Innovation dynamics in the medical device sector: network of collaborations, knowledge spillovers and regulation

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PAR

Monica COFFANO

acceptée sur proposition du jury:

Prof. D. Kuhn, président du jury
Prof. D. Foray, directeur de thèse
Prof. F. Lissoni, rapporteur
Prof. C. Fink, rapporteur
Dr G. De Rassenfosse, rapporteur

ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE
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Abstract

This thesis aims to provide new insights into the evolution of the medical device sector (MedTech). After the analysis of the history of the sector, I examine the key points that in the past 60 years, have led the industry to grow impressively, and I proceed to an analysis of the present situation. The scope of the thesis is to understand if what has stimulated the success of the sector at the beginning is still important, and if the introduction of new elements has positively changed the evolution of the sector.

The thesis is composed of three works. The first work (chapter 2) is co-authored by Dominique Foray and Michele Pezzoni. I analyze how the network structure of inventors in the Swiss regions can influence regional innovation performance within MedTech. I aim to contribute to the existing literature related to the debate on the importance of inventors' co-location for the creation of innovation. I claim that an increased degree centrality of MedTech inventors in the regional technological community is positively associated with the number of MedTech patent applications in the focal region. Moreover, the presence of MedTech inventors in the main component of the regional technological community is positively associated with the number of MedTech patent applications in the region. However, local connections are not enough to promote innovation. In fact, the results show that intense cross-regional linkages of MedTech inventors increase the number of MedTech patent applications in the region. The effect is amplified when this network structure is combined with a high degree of centrality of MedTech inventors. Thus, it is not only important that an inventor be well connected within her region, but also that she be exposed to external knowledge in order to increase her possibility of achieving high performance in MedTech within that region. Finally, I want also to understand how MedTech is open to other technological domains. I find that the average degree centrality and cross-regional linkages of academic inventors and inventors specialized in technologies complementary to MedTech affect regional innovation outcomes.

The second work (chapter 3) is developed in collaboration with Dominique Foray. I aim to study the impact of external technologies on the MedTech sector. I start analyzing the literature of knowledge spillovers, and I do a comprehensive review of the extant measures of knowledge spillovers. I argue that the classical measures based on patent 'backward citations' should be carefully interpreted. The reason as to why this type of index needs a prudent interpretation is linked to the characteristics of different technologies in terms of the speed at

which other sectors are capable of understanding, absorbing and using them. Therefore, I propose a new formulation of the classical measure of backward citations.

The third work (chapter 4) is developed in collaboration with Fabiana Visentin. I aim to understand the effects of the MedTech regulation that entered into force in Europe in 1993. I argue that the regulation has two effects. The first effect is related to the level of radicalness in the innovation. I claim that after the introduction of the regulation, and consequently with the tightening of the requirements to fulfill, firms became more careful and less motivated to propose radical innovations. At the same time, standardization of the requirements across European countries gives to firms the possibility of widening their market.

Keywords: patents, networks, inventors' centrality, academic inventors, medical devices, regulation, radical, incremental, diffusion, knowledge spillover measures

Sommario

Lo scopo di questa tesi è di proporre nuove intuizioni relativamente all'evoluzione del settore degli strumenti medicali (MedTech), valutando se ció che ha stimolato il successo del settore all'inizio sia importante per lo sviluppo attuale e se l'introduzione di nuovi elementi ne abbia cambiato l'evoluzione.

Dopo aver analizzato la storia del settore, vengono esaminati i punti chiave che negli ultimi 60 anni hanno portato il MedTech a cresere in misura esponenziale e infine si conclude con l'analisi della situazione attuale.

La tesi è composta da tre articoli. Il primo è stato sviluppato in collaborazione con D. Foray e M. Pezzoni. In questo lavoro analizzo come la stuttura della rete professionale di inventori nelle regioni svizzere influenzi la prestazione innovativa regionale nel MedTech. Lo scopo è di contribuire al dibattito sull'importanza della prossimità degli inventori per l' innovazione. I risultati mostrano che un aumento della centralità degli inventori MedTech all'interno della loro comunità tecnologica è associata positivamente al numero di brevetti di dispositivi medicali nella regione di riferimento. Inoltre, anche la presenza di inventori MedTech nella componente principale della propria comunità tecnologica potrebbe essere associata positivamente con il numero di brevetti MedTech nella regione di riferimento. Ciononostante, le connessioni locali da sole non sono sufficenti per promuovere l'innovazione. Infine un' alta connessione tra gli inventori di tecnologie affini a MedTech influenza positivamente la performance innovativa della regione.

