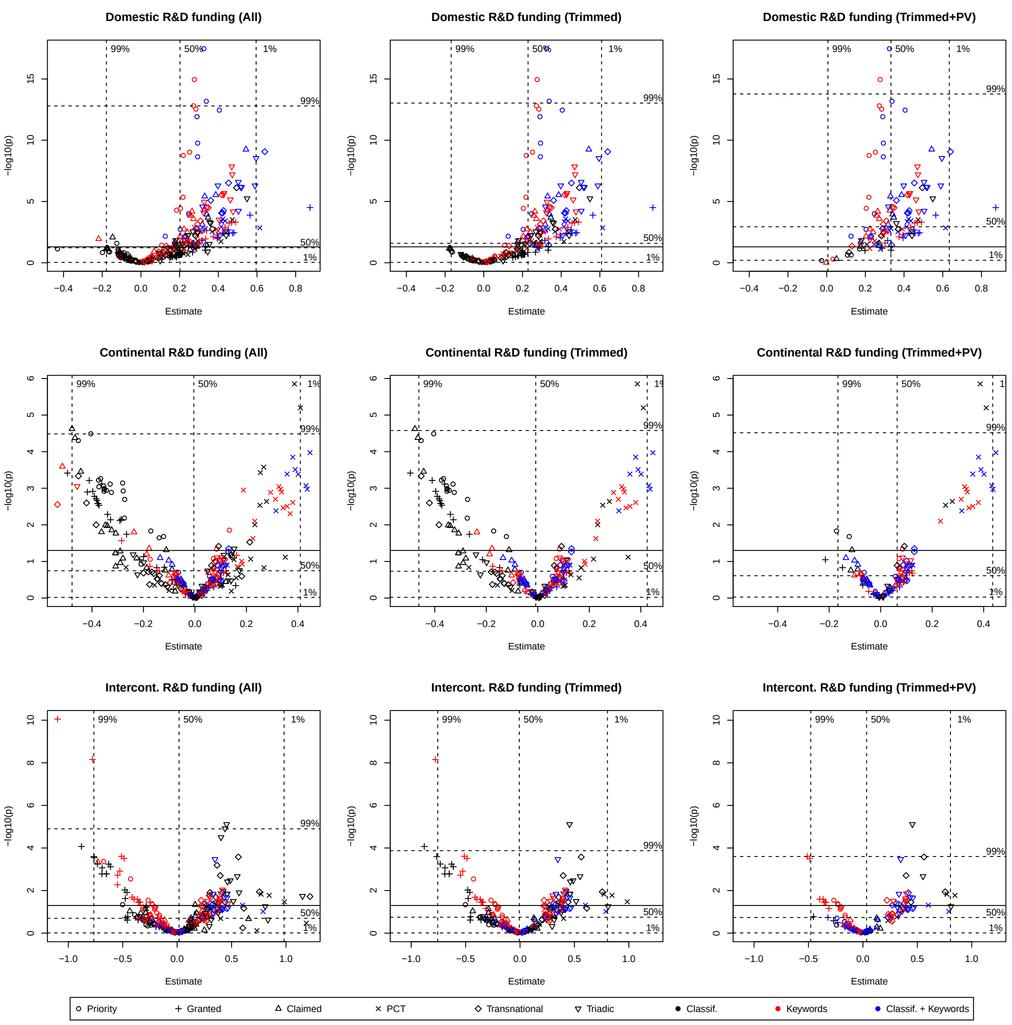


Figure 6.6: Vibration plots for the research design of Peters et al. (2012) (1/2).

Figure note: The y-axis displays $-log10(p - value)$. Thus, all estimates above the solid line are statistically significant at the $p = 0.05$ level. "All" covers 303 coefficients, "Trimmed" 231 coefficients and "Trimmed+PV" 125 coefficients.

between -0.026% and 0.87% and the effect of increasing capacity by 1% between -0.0042% and 0.38%.

Overall, the vibration plots demonstrate considerable uncertainty about the sizes and signs of the estimated policy effects. For almost all policy variables, both positive and negative estimates that are statistically significant can be obtained. Uncertainty regarding the signs of the estimated coefficients is greatly reduced for the core policy variables if outliers are excluded and only search strategies are considered for the technology analyzed in the original study. However, uncertainty regarding the estimated policy effect sizes remains.

6.4.4.3 Determinants of estimated effect sizes

While the EBA results reveal a wide range of effect sizes, in the following we estimate the determinants of this variation in effect size. For the research design of Johnstone et al. (2010), the results on the determinants of the estimated policy effect sizes are reported in Table 6.5. If

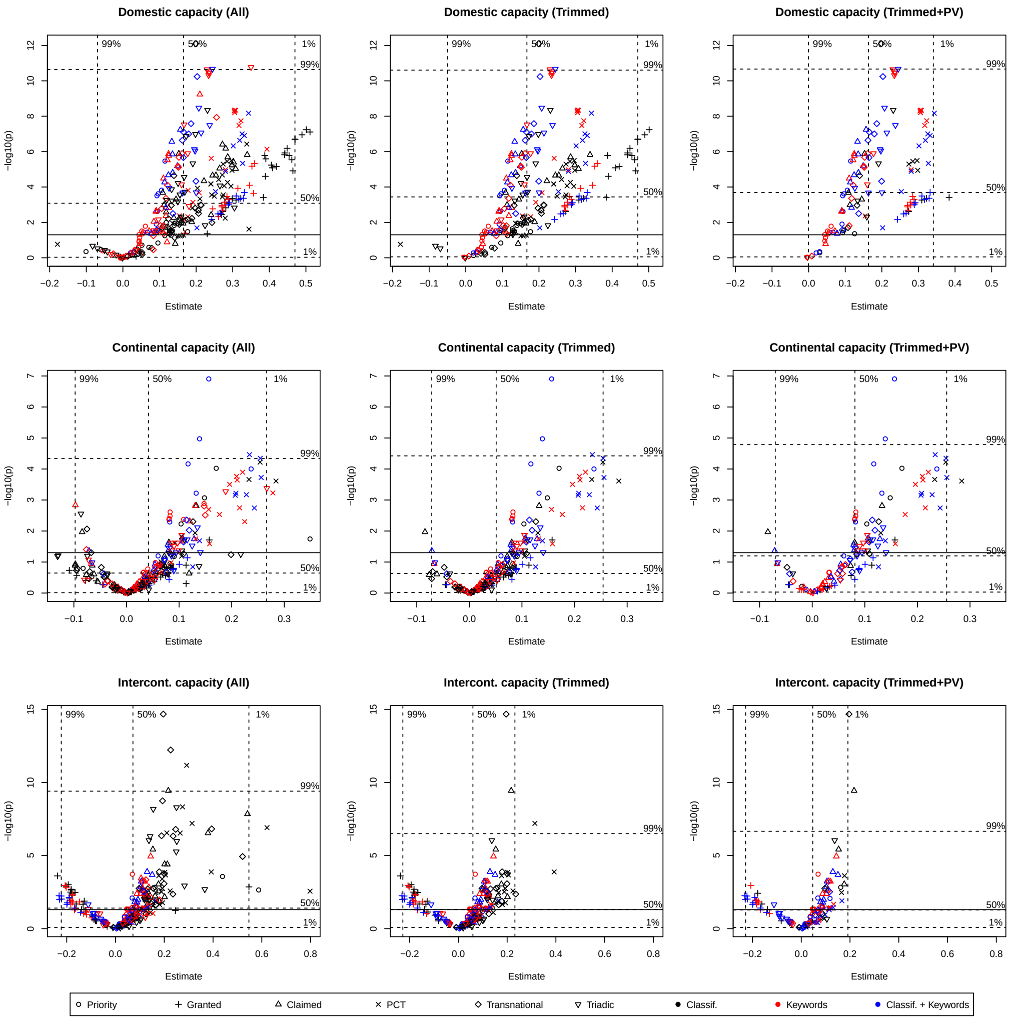


Figure 6.7: Vibration plots for the research design of Peters et al. (2012) (2/2).

Figure note: The y-axis displays $-log10(p - value)$. Thus, all estimates above the solid line are statistically significant at the $p = 0.05$ level. "All" covers 303 coefficients, "Trimmed" 231 coefficients and "Trimmed+PV" 125 coefficients.

search strategies for PV rather than for solar are used, the semi-elasticity of R&D expenditures decreases by 0.911 while the semi-elasticity of feed-in-tariff levels increases by 0.014. This is well in line with how the policy instruments are used to support the different technologies; R&D expenditures were mostly used to foster research activity for solar technologies in general, while feed-in tariff levels are usually available for PV only. For most other policy variables, using a search strategy for PV increases the semi-elasticities as well. The use of keywords or keywords in combination with classifications does not have an effect on the semi-elasticity of R&D expenditures and only the use of keywords decreases the semi-elasticity of feed-in-tariffs by 0.009. Generally, the use of keywords or the use of keywords in combination with classifications tends to reduces in most cases the semi-elasticities. This is because the classifications either do not capture all the relevant patents or the classifications are too broad, including too many patents which inflates the estimation results. As shown before, patent quality dimensions are decisive for the effect sizes. For R&D expenditures, the semi-elasticity is increased by 1.721 if granted patents are used instead of priority ones. At the same time, using other quality dimensions, the semi-elasticity decreases, for example by 1.269 in the case of triadic patents.

For feed-in-tariff levels, the use of granted patents decreases the semi-elasticity by 0.034 while the use of PCT patents increases the semi-elasticity by 0.043. The highly significant influence of using granted patents on the effect size is also present for all other policy variables and in some cases even with a reversed sign compared to the other patent quality dimensions.

In the case of Peters et al. (2012), results on the determinants of estimated effect sizes are reported in Table 6.6. Since all variables enter the regression for Peters et al. (2012) in logs, the coefficients can be interpreted as elasticities. Search strategies for PV increase the elasticity for domestic R&D funding by 0.123 while search strategies for CSP decrease the elasticity by 0.116. For domestic capacity, surprisingly, PV search strategies reduce the elasticity by 0.044 while for all other variables it increases it. The elasticity for domestic R&D funding increases with keywords and keywords in combination with classifications by 0.054 and 0.135 respectively. The effect size of domestic capacity is only affected negatively by search strategies based on keywords. The elasticities of the other variables are in most cases also reduced compared to classification searches. The patent quality dimension shows interesting pattern. For domestic R&D funding and domestic capacity, all quality dimensions increase the elasticity, strongest each for granted patents, with an increase of 0.261 and 0.268 respectively. For the other variables, there are mixed results, but higher quality dimensions (PCT, transnational, triadic) usually show positive effects. Again, granted patents showing deviating results, especially for intercontinental capacity, where the elasticity is reduced by 0.217 while PCT increases it by 0.086.

Overall, the regression results often have a high adjusted R^2, indicating that the selection approach is a fundamental determinant for the effect size. Thereby the number of patents which are selected by a search strategy seem to systematically reduce the effect size. With respect to the search strategies, some generalizable patterns across variables and studies emerge, as well as interesting effects for the individual variables, which can be related to the instrument they proxy or technology they are implemented for. The patent quality dimension has however in most cases the largest effect, especially the use of granted patents.

6.5 Discussion

6.5.1 Uncertainty in estimated policy effects

Our analysis demonstrates substantial uncertainty in econometric estimates of policy effects that is introduced by the flexibility of patent selection approaches. We identify 51 search strategies for solar energy technologies used in the literature and consider six different patent quality dimensions. The different search strategies lead to severe differences in overall patent counts and the overlap of patents among these search strategies varies considerably. While the distribution of patents across countries does not vary much between search strategies, it does considerably if different patent quality dimensions are considered.

Using the research designs of Johnstone et al. (2010) and Peters et al. (2012), we find that flexibility in the selection of patent counts results in a wide range of estimates for the effects of various policy instruments on patent counts. The uncertainty regarding signs and sizes of these policy effects is substantial as for almost all policy effects both positive and negative estimates that are statistically significant can be obtained. Using three different quality subsets reduces this uncertainty. Uncertainty regarding the signs of the core policy variables is substantially reduced if we exclude search strategies that result in the 10% smallest and 10% largest number of priority fillings. Interestingly, this is not necessarily the case if we reduce the set of search strategies to those that were published in articles with at least 20 citations or journals with a source normalized impact per paper factor of at least 1.5. This suggests that outliers with respect to the number of selected patents are a main contributor to the uncertainty regarding

Table 6.5: Determinants of estimated effect sizes for Johnstone et al. (2010) research design.

	R&D expenditures	Feed-in tariff levels	REC targets	Kyoto protocol	Investment incentives	Tax measures	Guaranteed price	Voluntary programs	Obligations
Intercept	3.777***	0.051**	0.636***	1.71***	-0.377**	-0.449***	1.706***	0.782***	0.913***
	(0.385)	(0.017)	(0.059)	(0.143)	(0.130)	(0.100)	(0.300)	(0.095)	(0.127)
CSP	-0.301*	-0.001	0.020	-0.172***	-0.047	0.090**	-0.095	-0.007	-0.153***
	(0.119)	(0.005)	(0.018)	(0.044)	(0.040)	(0.031)	(0.092)	(0.029)	(0.039)
PV	-0.911***	0.014**	-0.011	0.007	0.131***	0.177***	0.258**	-0.083**	0.145***
	(0.102)	(0.005)	(0.016)	(0.038)	(0.034)	(0.027)	(0.079)	(0.025)	(0.034)
Class.+Key.	0.184	-0.004	-0.121***	-0.226***	0.155***	-0.060’	-0.423***	-0.184***	-0.086*
	(0.120)	(0.005)	(0.018)	(0.044)	(0.040)	(0.031)	(0.093)	(0.030)	(0.040)
Keywords	-0.061	-0.009*	-0.107***	-0.261***	0.096**	0.005	-0.329***	-0.184***	-0.143***
	(0.096)	(0.004)	(0.015)	(0.036)	(0.032)	(0.025)	(0.075)	(0.024)	(0.032)
Granted	1.721***	-0.034***	-0.123***	-0.361***	0.346***	-0.326***	-0.480***	-0.891***	0.404***
	(0.132)	(0.006)	(0.020)	(0.049)	(0.044)	(0.034)	(0.102)	(0.033)	(0.043)
Claimed	-0.476***	0.000	-0.031	0.017	0.029	-0.161***	0.092	0.070*	0.209***
	(0.132)	(0.006)	(0.020)	(0.049)	(0.044)	(0.034)	(0.102)	(0.033)	(0.043)
PCT	-0.924***	0.043***	-0.071***	-0.092’	0.755***	-0.198***	0.640***	0.511***	0.532***
	(0.132)	(0.006)	(0.020)	(0.049)	(0.044)	(0.034)	(0.102)	(0.033)	(0.043)
Transnational	-1.283***	0.005	-0.052*	0.075	0.334***	-0.118***	0.185’	0.222***	0.182***
	(0.132)	(0.006)	(0.020)	(0.049)	(0.044)	(0.034)	(0.102)	(0.033)	(0.043)
Triadic	-1.269***	-0.007	-0.093***	0.161**	0.424***	-0.029	0.145	0.220***	-0.009
	(0.132)	(0.006)	(0.020)	(0.049)	(0.044)	(0.034)	(0.102)	(0.033)	(0.043)
No. of patents	-0.193***	-0.004*	-0.048***	-0.127***	0.017	0.056***	-0.144***	-0.050***	-0.085***
	(0.035)	(0.002)	(0.005)	(0.013)	(0.012)	(0.009)	(0.028)	(0.009)	(0.012)
Adj. R^2	0.752	0.391	0.398	0.481	0.621	0.413	0.360	0.890	0.550
Obs.	306	306	306	306	306	306	306	306	306

Standard errors in parentheses. Sig. at the ‘ 0.1, * 0.05, **0.01, ***0.001 level.

Table 6.6: Determinants of estimated effect sizes for Peters et al. (2012) research design.

	Domestic R&D funding	Continental R&D funding	Intercont. R&D funding	Domestic capacity	Continental capacity	Intercont. capacity
Intercept	0.497***	-0.321***	-0.014	0.310***	0.377***	0.269***
	(0.063)	(0.067)	(0.125)	(0.044)	(0.034)	(0.058)
CSP	-0.116***	-0.085***	-0.078*	-0.084***	-0.036***	0.035*
	(0.020)	(0.021)	(0.039)	(0.014)	(0.010)	(0.018)
PV	0.123***	0.168***	0.179***	-0.044***	0.033***	0.051***
	(0.017)	(0.018)	(0.033)	(0.012)	(0.009)	(0.015)
Class.+Key.	0.135***	0.022	-0.146***	-0.008	0.015	-0.163***
	(0.020)	(0.021)	(0.039)	(0.014)	(0.010)	(0.018)
Keywords	0.054***	0.054**	-0.237***	-0.045***	-0.003	-0.118***
	(0.016)	(0.017)	(0.031)	(0.011)	(0.008)	(0.014)
Granted	0.261***	-0.002	-0.201***	0.268***	-0.040***	-0.217***
	(0.022)	(0.023)	(0.043)	(0.015)	(0.011)	(0.020)
Claimed	0.041’	-0.024	0.130**	0.096***	-0.048***	0.033’
	(0.022)	(0.023)	(0.043)	(0.015)	(0.011)	(0.020)
PCT	0.165***	0.354***	0.325***	0.182***	0.069***	0.086***
	(0.022)	(0.023)	(0.043)	(0.015)	(0.011)	(0.020)
Transnational	0.127***	0.108***	0.497***	0.070***	-0.044***	0.039*
	(0.022)	(0.023)	(0.043)	(0.015)	(0.011)	(0.020)
Triadic	0.219***	0.153***	0.578***	0.080***	-0.015	-0.043*
	(0.022)	(0.023)	(0.043)	(0.015)	(0.012)	(0.020)
No. of patents	-0.053***	0.010	-0.015	-0.019***	-0.033***	-0.014**
	(0.006)	(0.006)	(0.011)	(0.004)	(0.003)	(0.005)
Adj. R^2	0.712	0.707	0.666	0.619	0.541	0.582
Obs.	303	303	303	303	303	303

Standard errors in parentheses. Sig. at the ‘ 0.1, * 0.05, **0.01, ***0.001 level.

the signs of many policy effects and these outliers are not necessarily published in journals with low impact factors or articles with only a few citations.

For the research design of Johnstone et al. (2010), we can demonstrate that the use of search strategies that focus on the identification of PV patents lead to higher estimates of many policy effects compared to search strategies that aim to identify solar or CSP patents. This indicates that the policy variables considered in Johnstone et al. (2010) seem to encourage inventive activity particularly in PV and not solar in general, which is the study's original technology choice. This is consistent with the findings for Peters et al. (2012) where estimates of policy effects are in most cases larger if search strategies for PV patents are considered compared to search strategies for solar patents. With respect to patent quality dimensions, we observe deviating results between Johnstone et al. (2010) and Peters et al. (2012). In the former, patent quality dimensions for higher value patents (PCT, transnational, triadic) result in many cases to a decrease in effect sizes while for Peters et al. (2012) we usually find an increase in effect sizes. Estimates of policy effects for granted patents, however, seem to follow no clear pattern, but show usually larger and in some cases opposing effects than obtained for the other quality dimensions.

We identify characteristics of patent selection approaches as key determinants of policy effects sizes as indicated by large adjusted R^2. All characteristics, that is, search strategy, technology, patent quality dimensions, and the total number of identified patents matter. However, none of the characteristics has a systematic influence on all policy effects besides the number of patents which is selected by a given search strategy. If the number of selected patents increases, the effect size is systematically reduced. This indicates that the policy effects are targeted towards the technology and do not increase patenting in general, which is likely to be measured if the search strategy is too broad.

Since the different patent quality dimensions are responsible for a substantial amount of variation in estimated policy effects, previous studies may need to be interpreted with caution or even reassessed as most studies present results only for one quality dimension. Many previous studies use granted patents from the US, but granted patents result in estimated policy effects that often deviated substantially from those estimates obtained by other patent quality dimensions. While there is certainly a theoretical meaning behind the different patent quality dimensions, a rigorous sensitivity analysis may help to improve reliability and credibility.

Nevertheless, we find that the core results of Johnstone et al. (2010) and Peters et al. (2012) tend to be fairly robust if we consider a subset of search strategies that excludes outliers and additionally focus on the respective technologies analyzed in the original studies, even though effects are larger for PV in the case of Johnstone et al. (2010). Especially the two variables measuring technology push and demand pull effects have in most cases a very high share of positive and statistically significant estimates. This is in line with the theoretical considerations on induced innovation.

6.5.2 Implications for *p*-hacking and policy recommendations

The flexibility of patent selection approaches does not only lead to severe uncertainty with respect to the sizes and significances of estimated policy effects, but also opens up the possibility to deliberately search for results that confirm a hypothesis of interest. The vibration plots intriguingly show that for almost all policy effects, positive and negative estimates that are statistically significant can be obtained. Moreover, our analysis of the determinants of the effects sizes reveals that characteristics of the patent selection approaches explain a large fraction of the observed variation in estimated policy effects. Hence, (small) changes to the selection approach can be used to alter the estimated policy effect until the hypothesis of interest is confirmed.

Since patent data for many patent offices and in various forms is nowadays easily available, the deliberate search comes at very low costs.

Although uncertainty opens up the possibility for deliberate p-hacking, we do not belief that empirical research is dominated by researchers that intentionally search for estimates that fulfil their prior beliefs. p-hacking may occur in a much subtler form. Researchers are usually aware of the vast range of estimates that can be often obtained for an effect of interest and they may be affected by motivated reasoning (Kunda, 1990) when they choose to present the empirical model that 'makes sense' according to prior beliefs. There is empirical evidence that such selective reporting is widespread in empirical economics research (Brodeur et al., 2016).

Moreover, our findings reveal that some policy effects show a considerably large share of positive estimates while the lower extreme bound was negative and the upper extreme bound was positive. For example, the core variables in Johnstone et al. (2010) (R&D expenditures and feed-in tariff levels) and Peters et al. (2012) (domestic R&D funding and domestic capacity) have in most cases a share of positive estimates of one or close to one. This finding particularly occurred if we use a subsample based on quality considerations, especially the subsample that excludes outliers with respect to the number of selected patents. These findings connect to a recent study by Ioannidis et al. (2017), who show that empirical economics research is characterized by low power. This means that the utilized sample sizes are too small to detect an effect that is likely to exist. Low power may incentivize authors to p-hack in order to find a statistically significant effect. Though one may argue that the harm of p-hacking is limited if indeed a true effect exist, the point estimate becomes exaggerated which may mislead policy makers. These exaggerations of effect sizes due to p-hacking can be substantial as shown by Ioannidis et al. (2017).

Policy conclusions have to be drawn carefully as effects sizes are likely to be exaggerated which may result in misallocation. Moreover, previous studies focus on presenting and discussing statistical significance and neglect the importance of economic significance (McCloskey and Ziliak, 1996; Cumming, 2014). The economic significance of the policy variables varies considerable between the different patent selection approaches, especially with respect to the patent quality dimension.

A rigorous documentation of why a specific search strategy is used and why certain quality dimensions are considered needs to be implemented to reduce measurement errors and the potential for p-hacking. Particularly, the quality dimensions of patents need more attention. Peters et al. (2012) can be seen as a good example how to deal with different patent quality dimensions since they demonstrate the flexibility of their results with respect to three patent quality dimensions. However, such robustness tests towards different measures of patent quality are not common, even in top economics journals.

6.6 Conclusions

We show that flexibility in the selection of patent counts has several implications for the use of patent data and calls for a careful interpretation of results obtained with patent data, providing empirical evidence for the warnings made by Griliches (1990). We demonstrate the potential for conscious and unconscious p-hacking by estimating policy effects based on varying patent counts obtained by different patent selection approaches that vary by search strategy, patent quality dimension, and the type of solar technology considered. Thereby we show how uncertainty in the estimated policy effects translates into uncertainty for policy makers in how to evaluate the effectiveness of policy instruments.

We use Johnstone et al. (2010) and Peters et al. (2012) as benchmark research designs for our comprehensive analysis of variation in estimated policy effects. To this end, our analysis includes a replication of these studies with a systematic sensitivity analysis. We can show that the key findings of the two studies tend to be robust which is good news given the large amount of alternative patent counts considered in our analysis. These robust results are also in line with the theoretical arguments that technology push and demand pull policies induce inventive activities.

Implications of our results concern the careful use of patent data. The many researchers' degrees of freedom to select patent data requires an elaborated selection approach which should be agreed on among researchers. Furthermore, a careful interpretation of results in light of the search strategy and patent quality dimension used is necessary. Therefore, we recommend improving the reliability of studies that use patent counts and patent data in general by systematic documentation of the search strategy and sensitivity analysis especially with respect to the patent quality dimensions. Moreover, a consensus in the literature which selection approaches should be used and which approaches result in undesirable effects would greatly reduce flexibility and increase comparability between different studies. It is essential to use patent quality dimensions that fit to the research question as we have demonstrated that this has a substantial influence on the econometric estimates.

We have analyzed how flexibility in patent selection approaches transmits to variation in estimated policy effects for a very simple case, the count of patents per country/year. Patent data, however, is used for more sophisticated analysis relying on the patent's content and further meta information. For example, patent data is frequently used to assess technological or economic performance, to map knowledge flows, to reconstruct innovation networks, or analyze other economic relationships. Such studies are most likely subject to greater flexibility in their results than the two present cases which rely on simple patent counts.

While we use a specific technology for our analysis, the difference in search strategies for solar energy technologies, the underlying problem of flexibility is very likely to be present in other technology studies using patent data. For example, similar problems are likely to exist in studies that analyze new and emerging technologies, which are not well captured by specific classifications or keywords, such as biotechnology or nanotechnology.

With respect to the flexibility in patent selection approaches, we focus on three different dimensions: the search strategy, the patent quality dimension as well as technological ambiguity. There are, however, further aspects which may increase flexibility, for example, the underlying database used. Also patent quality can be operationalized in different ways, such as weighting by patent citations. Here flexibility is manifold calling for further assessment.

6.7 Appendix

6.7.1 Solar energy technology search strategies

Table 6.7: Solar energy technology search strategies used in the literature.

Paper	Tech.	Search strategy	Priority filings	SNIP	Citations	Also used in
CPC Classification PV	PV	Class.	24,617			Bointner et al. (2013); Bointner (2014); Stek and van Geenhuizen (2015); Leydesdorff et al. (2015); Wu and Hu (2015); Bäckström et al. (2014); Diederich and Althammer (2016); Breul et al. (2015); Glachant and Dechezleprêtre (2016); Jamali et al. (2016)
WIPO Green Inventory PV	PV	Class.	67,305			Lei et al. (2013); Martinez et al. (2013); Groba and Cao (2015); Choi and Anadn (2014); Gallagher (2014)
Böhringer et al. (2014)	PV	Class.	688,292		11	Diederich and Althammer (2016)
Guan and Yan (2016)	PV	Class.	2,942	3.126	1	
Peters et al. (2012)	PV	Class.	8,088	3.126	120	Diederich and Althammer (2016)
Popp et al. (2011)	PV	Class.	22,511	1.851	205	Brunel (2016)
Wu and Mathews (2012)	PV	Class.	714,877	3.126	60	Wu (2014)
Binz et al. (2017)	PV	Class. + Key.	16,161	1.653	0	
de la Tour et al. (2011)	PV	Class. + Key.	37,352	1.653	177	
FRINNOV (2009)	PV	Class. + Key.	10,587			
Haller (2007)	PV	Class. + Key.	22,109			
Kalthaus (2017)	PV	Class. + Key.	17,926		3	Cantner et al. (2016); Herrmann and Töpfer (2017); Kalthaus (2016); Herrmann (2017)
Kazuyuki and Takanori (2014)	PV	Class. + Key.	8,954			
Lei et al. (2012)	PV	Class. + Key.	17,329	0.128	1	Lei et al. (2013)
Li et al. (2014b)	PV	Class. + Key.	11,571			
Wang and Chiu (2010)	PV	Class. + Key.	12,228	0.113	2	
Andersson and Jacobsson (2000)	PV	Keywords	17,756	1.653	126	
Bettencourt et al. (2013)	PV	Keywords	11,931	1.044	36	
Chen et al. (2010)	PV	Keywords	24,803	0.289	3	Huang et al. (2013)
Han and Niosi (2016)	PV	Keywords	13,736	1.889	1	
Jang et al. (2013)	PV	Keywords	19,721	1.318	6	
Jang et al. (2013)a	PV	Keywords	101,334	1.318	6	
Lee et al. (2012)	PV	Keywords	5,833	1.846	19	Lee and Lee (2013); Geng and Ji (2016); Wong et al. (2014, 2016)
Myong (2014)	PV	Keywords	74,890	3.109	5	
Rai et al. (2013)	PV	Keywords	6,155		3	Venugopalan and Rai (2015)
Shibata et al. (2010)	PV	Keywords	12,775	1.752	71	
Zheng and Kammen (2014)	PV	Keywords	19,139	1.653	54	
CPC Classification Solar	Solar	Class.	37,420			Marin and Lotti (2017); Calel and Dechezleprêtre (2016)
WIPO Green Inventory Solar	Solar	Class.	98,668			Albino et al. (2014); Colombelli et al. (2015); Marin and Lotti (2017); Kruse (2016); Kruse and Wetzel (2016)
Dechezleprêtre et al. (2009)	Solar	Class.	20,946		27	
Dechezleprêtre et al. (2011)	Solar	Class.	22,324	2.028	209	Costantini and Mazzanti (2012); Wurlod and Noailly (2016)
Guan and Yan (2016)a	Solar	Class.	4,588	3.126	1	
Johnstone et al. (2010)	Solar	Class.	38,350	0.954	721	Noailly and Shestalova (2017); Noailly and Smeets (2012); Noailly and Ryfisch (2015); Braun et al. (2010); Ayari et al. (2012); Zachmann et al. (2015); Dalmazzone and Corsatea (2012); Diederich and Althammer (2016)
Nesta et al. (2014)	Solar	Class.	23,946	1.795	70	Diederich and Althammer (2016)
Noailly et al. (2010)	Solar	Class.	19557		4	Noailly (2012); Costantini et al. (2014, 2015c)
Pillu (2009)	Solar	Class.	27,171		2	Pillu and Koléda (2009)
Popp (2001)	Solar	Class.	96307	1.145	197	
Popp et al. (2013)	Solar	Class.	35,632	1.145	12	Popp (2016b)
Wangler (2013)	Solar	Class.	23,946	0.866	23	Corsatea (2014)
Jamasb and Pollitt (2011)	Solar	Keywords	31,601	3.126	61	
Jamasb and Pollitt (2015)	Solar	Keywords	47,483	1.653	9	
Margolis and Kammen (1999b)	Solar	Keywords	25,437	7.478	202	Margolis and Kammen (1999a)
CPC Classification CSP	CSP	Class.	14,004			Wu and Hu (2015)
WIPO Green Inventory CSP	CSP	Class.	34,239			
Braun et al. (2011)	CSP	Class.	14,402	1.653	28	
Braun et al. (2011)a	CSP	Class.	195,172	1.653	28	
Gallagher (2014)	CSP	Class.	5,319		32	
Tseng (2014)	CSP	Class.	8,657			
Lanjouw and Mody (1996)	CSP	Class. + Key.	13,062	3.126	681	
Lee et al. (2012)a	CSP	Keywords	43,880	1.846	19	Lee and Lee (2013); Geng and Ji (2016)
Wong et al. (2014)	CSP	Keywords	4,693	1.653	7	Wong et al. (2016)

Citation counts from google scholar were collected on January 14th 2017.
A search strategy receiving an “a” indicates a second search strategy used in a paper.