Il secondo articolo è stato scritto in collaborazione con D. Foray. Lo scopo è di studiare piú in dettaglio l'impatto delle diverse tecnologie sul settore dei dispositivi medicali. Inizio analizzando la letteratura relativa ai flussi di conoscenza e proseguo proponendo una revisione delle misure piú frequentemente utilizzate. Voglio dimostrare che le classiche misure basate sull'uso delle citazioni dei brevetti dovrebbero essere interpretate con cautela. La ragione di ció è legata alla diversa velocità alla quale una nuova tecnologia riesce ad essere capita e impiegata da un altro settore. Propongo una nuova formula che utilizza le citazioni di brevetto che sia in grado di catturare l'effetto delle diverse caratteristiche delle tecnologie.

Il terzo lavoro è stato scritto in collaborazione con F. Visentin. Lo scopo è di capire entrambi gli effetti della regolamentazione entrata in vigore in Europa nel 1993 sull'innovazione

del settore dei dispositivi medicali. Il primo è legato al livello di radicalità di un'innovazione. Dopo l'introduzione della regolamentazione e in seguito ad un inasprimento dei requisti da soddisfare, le aziende siano diventate piu' prudenti e meno motivate a proporre innovazioni completamente radicali. Il secondo effetto è relativo alla espansione geografica del mercato dei dispositivi medicali. Infatti la standardizzazione dei requisiti in tutta Europa ha dato la possibilità alle aziende di ampliare il prorio mercato.

Parole chiave: brevetti, rete di inventori, centralità, inventori accademici, dispositivi medicali, regolamentazione, radicale, incrementale, misure di flussi di conoscenza

Contents

Chapter 1: Introduction

1.1 Motivation and thesis roadmap

The medical device sector in Switzerland has performed an extraordinary transformation since its early days in the sixties[1]. The seeds of transformation were planted by six Swiss surgeons located in the region of Basel and Biel, who visualized a revolution in the treatment of bone fractures. Their vision concerned not only the definition of new methods to fix broken bones, but also the creation of an organization that would involve companies, medical schools and doctors: the Association for the Study of Internal Fixation and Fractures (ASIF, or briefly, AO). Historically, the reason as to why these surgeons felt the need to collaborate and create something new in the field of orthopedics was related to increasing changes in the culture and lives of people in the 1950s. The economic boom made cars affordable to a higher number of people. At the same time, there was increasing interest in the practice of sports, such as skiing, soccer or motor sports. Cars and new sports led inevitably to an increased rate of unpredictable accidents. Social concern related to the exponential increase in accidents led, as a consequence, to the origination of a new stream of medicine, such as trauma surgery and sports medicine, as well as to the creation of accident insurance. The fact that insurance was forced to pay for the medical care and disabilities generated by accidents pushed insurance companies to establish collaborations with surgeons. The efficiency of surgical procedures had a high impact on the costs of rehabilitation; thus, surgeons were provided with instruments and, even in a few cases, were supported by hospital structures. The increasing need for the development of new techniques led to the creation of a spontaneous network of innovative surgeons. In Switzerland, regional origins have great significance, as well as personal relations among members of the same organization. For this reason, in 1958, the AO was created by a group of friends, Müller, Bandi, Schneider, Willenegger, and Allgöwer, with the aim of developing and teaching new techniques and practices in Swiss, and later, European medical schools and hospitals. The environment in which members of the AO were working was characterized by a strong sense of fraternity, high harmony, high importance of face-to-face interactions, high levels of trust, and very low

[1] The history of the medical device sector has been taken from Schlich (2002).

competition. The driving force of the AO was to develop new efficient solutions and to build a network of practitioners working in different places with the same standardized methods.

Subsequent to AO's creation, surgeons felt the need to set up a commonly financed laboratory. Their searches were concentrated in the region of Grison and culminated with the decision to establish the AO research laboratory in Davos. The region provided a structure to the AO for free because it wanted to incentivize the use of this structure for medical purposes. At this point, surgeons needed specialized suppliers in order to produce top-quality standard tools and devices. Müller contacted a young engineer, R. Mathys, who owned a small metal processing factory near Basel. He was convinced about shifting his production plan in order to produce only medical technologies. The collaboration between visionary surgeons and engineers was very productive, and after two years of trials, failures and experiments, Mathys succeeded in becoming the first company to enter the new fast-growing medical device market. Banks also played a key role in the emerging ecosystem: after two years of development without any products to sell, Mathys accumulated a debt of CHF 300,000, which worried the local bank supporting him. However, surgeons used their prestige and reputation to convince the local bank to extend credit to Mathys. Thanks to the extended support of the local bank, Mathys, together with the AO, soon achieved incredible success, which involved converting the medical world everywhere on the planet to a new technique that they collectively controlled.

Later, surgeons contacted a second firm to develop the same kinds of tools and instruments, led by Straumann, a professor at the University of Stuttgart. He was already known for developing sophisticated alloys, and he was a specialist in metallurgy. At the same time, the surgeons created their own company based in Davos, called Synthes, which was in charge of R&D, training and promotion of the new techniques all over the world. Afterwards, a spin-off of Straumann entered the market to develop specific manufacturing processes (Foray, 2014).