6.7.2 Patent counts analysis for triadic patents

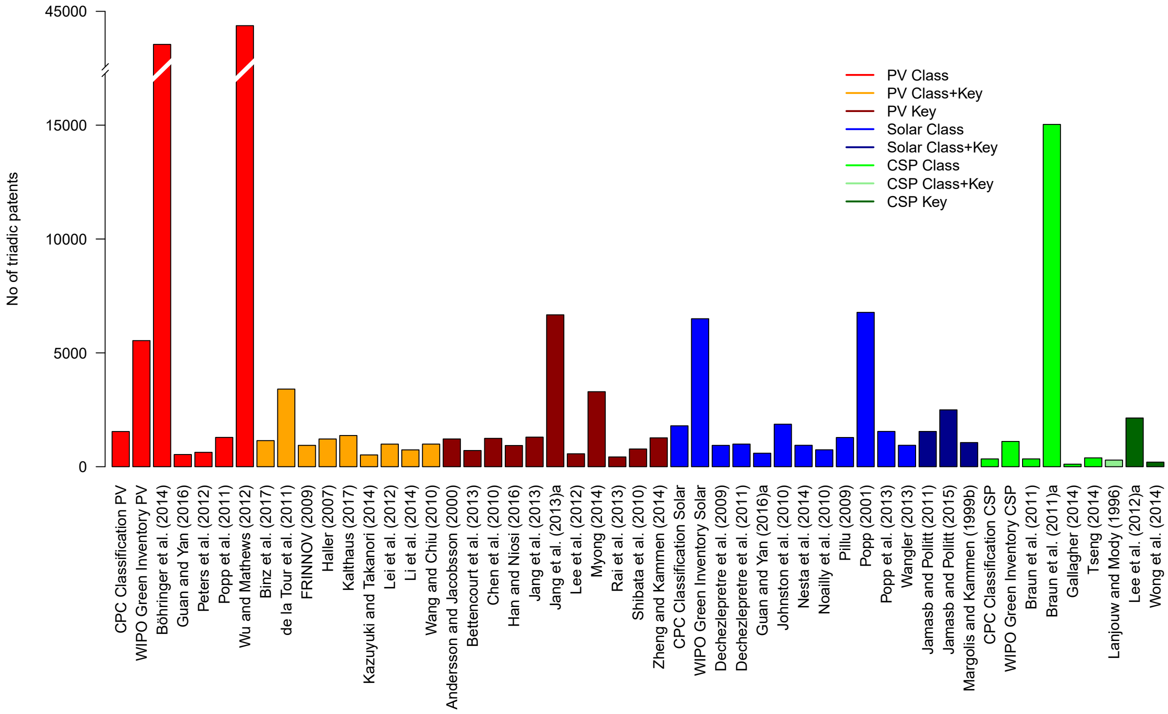


Figure 6.8: Patent counts for triadic filings of the 51 search strategies.

Figure note: 'Class' refers to the use of IPC or CPC classifications and 'Key' refers to the use of keywords.

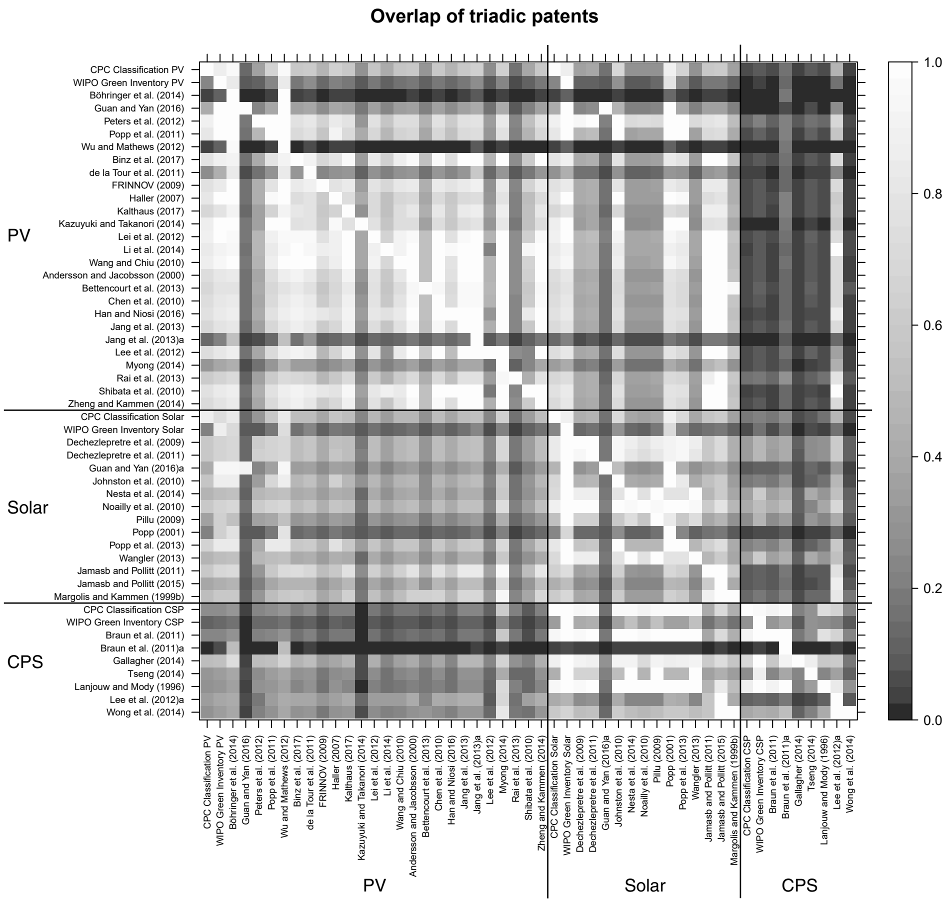


Figure 6.9: Overlap of triadic filings between the 51 search strategies.

Figure note: Each horizontal line is calculated by $\frac{PatentsA \cap PatentsB}{PatentsA}$ where PatentsA refers to the search strategy on the horizontal axis and PatentsB to the different search strategies on the vertical axis. The lower the overlap between two search strategies, the darker the corresponding area.

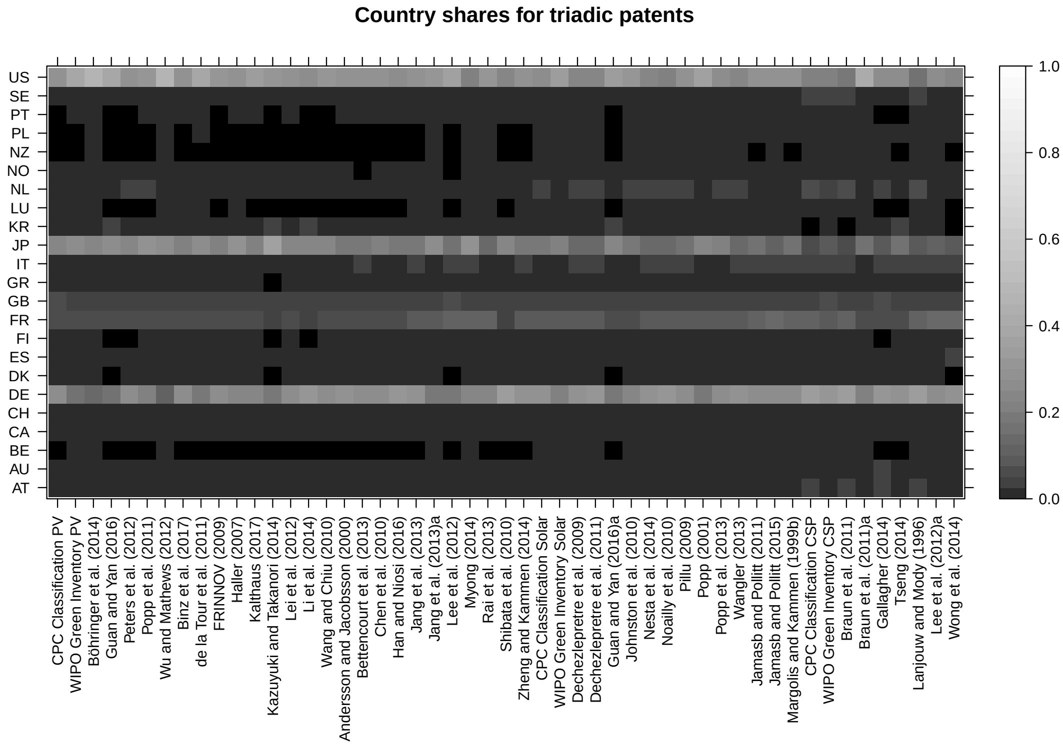


Figure 6.10: Share of countries for triadic filings between the 51 search strategies.

Figure note: The horizontal axis refers to the 23 countries in our sample while the vertical axis depicts the different search strategies. The darker the area, the lower is the share of a country in the patent selection. Black represents no patent at all.

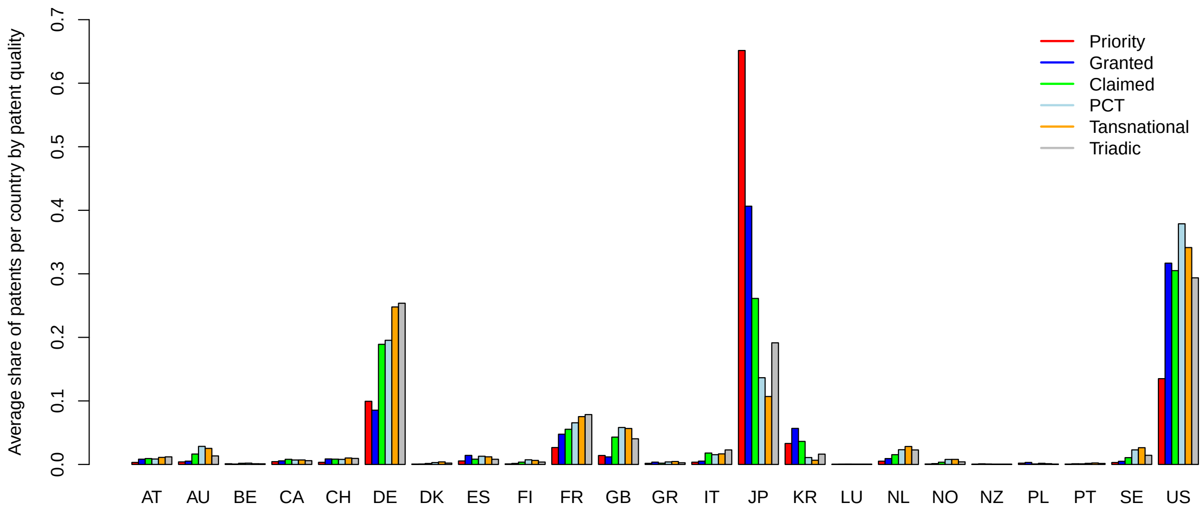


Figure 6.11: Average share of patents per countries for patent quality dimensions.

Figure note: The average share per country is calculated based on the country share per search strategy per patent quality dimension.

6.7.3 Extreme-Bounds Analysis results for search strategy disaggregation

Table 6.8: Extreme-Bounds Analysis for the research design of Johnstone et al. (2010) disaggregated by search strategy.

	PV									Solar						CSP					
	IPC			Keywords			IPC and Keyword			IPC			Keywords			IPC			Keywords		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-3.987	7.361	0.571	-3.692	4.046	0.621	-2.813	4.316	0.685	-2.473	6.174	0.972	-1.214	4.868	0.722	-4.634	6.601	0.857	-1.021	5.095	1
Feed-in tariff levels	-0.096	0.580	0.833	-0.079	0.195	0.742	-0.076	0.592	0.759	-0.184	0.082	0.722	-0.050	0.069	0.833	-0.241	0.111	0.714	-0.071	0.103	0.833
REC targets	-0.530	0.746	0.571	-0.559	0.463	0.455	-0.477	0.776	0.407	-0.502	0.789	0.861	-0.345	0.299	0.500	-0.430	1.268	0.810	-0.614	1.089	0.417
Kyoto protocol	-0.453	3.456	0.905	-0.904	1.237	0.712	-0.683	1.222	0.796	-0.357	1.846	0.931	-0.570	0.865	0.833	-0.926	1.279	0.762	-0.653	0.990	0.750
Investment incentives	-2.058	1.848	0.786	-0.326	1.404	0.909	-0.328	1.587	0.963	-1.071	1.175	0.597	-0.359	1.105	0.833	-0.860	1.604	0.548	-0.623	1.487	0.583
Tax measures	-1.019	1.811	0.833	-0.718	1.508	0.773	-1.075	1.203	0.685	-1.338	0.876	0.347	-0.580	0.536	0.722	-1.063	1.794	0.524	-0.902	1.164	0.583
Guaranteed price	-1.761	5.235	0.881	-1.606	2.260	0.742	-2.906	2.503	0.759	-1.183	4.224	0.722	-0.920	1.748	0.833	-2.052	2.407	0.643	-1.141	1.999	0.667
Voluntary programs	-1.126	1.669	0.833	-1.433	1.574	0.652	-1.422	1.189	0.704	-1.168	1.291	0.833	-1.371	1.098	0.833	-1.317	2.139	0.810	-1.349	1.530	0.833
Obligations	-0.688	2.106	0.786	-0.777	1.566	0.909	-0.538	1.765	0.963	-0.545	1.607	0.819	-0.622	0.878	0.778	-1.431	1.099	0.714	-1.327	0.650	0.583
Patent selections	42	42	42	66	66	66	54	54	54	72	72	72	18	18	18	42	42	42	12	12	12

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Table 6.9: Extreme-Bounds Analysis for the research design of Peters et al. (2012) disaggregated by search strategy.

	PV									Solar						CSP					
	IPC			Keywords			IPC and Keyword			IPC			Keywords			IPC			Keywords		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.914	0.794	0.714	-0.106	0.771	0.985	-0.037	1.294	1.000	-0.472	0.679	0.676	-0.170	0.598	0.944	-0.381	0.765	0.415	-0.391	0.551	0.500
Continental R&D funding	-0.480	0.763	0.595	-0.275	0.633	0.754	-0.289	0.703	0.648	-0.677	0.640	0.324	-0.433	0.477	0.500	-0.774	0.747	0.171	-0.891	0.419	0.167
Intercont. R&D funding	-4.022	5.487	0.833	-0.943	0.921	0.385	-0.803	1.738	0.630	-1.304	3.677	0.479	-1.046	0.735	0.389	-1.327	1.912	0.439	-1.439	0.577	0.250
Domestic capacity	-0.366	0.649	0.905	-0.186	0.552	0.923	-0.049	0.516	1.000	-0.187	0.701	0.986	-0.057	0.522	1.000	-0.440	0.677	0.878	-0.173	0.551	0.917
Continental capacity	-0.313	0.644	0.643	-0.218	0.440	0.800	-0.184	0.399	0.907	-0.260	0.324	0.718	-0.116	0.258	0.889	-0.256	0.341	0.659	-0.260	0.177	0.583
Intercont. capacity	-0.302	1.330	0.810	-0.342	0.290	0.708	-0.408	0.300	0.648	-0.311	0.856	0.831	-0.329	0.262	0.722	-0.368	0.598	0.829	-0.302	0.335	0.833
Patent selections	42	42	42	65	65	65	54	54	54	71	71	71	18	18	18	41	41	41	12	12	12

6.8 Supplementary materials

6.8.1 Patent counts analysis for granted, claimed, PCT, and transnational filings

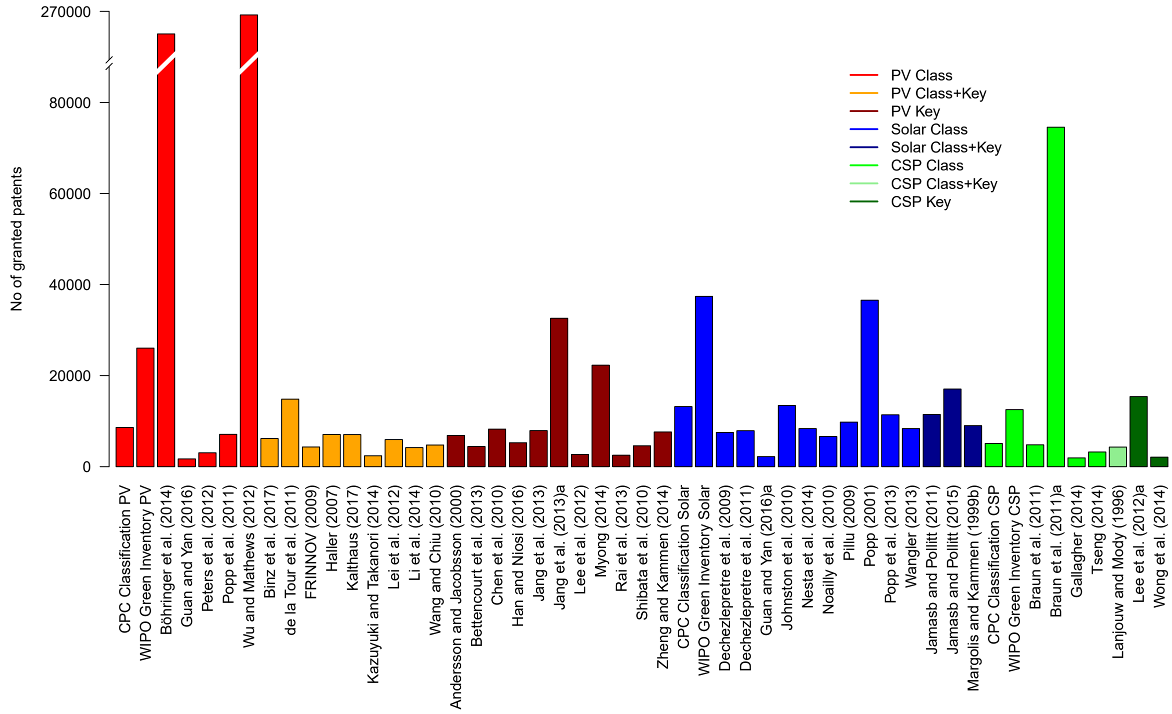


Figure 6.12: Patent counts for granted filings of the 51 search strategies.

Figure note: 'Class' refers to the use of IPC or CPC classifications and 'Key' refers to the use of keywords.

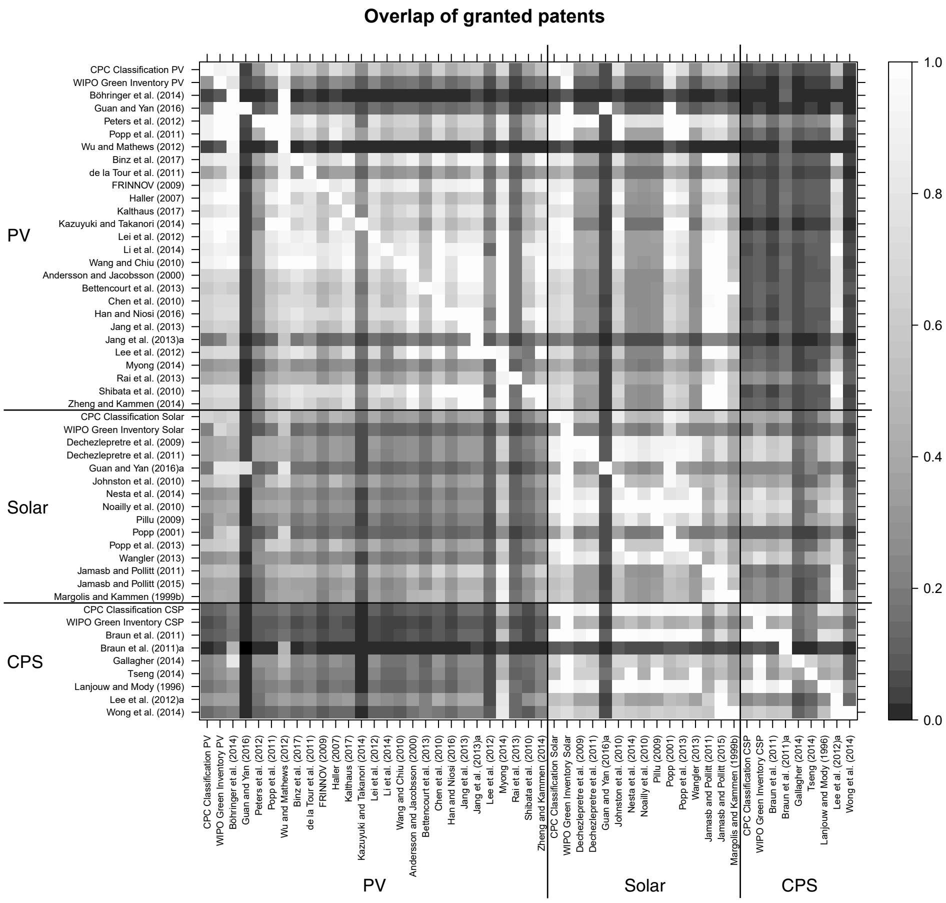


Figure 6.13: Overlap of granted filings between the 51 search strategies.

Figure note: Each horizontal line is calculated by $\frac{PatentsA \cap PatentsB}{PatentsA}$ where PatentsA refers to the search strategy on the horizontal axis and PatentsB to the different search strategies on the vertical axis. The lower the overlap between two search strategies, the darker the corresponding area.

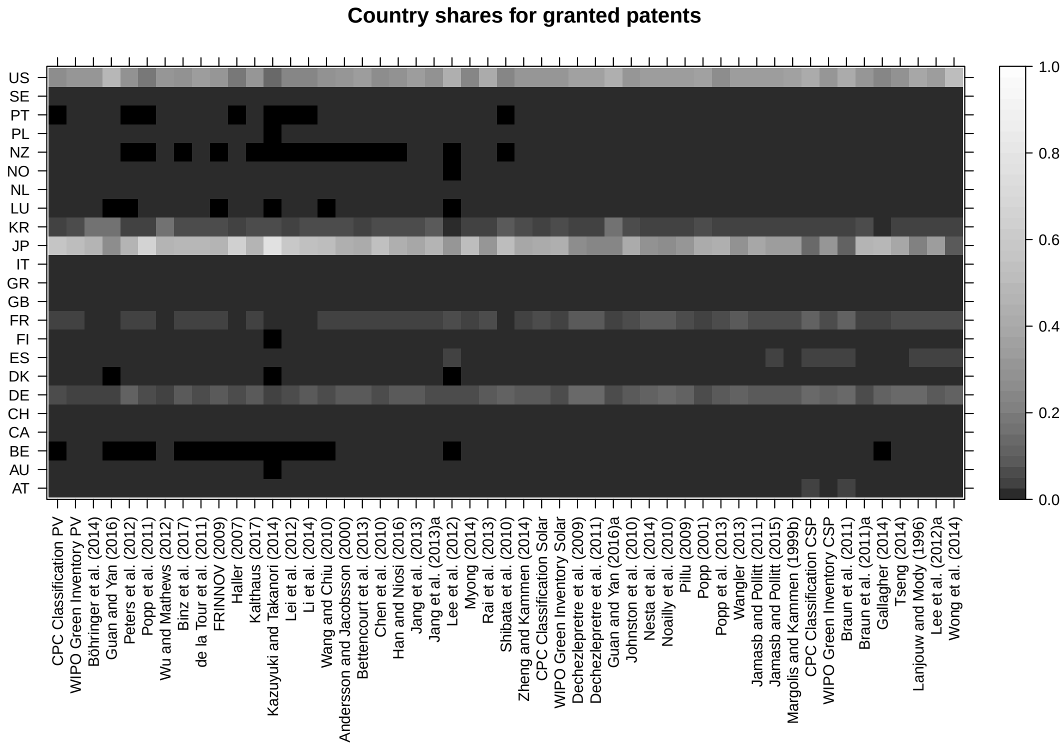


Figure 6.14: Share of countries for granted filings between the 51 search strategies.

Figure note: The horizontal axis refers to the 23 countries in our sample while the vertical axis depicts the different search strategies. The darker the area, the lower is the share of a country in the patent selection. Black represents no patent at all.

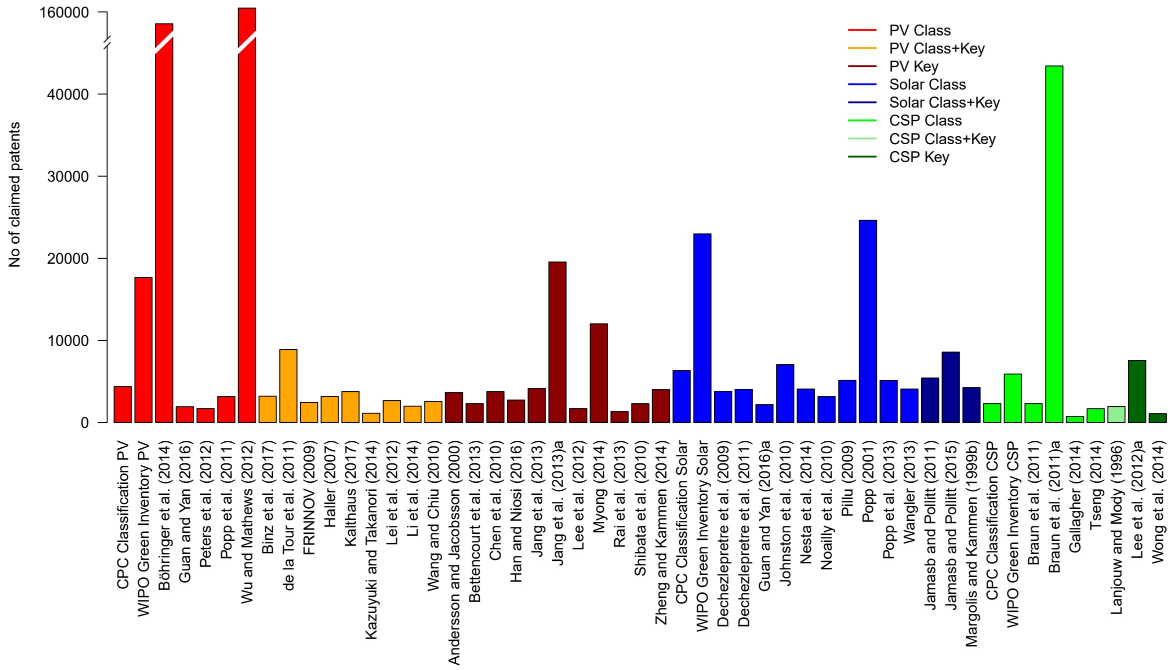


Figure 6.15: Patent counts for claimed filings of the 51 search strategies.

Figure note: 'Class' refers to the use of IPC or CPC classifications and 'Key' refers to the use of keywords.

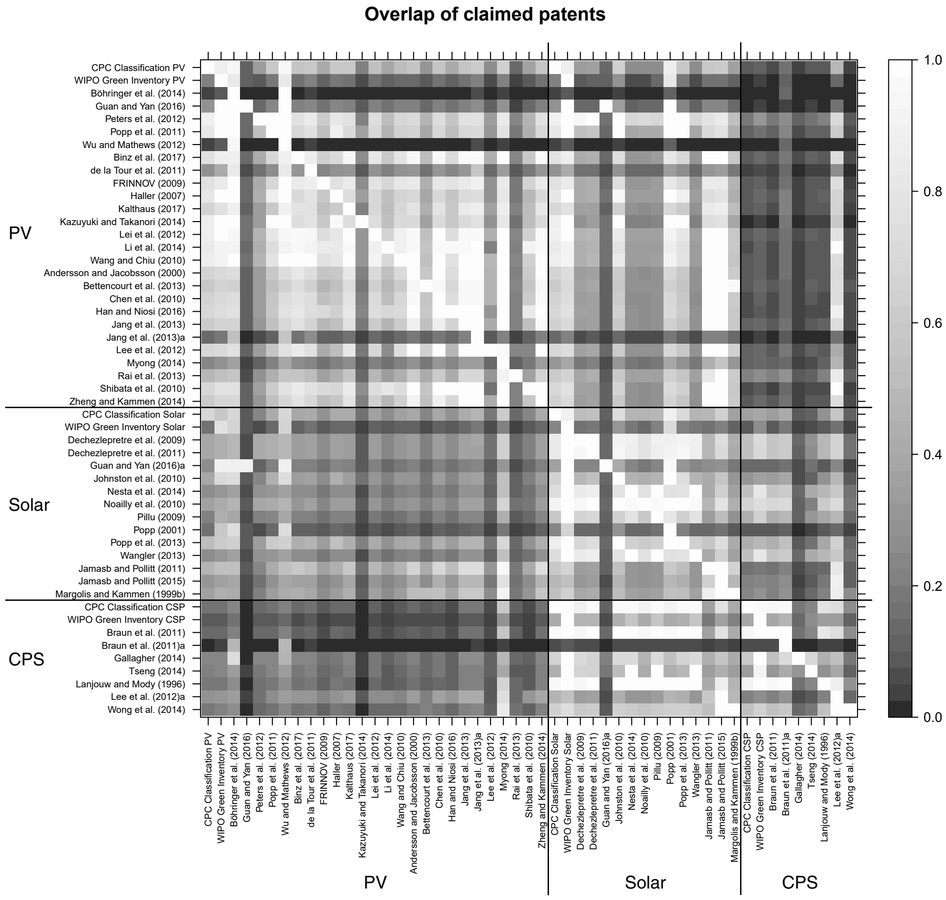


Figure 6.16: Overlap of claimed filings between the 51 search strategies.

Figure note: Each horizontal line is calculated by $\frac{PatentsA \cap PatentsB}{PatentsA}$ where PatentsA refers to the search strategy on the horizontal axis and PatentsB to the different search strategies on the vertical axis. The lower the overlap between two search strategies, the darker the corresponding area.

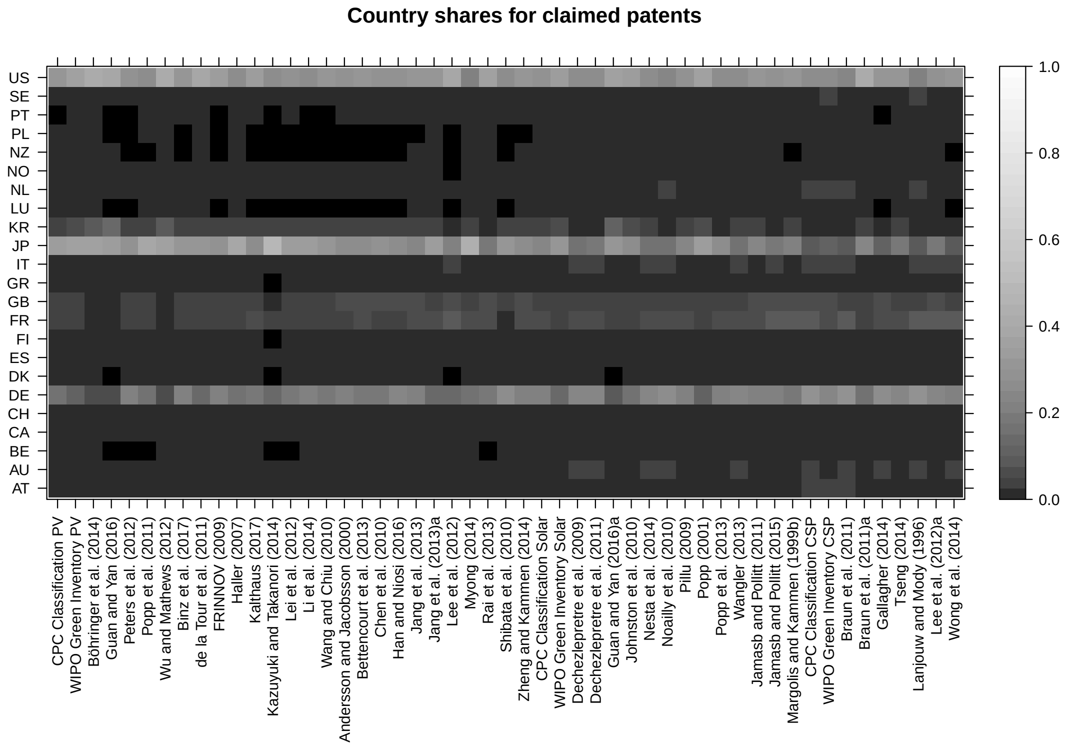


Figure 6.17: Share of countries for claimed filings between the 51 search strategies.

Figure note: The horizontal axis refers to the 23 countries in our sample while the vertical axis depicts the different search strategies. The darker the area, the lower is the share of a country in the patent selection. Black represents no patent at all.

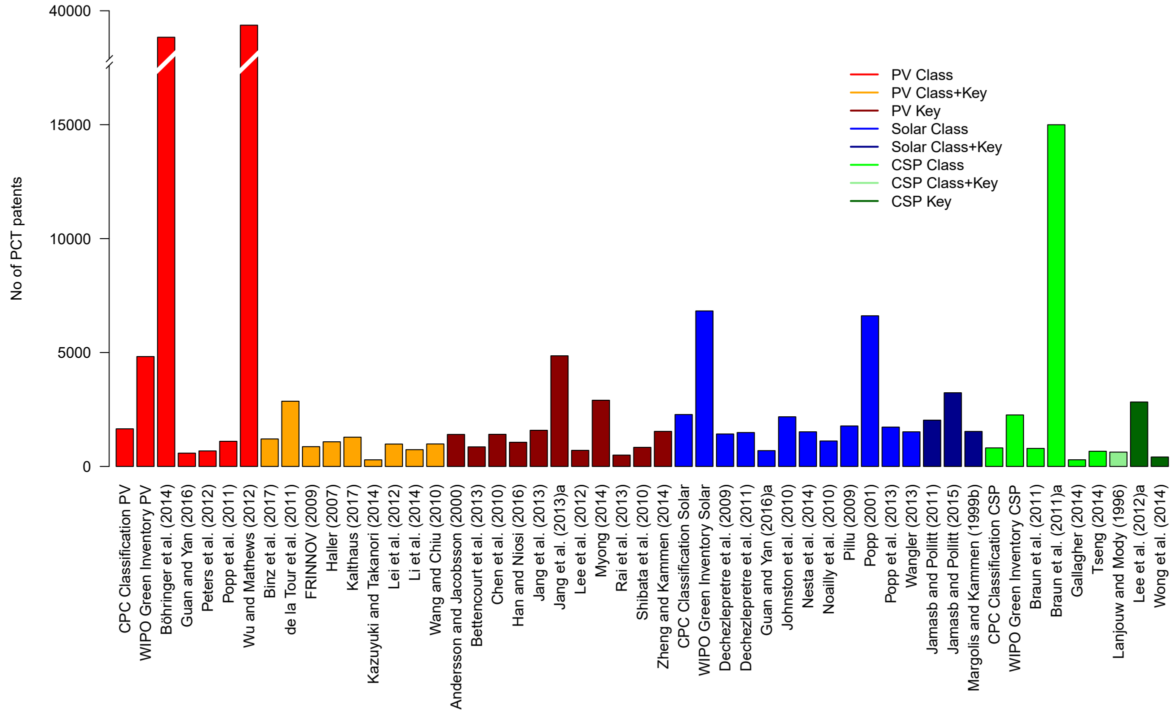


Figure 6.18: Patent counts for PCT filings of the 51 search strategies.

Figure note: 'Class' refers to the use of IPC or CPC classifications and 'Key' refers to the use of keywords.

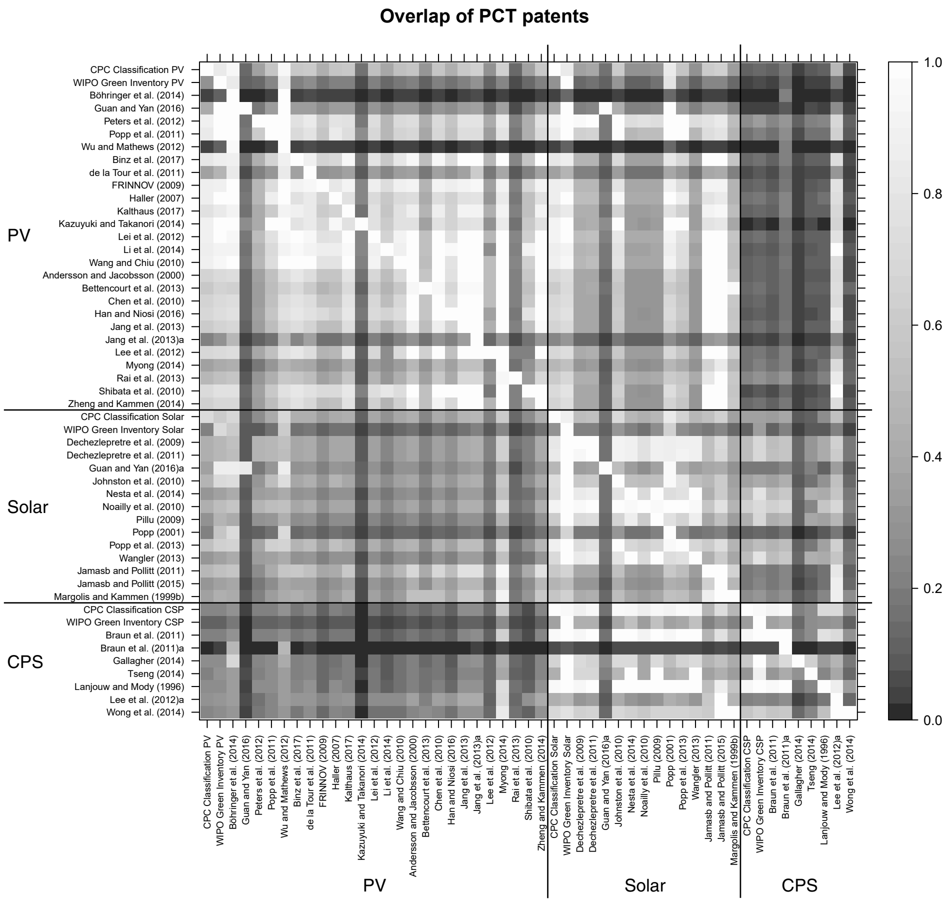


Figure 6.19: Overlap of PCT filings between the 51 search strategies.

Figure note: Each horizontal line is calculated by $\frac{PatentsA \cap PatentsB}{PatentsA}$ where PatentsA refers to the search strategy on the horizontal axis and PatentsB to the different search strategies on the vertical axis. The lower the overlap between two search strategies, the darker the corresponding area.

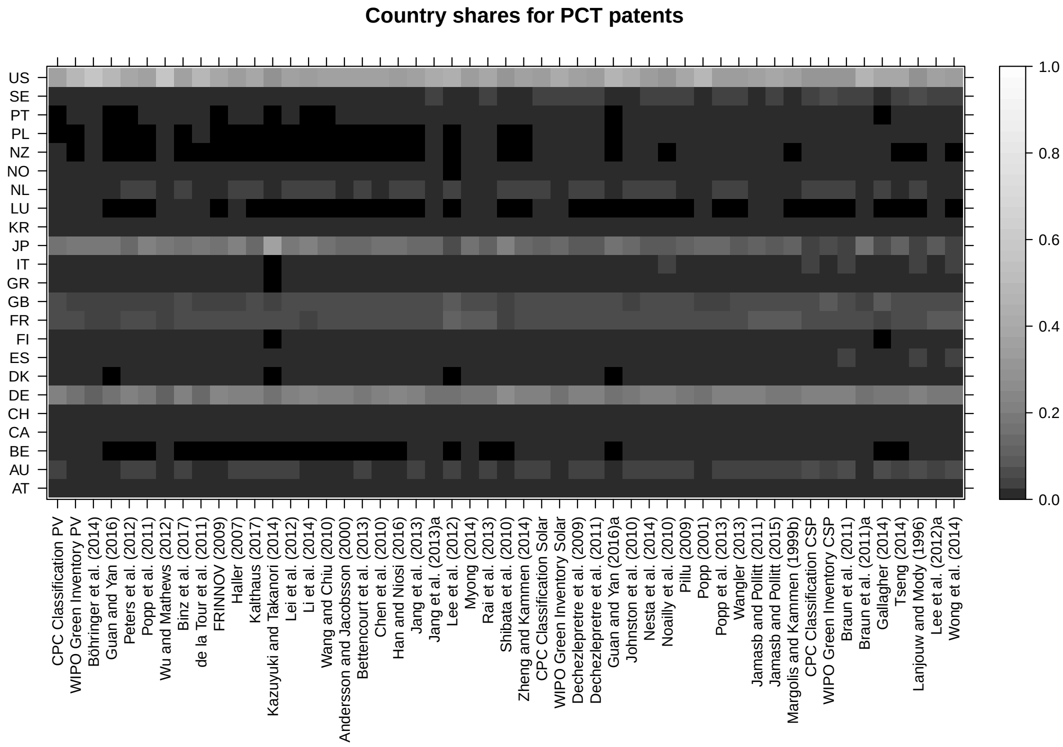


Figure 6.20: Share of countries for PCT filings between the 51 search strategies.

Figure note: The horizontal axis refers to the 23 countries in our sample while the vertical axis depicts the different search strategies. The darker the area, the lower is the share of a country in the patent selection. Black represents no patent at all.

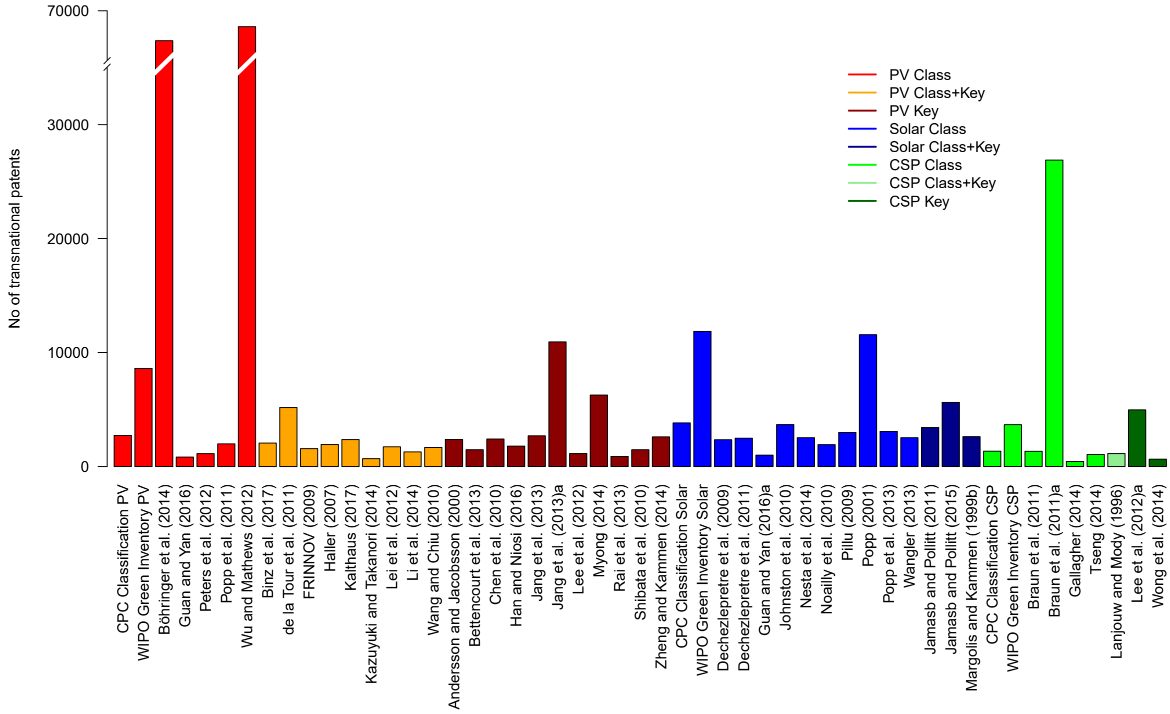


Figure 6.21: Patent counts for transnational filings of the 51 search strategies.

Figure note: 'Class' refers to the use of IPC or CPC classifications and 'Key' refers to the use of keywords.

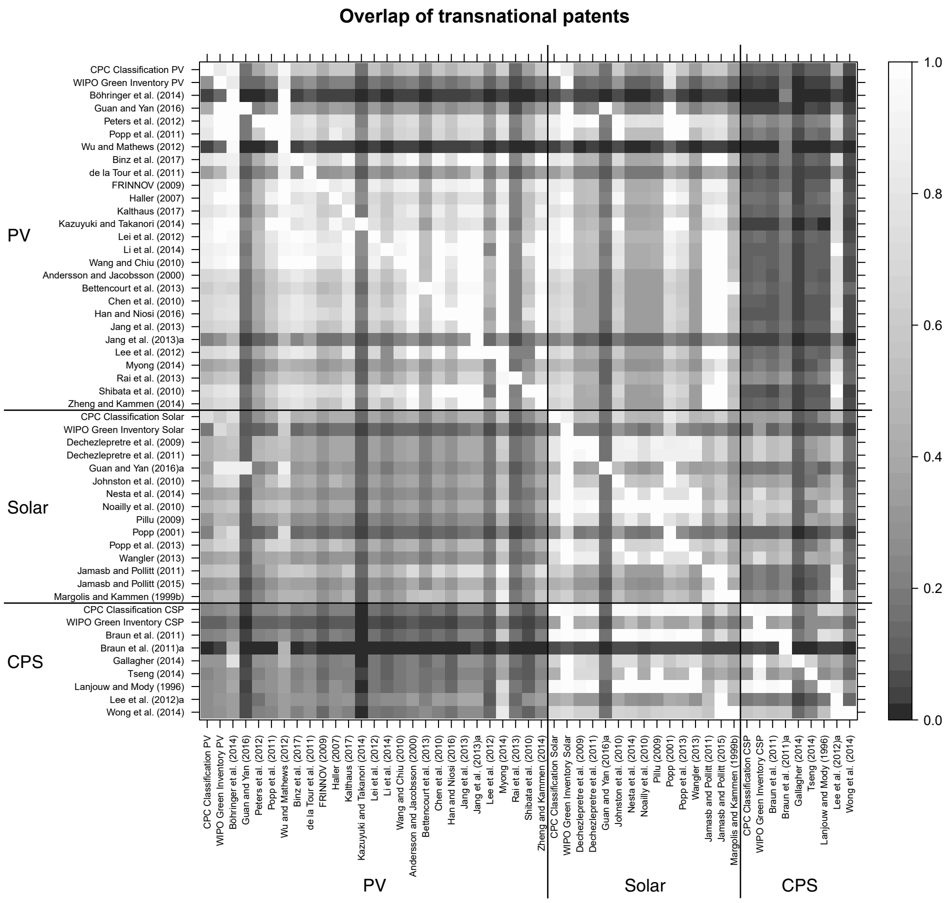


Figure 6.22: Overlap of transnational filings between the 51 search strategies.

Figure note: Each horizontal line is calculated by $\frac{PatentsA \cap PatentsB}{PatentsA}$ where PatentsA refers to the search strategy on the horizontal axis and PatentsB to the different search strategies on the vertical axis. The lower the overlap between two search strategies, the darker the corresponding area.

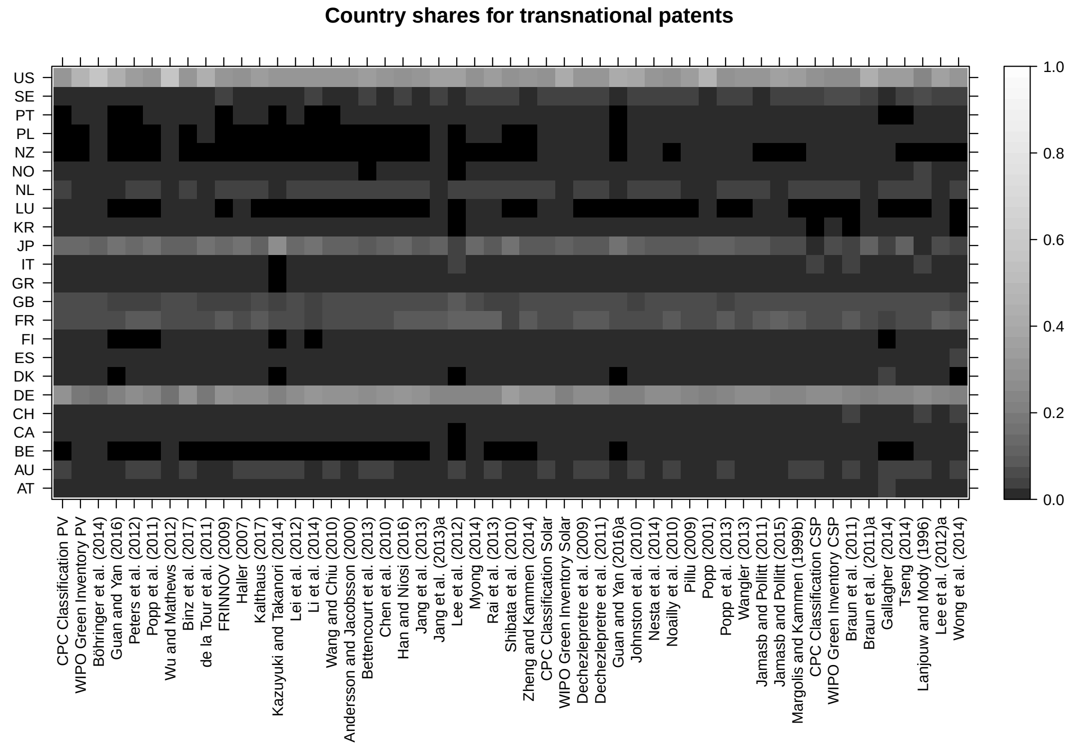


Figure 6.23: Share of countries for transnational filings between the 51 search strategies.

Figure note: The horizontal axis refers to the 23 countries in our sample while the vertical axis depicts the different search strategies. The darker the area, the lower is the share of a country in the patent selection. Black represents no patent at all.

6.8.2 Extreme-Bounds Analysis robustness subsamples

Table 6.10: Extreme-Bounds Analysis for the research design of Johnstone et al. (2010) – Trimmed subsample.

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	0.07	2.649	1	0.096	4.316	1	-0.886	2.856	0.952	-3.987	2.682	0.143	-1.753	2.151	0.333	-1.488	1.975	0.429
Feed-in tariff levels	-0.009	0.090	1	-0.079	0.029	0	-0.061	0.072	0.905	-0.018	0.592	1	-0.066	0.080	0.810	-0.096	0.089	0.762
REC targets	-0.132	0.564	1	-0.540	0.776	0.095	-0.233	0.566	0.857	-0.369	0.635	0.190	-0.322	0.447	0.286	-0.520	0.433	0.238
Kyoto protocol	-0.226	0.837	0.857	-0.779	0.536	0.143	-0.334	0.796	0.952	-0.683	0.942	0.810	-0.221	0.940	1	-0.161	1.222	1
Investment incentives	-0.311	0.691	0.81	-0.328	1.272	1	-0.331	0.748	0.810	0.066	1.848	1	-0.165	1.220	1	-0.159	1.280	1
Tax measures	-0.282	0.545	0.905	-1.075	0.525	0.190	-0.475	0.605	0.857	-1.069	0.640	0.571	-0.441	0.705	0.857	-0.604	1.203	0.952
Guaranteed price	-0.668	1.606	1	-1.761	2.471	0.143	-1.116	1.419	0.952	-1.621	3.793	1	-1.605	1.629	0.905	-2.906	1.506	0.714
Voluntary programs	-0.397	0.666	0.476	-1.422	0.024	0	-0.496	0.578	0.857	-0.351	1.207	1	-0.456	0.648	0.952	-0.777	0.818	0.952
Obligations	-0.302	0.518	0.952	-0.146	1.302	1	-0.140	0.907	1	0.024	1.765	1	-0.272	1	1	-0.680	0.889	0.810
Patent selections	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	1.011	2.586	1	1.988	5.955	1	-0.392	2.326	1	-0.990	2.890	1	-1.214	1.679	0.818	-1.139	1.572	0.727
Feed-in tariff levels	-0.008	0.030	1	-0.050	0.009	0	-0.011	0.033	1	-0.010	0.071	1	-0.009	0.044	1	-0.105	0.051	0.545
REC targets	-0.054	0.248	1	-0.345	0.364	0.455	-0.138	0.247	1	-0.263	0.255	0.636	-0.169	0.247	0.818	-0.289	0.311	0.727
Kyoto protocol	-0.023	0.647	1	-0.570	0.462	0.636	-0.004	0.771	1	-0.351	0.509	0.636	0.026	0.748	1	-0.008	1.043	1
Investment incentives	-0.534	0.265	0.182	-0.317	0.753	1	-0.625	0.286	0.091	0.229	1.163	1	-0.203	0.600	1	-0.123	0.832	1
Tax measures	-0.090	0.537	1	-0.580	0.247	0	-0.475	0.408	0.273	-0.531	0.444	0.182	-0.461	0.433	0.182	-0.606	0.536	0.545
Guaranteed price	-0.399	0.469	0.273	-1.088	0.144	0	-0.361	0.666	1	-0.119	1.748	1	-0.278	1.009	1	-0.853	1.400	1
Voluntary programs	-0.182	0.544	1	-1.371	-0.278	0	-0.035	0.643	1	0.276	1.253	1	0.083	0.845	1	-0.029	1.056	1
Obligations	-0.457	0.302	0.182	-0.219	0.849	1	-0.163	0.618	1	0.004	0.931	1	-0.185	0.650	1	-0.622	0.599	0.545
Patent selections	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-0.207	3.003	1	1.394	6.601	1	-1.014	2.440	1	-2.031	3.809	1	-3.377	1.975	0.714	-4.634	2.324	0.714
Feed-in tariff levels	-0.017	0.037	1	-0.046	0.012	0	-0.024	0.068	1	-0.019	0.099	1	-0.049	0.065	0.857	-0.241	0.111	0.571
REC targets	-0.237	0.482	0.857	-0.389	0.404	0.571	-0.361	0.548	0.714	-0.265	0.650	0.571	-0.312	0.535	0.714	-0.430	1.268	0.857
Kyoto protocol	0.083	0.883	1	-0.652	0.426	0.571	-0.375	0.824	1	-0.926	0.781	0.429	-0.350	0.963	1	-0.781	1.279	1
Investment incentives	-0.663	0.299	0.143	-0.335	0.772	1	-0.860	0.339	0	-0.776	1.191	1	-0.536	0.738	0.429	-0.717	1.604	0.571
Tax measures	-0.535	0.680	0.857	-1.063	0.274	0	-0.729	0.427	0.429	-0.710	1.194	0.571	-0.736	0.692	0.714	-1.034	1.794	0.429
Guaranteed price	-0.731	0.425	0.286	-1.177	0.510	0	-0.732	0.793	0.857	-0.542	1.921	1	-0.966	1.252	0.857	-2.052	2.407	0.857
Voluntary programs	-0.068	0.651	1	-1.349	-0.133	0	-0.271	0.907	1	0.030	2.139	1	-0.029	1.176	1	-0.622	1.645	0.857
Obligations	-0.624	0.286	0.143	-0.318	0.862	1	-0.339	0.925	1	-0.373	1.057	1	-0.498	0.811	0.857	-1.431	1.099	0.286
Patent selections	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Table 6.11: Extreme-Bounds Analysis for the research design of Johnstone et al. (2010) – Citation subsample.

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-1.153	2.541	0.875	0.386	3.961	1	-0.886	2.355	0.750	-3.987	1.407	0.250	-1.753	1.464	0.250	-1.836	1.444	0.250
Feed-in tariff levels	-0.009	0.038	1	-0.079	0.011	0	-0.061	0.045	0.875	-0.018	0.228	1	-0.064	0.060	0.750	-0.096	0.064	0.500
REC targets	-0.148	0.230	0.875	-0.540	0.315	0.125	-0.171	0.237	0.625	-0.343	0.210	0.125	-0.273	0.222	0.250	-0.520	0.353	0.125
Kyoto protocol	-0.226	0.837	0.750	-0.779	0.536	0.250	-0.334	0.796	0.875	-0.501	0.942	0.875	-0.218	0.940	1	-0.161	1.194	1
Investment incentives	-0.249	0.691	0.750	-0.079	1.272	1	-0.271	0.748	0.875	0.192	1.848	1	0.020	1.220	1	0.020	1.280	1
Tax measures	-0.214	0.735	1	-0.658	0.525	0.375	-0.475	0.613	0.750	-0.802	1.171	0.375	-0.441	0.791	0.625	-0.604	0.872	0.875
Guaranteed price	-0.668	0.952	1	-1.761	1.006	0.125	-0.607	1.207	1	-0.479	3.793	1	-0.790	1.629	0.875	-1.488	1.506	0.750
Voluntary programs	-0.394	0.666	0.500	-1.422	0.024	0	-0.295	0.578	0.875	-0.023	1.207	1	-0.198	0.645	1	-0.315	0.818	1
Obligations	-0.302	0.518	0.75	-0.146	1.157	1	-0.291	0.768	0.875	-0.017	1.220	1	-0.481	0.691	0.875	-0.688	0.632	0.625
Patent selections	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	0.450	2.529	1	1.988	5.955	1	-0.392	2.326	1	-0.990	2.890	1	-1.214	1.679	0.875	-1.139	1.572	0.750
Feed-in tariff levels	-0.011	0.030	1	-0.050	0.009	0	-0.014	0.033	1	-0.006	0.071	1	-0.009	0.044	1	-0.105	0.048	0.500
REC targets	-0.052	0.259	1	-0.345	0.364	0.500	-0.138	0.244	1	-0.173	0.255	0.750	-0.095	0.222	1.000	-0.285	0.311	0.875
Kyoto protocol	-0.023	0.647	1	-0.570	0.462	0.625	-0.004	0.771	1	-0.351	0.522	0.625	0.004	0.748	1	-0.080	1.043	1
Investment incentives	-0.559	0.265	0.250	-0.367	0.753	0.875	-0.625	0.286	0.125	0.288	1.105	1	-0.147	0.600	1	-0.123	0.832	1
Tax measures	-0.090	0.537	1	-0.580	0.393	0.125	-0.475	0.408	0.375	-0.531	0.396	0.250	-0.461	0.433	0.25	-0.606	0.536	0.500
Guaranteed price	-0.399	0.469	0.375	-1.088	0.144	0	-0.361	0.666	1	-0.119	1.748	1	-0.278	1.009	1	-0.853	1.400	1
Voluntary programs	-0.182	0.544	1	-1.367	-0.297	0	-0.035	0.643	1	0.276	1.253	1	0.083	0.845	1	-0.029	1.056	1
Obligations	-0.457	0.302	0.250	-0.219	0.849	1	-0.163	0.567	1	0.004	0.931	1	-0.185	0.620	1	-0.622	0.591	0.500
Patent selections	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-0.012	3.003	1	1.321	6.601	1	-0.828	2.440	1	-2.031	3.809	1	-3.377	1.975	0.500	-4.634	2.324	0.500
Feed-in tariff levels	-0.017	0.037	1	-0.046	0.012	0	-0.009	0.068	1	-0.019	0.099	1	-0.043	0.065	1	-0.241	0.111	0.500
REC targets	-0.237	0.482	0.750	-0.390	0.353	0.500	-0.361	0.548	0.750	-0.262	0.650	0.750	-0.312	0.535	0.750	-0.430	1.268	1
Kyoto protocol	-0.132	0.883	0.750	-0.650	0.417	0.500	-0.375	0.824	1	-0.926	0.781	0.250	-0.350	0.963	1	-0.781	1.279	0.750
Investment incentives	-0.663	0.226	0	-0.335	0.772	1	-0.860	0.275	0.250	-0.776	1.191	1	-0.536	0.738	0.500	-0.717	1.604	0.750
Tax measures	-0.535	0.680	0.750	-1.063	0.349	0.250	-0.729	0.503	0.500	-0.596	1.194	0.750	-0.617	0.692	0.750	-0.929	1.794	0.500
Guaranteed price	-0.731	0.344	0.250	-1.177	0.510	0	-0.732	0.793	0.750	-0.542	1.921	1	-0.831	1.252	1	-1.451	2.407	1
Voluntary programs	-0.073	0.651	1	-1.317	-0.133	0	-0.271	0.907	1	0.030	2.139	1	-0.029	1.176	1	-0.606	1.645	1
Obligations	-0.624	0.286	0	-0.318	0.862	1	-0.339	0.557	1	-0.373	0.920	1	-0.498	0.578	0.500	-1.431	0.625	0.250
Patent selections	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Notes: ‘LB’ denotes Lower Bound, ‘UB’ denotes Upper Bound and ‘Pos. Sign’ denotes the share of point estimates with a positive sign.

Table 6.12: Extreme-Bounds Analysis for the research design of Johnstone et al. (2010) – SNIP subsample.

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-2.758	2.541	0.833	0.105	4.046	1	-0.736	4.451	0.917	-3.987	7.361	0.333	-1.753	3.177	0.333	-1.836	3.623	0.417
Feed-in tariff levels	-0.036	0.076	1	-0.079	0.072	0.083	-0.061	0.178	0.917	-0.039	0.228	1	-0.064	0.233	0.833	-0.096	0.580	0.750
REC targets	-0.148	0.746	0.917	-0.540	0.492	0.250	-0.176	0.547	0.750	-0.343	0.611	0.333	-0.273	0.593	0.333	-0.520	0.627	0.167
Kyoto protocol	-0.245	2.431	0.833	-0.904	1.726	0.250	-0.334	1.923	0.917	-0.501	3.456	0.917	-0.218	2.311	1	-0.161	2.027	1
Investment incentives	-2.058	0.691	0.667	-1.496	1.272	0.917	-0.525	0.748	0.750	-1.466	1.848	0.917	-1.028	1.220	0.917	-0.949	1.280	0.917
Tax measures	-0.247	1.811	0.917	-0.784	1.314	0.333	-0.475	0.967	0.833	-1.019	1.171	0.583	-0.441	1.021	0.833	-0.604	1.386	0.917
Guaranteed price	-0.734	4.617	0.917	-1.761	5.168	0.167	-0.607	4.301	1	-0.687	5.044	1	-0.797	4.801	0.833	-1.606	5.235	0.750
Voluntary programs	-0.397	1.295	0.583	-1.422	0.545	0	-0.328	0.951	0.833	-0.801	1.574	1	-0.198	1.436	1	-0.315	1.669	1
Obligations	-0.302	1.471	0.833	-0.146	1.556	1	-0.291	1.366	0.917	-0.017	2.106	1	-0.481	1.521	0.917	-0.688	1.442	0.750
Patent selections	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-0.661	2.428	1	1.662	5.888	1	-0.392	3.105	1	-1.241	5.138	1	-2.473	1.753	0.500	-1.952	2.020	0.500
Feed-in tariff levels	-0.034	0.048	1	-0.050	0.029	0	-0.038	0.059	1	-0.030	0.082	1	-0.031	0.062	1	-0.184	0.052	0.500
REC targets	-0.052	0.789	1	-0.345	0.672	0.333	-0.138	0.697	1	-0.175	0.472	0.500	-0.108	0.626	0.833	-0.285	0.723	0.667
Kyoto protocol	-0.023	1.637	1	-0.570	0.940	0.500	-0.004	1.748	1	-0.351	1.846	0.833	0.060	1.792	1	0.016	1.736	1
Investment incentives	-1.071	0.265	0.333	-0.801	0.753	0.833	-0.885	0.286	0.167	-0.926	1.105	0.833	-0.988	0.600	0.833	-0.707	0.776	0.833
Tax measures	-0.493	0.645	1	-1.338	0.206	0	-1.024	0.408	0.500	-0.607	0.561	0.333	-0.915	0.433	0.333	-0.606	0.876	0.667
Guaranteed price	-0.399	1.769	0.667	-1.074	2.017	0.167	-0.351	1.959	1	-0.360	2.390	1	-0.278	2.257	1	-0.853	4.224	1
Voluntary programs	-0.182	0.831	1	-1.371	0.003	0	-0.311	0.643	1	-0.160	1.253	1	0.083	1.119	1	-0.029	1.291	1
Obligations	-0.457	0.543	0.500	-0.219	1.131	1	-0.163	1.304	1	0.004	1.607	1	-0.185	1.379	1	-0.622	1.533	0.333
Patent selections	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
R&D expenditures	-0.012	3.003	1	1.321	6.601	1	-0.435	2.417	1	-0.503	3.809	1	-1.021	2.426	0.800	-1.065	3.038	0.800
Feed-in tariff levels	-0.019	0.037	1	-0.041	0.022	0	-0.016	0.049	1	-0.021	0.071	1	-0.015	0.065	1	-0.071	0.111	0.800
REC targets	-0.237	0.172	0.600	-0.390	0.353	0.200	-0.361	0.327	0.600	-0.364	0.370	0.600	-0.312	0.437	0.600	-0.614	1.089	0.800
Kyoto protocol	-0.132	0.689	0.800	-0.653	0.417	0.400	-0.176	0.824	1	-0.518	0.584	0.400	-0.229	0.911	1	-0.572	1.279	0.800
Investment incentives	-0.663	0.223	0	-0.335	0.738	1	-0.860	0.292	0.200	0.213	1.487	1	-0.536	0.553	0.600	-0.717	0.781	0.600
Tax measures	-0.188	0.680	1.000	-0.819	0.349	0.200	-0.628	0.503	0.600	-0.902	0.716	0.600	-0.615	0.504	0.600	-0.929	1.164	0.600
Guaranteed price	-0.822	0.425	0.400	-1.177	0.138	0	-1.115	0.793	0.800	-0.677	1.515	1	-0.731	1.252	1	-0.592	2.407	1
Voluntary programs	-0.115	0.651	1	-1.349	-0.271	0	-0.039	0.907	1	0.030	1.280	1	0.009	1.144	1	-0.055	1.645	1
Obligations	-0.624	0.183	0	-0.318	0.622	1	-0.352	0.489	1	-0.449	0.650	1	-0.482	0.578	0.600	-1.355	0.625	0.200
Patent selections	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Table 6.13: Extreme-Bounds Analysis for the research design of Peters et al. (2012) – Trimmed subsample.

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.146	0.517	0.952	-0.065	1.294	1	-0.106	0.718	0.952	-0.037	0.999	1	-0.044	0.849	1	0.032	0.825	1
Continental R&D funding	-0.312	0.176	0.524	-0.468	0.318	0.619	-0.289	0.170	0	-0.038	0.703	1	-0.149	0.313	0.905	-0.212	0.276	0.900
Intercont. R&D funding	-0.838	0.580	0.190	-1.113	0.591	0.095	-0.539	0.778	0.571	-0.622	1.738	0.524	-0.224	1.354	1	-0.095	1.654	1
Domestic capacity	-0.088	0.250	0.952	0.064	0.600	1	-0.020	0.229	1	0.028	0.470	1	-0.059	0.298	1	-0.079	0.323	0.950
Continental capacity	-0.096	0.359	0.905	-0.193	0.292	0.762	-0.152	0.238	0.762	-0.046	0.439	1	-0.125	0.221	0.810	-0.146	0.283	0.900
Intercont. capacity	-0.093	0.264	0.952	-0.408	0.073	0	-0.046	0.286	1	-0.125	0.300	1	-0.138	0.245	0.905	-0.211	0.275	0.250
Patent selections	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	20	20	20
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.318	0.211	0.273	-0.148	0.598	1	-0.264	0.263	0.273	-0.144	0.448	1	-0.176	0.384	1	-0.076	0.560	1
Continental R&D funding	-0.592	0.169	0.091	-0.642	0.214	0.091	-0.652	0.073	0	-0.179	0.477	1	-0.458	0.206	0.091	-0.165	0.243	0.800
Intercont. R&D funding	-0.892	0.282	0	-1.157	-0.056	0	-0.673	0.330	0	-0.481	0.732	0.545	-0.202	0.664	1	0.014	0.995	1
Domestic capacity	-0.057	0.268	1	0.151	0.686	1	0.007	0.481	1	0.052	0.446	1	0.002	0.346	1	0.007	0.273	1
Continental capacity	-0.046	0.159	1	-0.116	0.187	1	-0.088	0.150	0.818	-0.048	0.258	1	-0.126	0.129	0.455	-0.095	0.184	1
Intercont. capacity	-0.080	0.194	1	-0.329	0.014	0	-0.080	0.215	1	-0.045	0.316	1	-0.029	0.273	1	-0.162	0.211	0.700
Patent selections	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	10	10	10
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.381	0.141	0	-0.193	0.626	1	-0.375	0.289	0.143	-0.260	0.765	0.714	-0.328	0.490	0.429	-0.375	0.573	0.500
Continental R&D funding	-0.676	0.067	0	-0.774	0.072	0	-0.722	0.273	0	-0.636	0.747	0.429	-0.711	0.311	0.143	-0.593	0.210	0.333
Intercont. R&D funding	-1.005	0.591	0	-1.327	0.327	0	-0.951	0.756	0	-0.810	1.912	0.429	-0.334	1.286	1	-0.520	1.110	1
Domestic capacity	-0.108	0.343	1	0.202	0.677	1	-0.061	0.361	1	-0.440	0.425	0.857	-0.176	0.309	1	-0.216	0.408	0.500
Continental capacity	-0.124	0.190	0.857	-0.160	0.192	0.857	-0.212	0.144	0.714	-0.181	0.215	1	-0.223	0.128	0.143	-0.256	0.341	0.667
Intercont. capacity	-0.093	0.273	1	-0.368	0.056	0	-0.096	0.350	1	-0.020	0.598	1	-0.026	0.400	1	-0.227	0.337	1
Patent selections	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	6	6	6

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Table 6.14: Extreme-Bounds Analysis for the research design of Peters et al. (2012) – Citation subsample.

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.255	0.362	0.875	-0.065	0.771	1	-0.259	0.534	0.875	-0.231	0.739	0.875	-0.273	0.694	0.875	-0.255	0.790	0.857
Continental R&D funding	-0.312	0.175	0.625	-0.468	0.309	0.500	-0.289	0.190	0.125	-0.038	0.631	1	-0.149	0.305	0.875	-0.212	0.305	0.857
Intercont. R&D funding	-0.838	0.498	0.250	-1.113	0.425	0.250	-0.539	0.778	0.625	-0.622	1.552	0.375	-0.224	1.354	1	-0.236	1.654	1
Domestic capacity	-0.144	0.250	1.000	0.083	0.600	1	0.001	0.230	1	0.070	0.437	1	-0.133	0.254	0.875	-0.162	0.310	0.857
Continental capacity	-0.193	0.258	0.750	-0.266	0.292	0.500	-0.226	0.217	0.625	0.016	0.439	1	-0.238	0.221	0.625	-0.273	0.210	0.714
Intercont. capacity	-0.040	0.300	1.000	-0.341	0.139	0	0.007	0.316	1	-0.078	0.369	1	-0.081	0.341	0.875	-0.157	0.354	0.429
Patent selections	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	7	7	7
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.318	0.211	0.250	-0.142	0.598	1	-0.261	0.263	0.25	-0.144	0.448	1	-0.176	0.369	0.875	-0.041	0.492	1
Continental R&D funding	-0.592	0.169	0.125	-0.642	0.214	0.125	-0.636	0.072	0	-0.179	0.477	1	-0.458	0.206	0.125	-0.165	0.243	0.857
Intercont. R&D funding	-0.892	0.269	0	-1.157	0.019	0	-0.673	0.330	0.125	-0.481	0.732	0.500	-0.202	0.664	1	0.022	0.995	1
Domestic capacity	-0.057	0.268	1	0.151	0.686	1	0.007	0.447	1	0.052	0.424	1	0.002	0.346	1	0.025	0.247	1
Continental capacity	-0.123	0.154	0.875	-0.195	0.166	0.875	-0.151	0.124	0.750	-0.042	0.258	1	-0.132	0.111	0.375	-0.144	0.161	0.857
Intercont. capacity	-0.080	0.239	1	-0.329	0.070	0	-0.080	0.244	1	-0.045	0.315	1	0.002	0.257	1	-0.162	0.208	0.714
Patent selections	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	7	7	7
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.377	0.141	0	-0.177	0.626	1	-0.364	0.229	0	-0.260	0.765	0.750	-0.302	0.490	0.250	-0.375	0.573	0.250
Continental R&D funding	-0.676	-0.017	0	-0.774	0.024	0	-0.722	0.118	0	-0.636	0.747	0.500	-0.711	0.268	0.250	-0.593	0.235	0.250
Intercont. R&D funding	-1.005	0.397	0.250	-1.327	0.327	0	-0.951	0.756	0.250	-0.810	1.912	0.500	-0.334	1.286	1	-0.520	1.110	1
Domestic capacity	-0.108	0.343	1	0.128	0.677	1	-0.061	0.347	1	-0.440	0.323	0.750	-0.176	0.281	1	-0.203	0.408	0.250
Continental capacity	-0.124	0.190	0.750	-0.156	0.192	1	-0.212	0.144	0.500	-0.181	0.215	1	-0.223	0.128	0.250	-0.256	0.341	0.500
Intercont. capacity	-0.081	0.273	1	-0.331	0.062	0	-0.096	0.350	1	-0.020	0.598	1	-0.026	0.400	1	-0.227	0.337	1
Patent selections	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Table 6.15: Extreme-Bounds Analysis for the research design of Peters et al. (2012) – SNIP subsample.

	Priority			Granted			Claimed			PCT			Transnational			Triadic		
PV																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.914	0.385	0.833	-0.222	0.771	1	-0.259	0.534	0.833	-0.231	0.739	0.917	-0.273	0.694	0.917	-0.255	0.794	0.917
Continental R&D funding	-0.405	0.396	0.583	-0.468	0.584	0.583	-0.289	0.384	0.167	-0.480	0.763	1	-0.149	0.500	0.833	-0.212	0.432	0.917
Intercont. R&D funding	-0.994	0.498	0.167	-1.197	0.425	0.167	-1.191	1.692	0.500	-4.022	5.487	0.417	-1.518	2.725	1	-0.571	2.240	1
Domestic capacity	-0.366	0.250	0.833	-0.311	0.600	1	-0.020	0.450	1	0.039	0.649	1	-0.133	0.433	0.917	-0.162	0.496	0.833
Continental capacity	-0.193	0.644	0.833	-0.266	0.448	0.667	-0.226	0.318	0.583	-0.313	0.440	1	-0.238	0.408	0.667	-0.273	0.445	0.833
Intercont. capacity	-0.041	0.971	1.000	-0.398	0.890	0.083	-0.029	0.732	1	-0.078	1.330	1	-0.081	0.759	0.917	-0.224	0.603	0.417
Patent selections	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
Solar																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.472	0.211	0.500	-0.158	0.598	1	-0.261	0.549	0.500	-0.144	0.484	1	-0.176	0.560	1	-0.076	0.679	1
Continental R&D funding	-0.568	0.169	0.167	-0.628	0.218	0.167	-0.636	0.349	0.167	-0.170	0.640	1	-0.458	0.409	0.333	-0.119	0.429	1.000
Intercont. R&D funding	-0.844	0.694	0.167	-1.102	0.395	0	-0.652	1.712	0.167	-1.304	3.677	0.500	-0.202	2.262	1	0.022	2.127	1
Domestic capacity	-0.187	0.246	0.833	0.002	0.674	1	0.007	0.429	1	0.052	0.482	1	-0.016	0.339	1	0.007	0.400	1
Continental capacity	-0.133	0.183	1	-0.260	0.166	0.833	-0.193	0.110	0.667	-0.220	0.258	0.833	-0.157	0.162	0.500	-0.066	0.324	1
Intercont. capacity	-0.070	0.680	1	-0.329	0.505	0.167	-0.073	0.527	1	-0.045	0.856	1	0.002	0.545	1	-0.162	0.457	0.600
Patent selections	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	5	5	5
CSP																		
	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign	LB	UB	Pos. Sign
Domestic R&D funding	-0.377	0.119	0	-0.177	0.626	1	-0.391	0.092	0	-0.308	0.319	0.600	-0.335	0.167	0.200	-0.301	0.340	0.400
Continental R&D funding	-0.599	0.067	0	-0.650	0.072	0	-0.796	0.118	0	-0.636	0.419	0.400	-0.891	0.175	0.200	-0.732	0.235	0.400
Intercont. R&D funding	-1.059	0.315	0.200	-1.439	0.170	0	-1.144	0.332	0.200	-0.910	0.438	0.400	-0.789	0.665	0.800	-0.780	0.845	0.800
Domestic capacity	-0.116	0.162	1	0.128	0.625	1	-0.039	0.283	1	-0.110	0.323	1.000	-0.106	0.262	1	-0.203	0.142	0.200
Continental capacity	-0.078	0.190	1.000	-0.147	0.192	0.800	-0.108	0.144	0.600	-0.116	0.215	1	-0.167	0.128	0.200	-0.260	0.214	0.400
Intercont. capacity	-0.081	0.218	1	-0.331	0.062	0	-0.096	0.259	1	-0.028	0.368	1	-0.026	0.322	1	-0.192	0.336	1
Patent selections	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5

Notes: 'LB' denotes Lower Bound, 'UB' denotes Upper Bound and 'Pos. Sign' denotes the share of point estimates with a positive sign.

Chapter 7

Conclusion

This thesis contributes to our understanding of knowledge dynamics and technological change, particularly for environmentally friendly technologies. The overarching research aims of this thesis are to uncover dynamics of knowledge generation along technological trajectories, to improve our understanding of knowledge exchange in networks, and to analyze effects of policy instruments and their mix on knowledge generation and exchange. In the five core Chapters 2-6, the innovation process is analyzed with respect to these three objectives, using the example of wind power and solar energy technologies, especially photovoltaics (PV). These technologies are of special interest, since they bear the possibility to transform the carbon-based economic system into a sustainable one, mitigate climate change, and foster green growth. Furthermore, these technologies face several market and system failures, which makes analyzing their innovation process and the effect policies have on this process particularly interesting for economic analysis and provides valuable insights for policy makers.

To reveal and understand knowledge dynamics and knowledge exchange, this thesis itself was an interactive process, which recombines various streams of literature, different data sources, and methods from different fields to create new knowledge. In the following, I summarize key findings and overarching results, formulate policy recommendations, and point out avenues for further research.

7.1 Main findings and contributions

With respect to the first research objective of this thesis, to uncover dynamics of knowledge generation within technological trajectories, Chapter 3 provides valuable insights. I developed a theoretical framework in which knowledge recombination is dynamic and was able to show that its empirical application provides new insights on knowledge recombination. In previous studies, it is assumed that the mechanisms of knowledge recombination are static and do not depend on the maturity of the technology. However, I can show using patent data for wind power and PV that different sources of knowledge for recombination are relevant for technological progress in different phases of the technology life cycle. This dynamic analysis reveals that different kinds of knowledge, internal but especially external to the trajectory, influence technological progress and the relevance of different sources of knowledge changes along the technology life cycle. The results show some differences between the technologies, but external knowledge is of particular relevance in the emergence and early stage of the technologies, while over time, recombination of knowledge internal to the technologies fuels technological progress. The results provide a more profound understanding of the relevance of knowledge dynamics along the technology life cycle and how recombinatorial patterns change over time.

Further knowledge dynamics inside the PV trajectory are revealed using the notion of sub-trajectories proposed by Durand (1992). In Chapter 2, sub-trajectories were identified using patent data for PV, which provide more insights into the dynamics within the trajectory. The analysis at this micro-technological level shows that the focus of inventive activity changed between sub-trajectories over time, which would have been averaged out in an analysis at the aggregate level of the trajectory. Furthermore, descriptive results show that patenting intensity differs between sub-trajectories. Countries focus their research activities on particular sub-trajectories, most likely to seek a competitive advantage. In Chapter 3, sub-trajectories for PV show different patterns of knowledge recombination since they are in different phases of their life-cycle. While such sub-trajectories are relevant for technological development, they also translate to other economic dimensions, such as industrial dynamics, where, for example, Kapoor and Furr (2015) can show that entry patterns differ by PV sub-trajectory. Therefore, using sub-trajectories to understand technological change provides further insights and helps to understand micro patterns as the ones discovered for technological change, but they can and should be applied elsewhere in economics.

Since knowledge generation seldomly takes place in isolation, the second research objective of this thesis aims to add to our understanding of knowledge exchange in networks. Networks of knowledge exchange are a pervasive phenomenon in the innovation process and actors participating in such networks increase their innovative performance. Even though knowledge exchange takes place between individuals, different levels of aggregation of collaboration and knowledge exchange are analyzed. The micro level of collaboration is analyzed in Chapter 4 by looking at networks of patent inventors in wind power and PV, whereas Chapter 5 considers the meso and macro levels, using co-authorship information from PV publications. While Chapter 4 allows to compare the development of the wind power and PV networks in Germany, Chapter 5 allows to compare developments across countries. Both chapters help to better understand the structure, dynamics, and interplay between networks of knowledge exchange on different levels of aggregation, the functionality of the innovation process, and the influence of policy intervention on networks of knowledge exchange.

Results show that on all levels of aggregation, an increase in network size and connectivity among actors is prolific, which indicates increasing potential for knowledge exchange. However, on the micro level, there are differences between technologies. The level of connectivity is higher in PV than in wind power and inventor teams are much smaller in wind power than in PV. This indicates that the nature of the innovation process differs between the technologies and hints towards lower complexity in the innovation process for wind power. Furthermore, in both networks, there is very low concentration on specific actors and the networks are highly fragmented, even though consolidation takes place over time. At the meso level, where national research organizations establish connections by co-authoring PV publications, notable differences between countries exist. In general, Asian countries show fast growing national research networks, which are in most cases centralized and have a high degree of repeated interactions. Western countries show a lower increase in network size, but the national networks are less centralized and show more fragmentation than the Asian ones, even though fragmentation is reduced over time for all countries. At the macro level, the position of countries in the global network, the countries' embeddedness, is important, since it allows to participate in global knowledge flows. While over time the network increases and more countries engage in PV research, connections among countries become more frequent, the network becomes denser, and there are hardly any unconnected countries. This indicates that the global system functions well and allows for knowledge diffusion. But there seems to be an ongoing centralization process, such that some countries form a highly interconnected core. At the same time, the network periphery is characterized by a substantial degree of turbulence.

These network dynamics are interesting per se and found also in the literature, explaining the cause of such dynamics has been, so far, a challenging and widely neglected task. In both Chapters, 4 and 5, factors influencing the network size and structure as well as the position of actors in the network are analyzed. With respect to the macro embeddedness of countries in the global research network, two groups of determinants are identified: the structure of the national research network and policy interventions. The first group of determinants considers the interaction structures of the research network at the meso level, which account for the knowledge diffusion within the research system. A national research system which functions well in terms of possible knowledge diffusion might create an environment beneficial for international collaboration and increases embeddedness. This group of determinants is related to the links between micro, meso, and macro levels in economics (Dopfer et al., 2004), which is an emerging theme in empirical analysis (Gupta et al., 2007; Guan et al., 2015b). Results show for three concepts of network centrality, which emphasize different aspects of knowledge access, embeddedness is increased by an overall cohesion and connectedness of the national research system. Furthermore, countries with a decentralized research network are internationally more embedded, indicating that diffusion oriented national research systems are more open towards external knowledge flows. This shows that the establishment of an institutional system, which is well connected and conducive for knowledge diffusion can be an objective for policy intervention and strategic decision-making of governments. Preventing a research system from being fragmented or dominated by a few key actors can increase the overall functionality and increase access to global knowledge flows. The overall structure and functionality of the national research system should therefore be higher on policy makers' agenda to increase inventive and innovative activity.

The second set of determinants relates to the third research objective of this thesis and sheds light on the effect of policy instruments and their mix on knowledge networks. This set consists of various policy instruments that constitute the policy mix for renewable energies (Flanagan et al., 2011; Rogge and Reichardt, 2016). Policy might create an environment conducive to international collaboration and increased embeddedness within the international research network. While there is a broad literature on the effects of policies on knowledge generation, no study so far considered the effect on the characteristics of knowledge networks. Using a set of four different policy instruments, results show differential effects on international embeddedness. R&D expenditures for PV show mixed effects and are sensitive to the measure of embeddedness. A positive effect is present if the relative position of countries in the network is considered, which implies that R&D expenditures are used to establish or intensify connections to well embedded countries. Demand pull policies show robust positive effects on international embeddedness. Especially the effect of public procurement is interesting, since it does not only increases inventive and innovative activity, but also fosters interaction and facilitates knowledge exchange. The ratification of the Kyoto Protocol seems only relevant for countries which have binding reduction targets. Overall, policy instruments have an effect on international embeddedness and knowledge exchange, which has so far been neglected from discussions about an effective policy mix for innovation.

Similar effects of different instruments and the policy mix are uncovered on the micro level of inventor networks. In Chapter 4, the effect of demand pull, technology push, and systemic instruments as well as their interaction on size and structure of inventor networks is analyzed. The effects are again dependent on the technology, but overall there are significant effects for all policy variables on size and structure of the networks. Domestic as well as foreign demand pull and technology push instruments have positive effects on the size of both networks. Systemic instruments show an effect only for wind power. With respect to the structure of the network, systemic instruments, which are especially designed to induce cooperation, show a positive effect for wind power, whereas for PV the effect is inconclusive. Technology push policies do not increase cooperation in wind power at all, while for PV, the effect is ambiguous. Demand pull instruments show a strong positive influence on collaboration in both technologies. With respect to the interaction of instruments in the policy mix, push and pull instruments work hand in hand in increasing network size, whereas pull and systemic instruments together spur cooperation. These findings point towards strong consistency of the policy mix. Nevertheless, some inconsistencies are present in the interaction between pull and systemic instruments, which is detrimental to network size in PV. Apparently, this combination of instruments favors existing actors rather than attracting new ones. In a similar vein, a combination of push and pull instruments works against collaboration in PV and rather favors individual research activities. Here, further research is required to understand the cause and consequences of the effects of different interactions. Nevertheless, policy makers need to be aware of the complexity of interactions in the policy mix, which can either spur innovative activity or be detrimental to it.

While strong support for the existence of demand pull and technology push effects is found throughout this thesis, in the literature some contributions question the existence of such effects for knowledge generation in renewable energies. To explore if these effects are persistent and why deviating results are obtained in the literature, the last chapter performs a sensitivity and robustness analysis of Johnstone et al. (2010) and Peters et al. (2012). Since researchers have great flexibility in using patent data, especially with respect to the search strategies and choice between different patent quality dimensions, Chapter 6 explores implications of these flexibilities on estimated policy effects. 51 different selection approaches for solar energy technologies are identified in the literature and used for a sensitivity analysis of both studies. The flexibility in the selection of patent counts results in a wide range of estimates for the effects of policies on patent counts. There is substantial uncertainty regarding signs and sizes of policy effects. For almost all policy effects both positive and negative estimates that are statistically significant can be obtained. Especially patent quality contributes to the uncertainty in the effect size, but also other influential factors can be identified, especially the overall number of selected patents. Using three different quality subsets of patent selections reduces the uncertainty, which nevertheless remains substantial. If furthermore the respective technologies of the studies are used, the core findings of both studies can be supported in terms of the direction of policy effects. However, there still remains potential uncertainty for policy makers about the effectiveness of the policy instruments, since the size of the effects varies considerably. Furthermore, the great flexibility in the selection of patent counts opens up the possibility of scientific misconduct. Therefore, more rigorous documentation and sensitivity tests are required and results should be supported with evidence from other sources, such as qualitative data to sustain scientific credibility for the use of patent data and to inform policy makers correctly.

7.2 Policy implications

The findings in this thesis have several implications for policy makers, especially to accelerate technological progress in environmentally friendly technologies. In general, policy effects are technology specific, which might be related to the technology's state of development, its relative competitiveness, market dynamics, and the specific nature of its innovation process. Therefore, technological differences need to be considered when implementing a policy instrument or designing the overall policy mix for innovation.

First of all, understanding that technologies differ, that recombinatorial success requires different sources of knowledge at different stages of a technology life cycle, and that even within a technological trajectory several possible solutions exists is relevant for the implementation of targeted policies. Policies supporting R&D activities need to account for these particularities in the innovation process. A one-size fits all solution could lead to misallocation of resources, foster lock-in into inferior technologies, or slow down technological progress. For example, in the case of PV, it is immanent that the current market-dominating sub-trajectory cannot overcome physical limits and therefore the emerging sub-trajectory, which has more favorable physical characteristics, need to be supported for sustained technological progress in PV. However, as shown in Chapter 2, the German government, for example, supports R&D activities especially in the market-dominating sub-trajectory and not in the emerging one. Overall, widening support schemes to cover emerging technologies, include heterogeneous actors along the innovation process and along the technological development is required and calls for tailor made policy mix for innovation. This would allow to accelerate technological progress by integrating different sets of knowledge and opens up new technological opportunities. This is not only a requirement for innovation in environmentally friendly technologies, but a pervasive challenge for policy makers.

With respect to the effect of policy instruments on the innovation process, the robustness analysis in the last chapter provides evidence that demand pull and technology push instruments foster inventive activity. However, policy makers should be careful in assessing the magnitude of the effects and ask for a variety of results, stemming from different data sources and methods. Nevertheless, both types of instruments should be implemented, especially simultaneously, since they complement each other in the innovation process. Furthermore, there are effects of instruments which have not been considered in greater detail by policy makers. Both types of instruments also intervene on the exchange of knowledge and increase collaboration. These partly unintended effects on the underlying research system have been neglected so far from policy discussions and should be considered when implementing or assessing such policies and harnessed actively. For this purpose, systemic instruments, which are particularly relevant to increase collaboration and bring together relevant actors, should be higher on the policy makers agenda. Policy makers can use these instruments to foster interaction and deliberately shape the research system.

Furthermore, the overall structure and performance of the research system needs to move in the center of policy makers' attention. Research in isolation is detrimental to inventive and innovative activity and scientific evidence about the benefit of interaction in research is overwhelming. Avoiding fragmentation of different groups of actors and decentralizing the research system can increase the system's functionality and foster innovation performance. One particular positive effect is the access to global knowledge flows, which can be integrated in national research activities. Systemic instruments can be used to intervene in the system structures and create a diffusion oriented research system which helps to increase knowledge exchange and eases access to external knowledge. The participation in and the integration of global knowledge flows is of particular importance to engage in the challenges imposed by climate change and sustainability issues, since solutions cannot be achieved in isolation.

In the same vein, policy makers need to coordinate the implementation of policy instruments and consider the overall policy mix for innovation. For the case of Germany, the results reveal that in some cases the policy mix is consistent, especially in providing incentives to engage in R&D and collaborative activities, as well as in supporting market creation. However, there are also detrimental effects due to the presence of multiple instruments. Policy makers need to assess in more detail how different policy instruments influence each other to increase overall efficiency. Providing a tailor-made policy mix, which supports inventive and innovative activity along the innovation process, but also on the system level is required, to accelerate technological change and foster a transition towards environmentally friendly technologies. Thereby the set of instruments should include a great variety of instruments to support different actors. For example, the policy support should include (pre-)commercial support as well as classical R&D support and experimentation with other forms of instruments, which open up the innovation process for heterogeneous actors.

7.3 Limitations and further research avenues

While this thesis provides new insights and perspectives on knowledge dynamics and technological change, several restrictions and assumptions had to be made, which can be relaxed in further research. Furthermore, some derived insights open up new directions for research and the results presented here can be better integrated in economic theorizing and can be seen as a starting points for further scientific endeavors.

First, the analyses in this thesis are based on the level of the technology and leave out a closer look at how economic actors, in particular firms, engage in innovative activity. Shifting the level of analysis from the technology level to the firm level can deepen our understanding how firms engage in knowledge recombination and how their usage of knowledge changes over time. This would allow to link the insights on knowledge dynamics gained on the technology level with industrial dynamics and explain how knowledge influences industry structures over time. While there are several contributions with respect to previous knowledge and the influence on entry and survival, accounting for the dynamic nature of knowledge and the evolution of industries over time is missing so far.

Second, the insights into the relationships between knowledge networks on different levels of aggregation provide a novel perspective on the functionality of research systems. Nevertheless, the results are most likely technology specific and a broader inquiry is necessary to understand how these different levels of aggregation interact, which kind of network structures are relevant for knowledge exchange between different levels of aggregation, and especially how the relationship translates into inventive and economic output. These insights would help to extend our understanding of innovation systems and its functions. Furthermore, they would be particular relevant for policy makers, which could use systemic instruments, or design new instruments, to shape the research system accordingly and increase inventive and innovative performance.

Regarding policy intervention on networks, the effects are still ambiguous and the analyses conducted capture only a small fraction of possible interventions and outcomes. In most cases, policies had an effect on size, structure, or embeddedness, however, conclusive evidence requires more cases and different instruments to be analyzed. Thereby most instruments were not designed to effect knowledge exchange and assessing the magnitude of these effects and how they contribute to inventive output should be analyzed to fully account for the effect of policy intervention. Furthermore, the use of systemic instruments increases over time, but a holistic assessment of their effects on inventive and innovative outputs as well as on the functionality of the research system is absent so far. Providing these assessments would allow to use them more precisely and help to design a more comprehensive and consistent policy mix.

With respect to the policy mix, the scope of analysis was limited and calls for further assessment of the consistency of the policy mix. Furthermore, other dimensions of the mix were neglected in this thesis, but are worth assessing from a theoretical and empirical perspective. While in this thesis a basic approach to operationalize the consistency of the policy mix is used, developing new empirical approaches to capture the policy mix and its dimensions provides a challenging task for further research, but it is essential for calibrating the policy mix for innovation.

The results obtained in Chapter 6 show that patent data imposes several methodological problems and challenges for economic research and in particular for evidence based policy evaluations. As shown, the severe flexibility in the use of patent data can be detrimental to the credibility of econometric results. A larger scale effort has to engage in analyzing the problem of flexibility in observational research in general and particularly for patent data. Further evidence how sensitive economic analysis is with respect to patent data and which determinants can influence results can help to assess the credibility of previous findings. Based on a deeper understanding of cause and consequences of flexibility in the use of patent data, researchers as well as other stakeholders should engage the problem. Best practice guidelines should be formulated, to keep up the credibility of results obtained with such data and to inform policy makers correctly in the future. Furthermore, replication studies should be encouraged in economics to guarantee robustness and credibility of economic research, since such studies are nearly absent in economics so far (Duvendack et al., 2016; Mueller-Langer et al., 2017).

Lastly, the insights provided here increase our understanding of the innovation process. While these findings can be used to accelerate the development of environmentally friendly technologies, the particular problem regarding climate change and sustainability is on the system level. Translating the insights of the innovation process to the system level and providing a better understanding of transformation processes of whole systems requires further research. In the wake of climate change, we need to understand how to govern a transition towards an environmentally friendly and sustainable economic system more than ever.

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