Nowadays, it is common sense to expect that devices used on or in the human body have to be tested to assure their safety. In the 1960's, the risk perceived by a device producer when introducing a new product into the market was more related to acceptance by surgeons than to the fulfillment of general safety requirements. Orthopedic devices had experienced reputational issues concerning a lack of standardized material. Some tools were built by more experienced craftsman, which were not touched by corrosion, while other tools had a much shorter duration and quality. There was no quality control, and thus, in order to earn more money, some craftsmen employed a lower percentage of steel than agreed. For this reason, it was not an uncommon practice for surgeons to develop personal instruments by themselves. Albin Lambrotte was a surgeon and also an instrument maker. Gerhard Kuntscher, a surgeon, met

Ernest Phol, an engineer, to develop instruments. Some surgeons decided to pursue a double degree in medicine and engineering in order to have the skills needed to develop tools. But without any standards, it is impossible to create a discipline. Thus, the very first clinical trials were developed by the AO, which takes documentation of all the trials, with the aim of standardizing procedures and making them more replicable in order to avoid the production of poor-quality tools.

After the creation of Synthes, the ethical problem of surgeons who were earning money from the commercialization of tools surfaced. Thus, one of the rules for AO members who were also stakeholders in Synthes was related to the income generated by the trade of medical instruments: it stated that each Swiss franc had to be reinvested in R&D.

Indeed, the AO developed a very fine-grained policy concerning intellectual property rights: patents protecting the inventions of special instruments and implants developed by AO surgeons or manufacturers were all transferred to Synthes that granted the right to exclusive production and marketing of the AO equipment. Synthes also produced the new activity-specific public goods (R&D, training and quality standards). Thanks to the AO and the entrepreneurial spirit of the SMEs, the emerging ecosystem was remarkable in building connections to integrate the dispersed knowledge and to realize the entrepreneurial discovery process, as well as in producing a private institution. Synthes was founded to solve the coordination problems arising from early growth of the new activity, support capability formation and reward pioneers in such a way that spillovers were maximized.

Again, and in spite of the complex coordination problems, this was a successful process without any policy interventions. It involved the structuring of entrepreneurial knowledge that was initially dispersed and fragmented (among surgeons and engineers). It also involved the creation of private institutions to solve important coordination problems that arose as the new activity started to grow.

Why did I start with this story? I did so because this is a story about the relevance of: networks, knowledge spillovers, and (the absence of) regulation as essential determinants of R&D, creativity and innovation in the medical device industry. In my thesis, I will take these three topics - networks, spillovers, and regulation - to empirically explore their influence on the present dynamics of innovation in the medical device industry.

The reason I became so passionate about this sector, to the point that I wanted to dedicate my efforts to it in my PhD thesis, is that medical devices are not only a group of instruments and techniques developed to help people with injuries. Rather, they represent the products of a social evolution. The core engine of the AO was the network connecting surgeons,

patients and industries. The changes happening in that historical period led to more sophisticated surgical procedures to address the increasing probability of accidents: people truly perceived its necessity in order to feel safe. At the same time, the industry had developed the technology necessary to support surgeons, and these surgeons were ready to open their minds and try something new. The same revolution could not have happened 10 years before. All of the small pieces of this big system formed the basis for what is the medical device sector now. For example, the network of inventors of medical devices is still one of the core forces for the growth of the sector. This sector is still looking outside, into other new fields such as ICT, to ameliorate the tools. Further, additional changes such as the quality control of their instruments have formed the basis of the current regulations.

In the next paragraph, I review the main strands of literature that have helped me develop the three parts of my thesis. In the last paragraph of this introduction, I summarize the findings and the contributions of the thesis.

In the subsequent chapters, I present three studies that theoretically and empirically describe the current evolution of this sector. Each study is thought to bring new insights into the story of this sector.

1.2 Background Literature

1.2.1 Collaboration networks and innovation

The first study of my dissertation focuses on one of the main aspects of the medical device sector: the inventors' networks. In the first chapter of the introduction, I reported the story of AO's creation to show how, since the very beginning, the driving force of innovation in the sector was represented by a network of people. This network was composed of people with very different backgrounds, such as engineers, craftsmen and surgeons. What they all had in common was geographical proximity, a common culture, and the willingness to change something. In my first study, I analyze the importance of the network in recent years. My aim is to understand what kinds of collaborations contribute to the evolution of the sector, and if the composition and role of the network have changed over time. Specifically, I investigate if the network is still composed of people with different skills, and if the geographical connotation of these collaborations still persists.

The impact of professional collaboration networks on regional innovation is a relevant topic in the innovation literature. Previous empirical findings have suggested that innovation exhibits a pronounced tendency to cluster spatially (Feldman and Kogler, 2010). In the 1990s,

several works documented the importance of geographic proximity in fostering knowledge flows among co-located agents (Feldman and Audretsch, 1999; Jaffe at al., 1993). Storper and Venables (2004) explain the beneficial effects of geographical proximity in knowledge exchanges among individuals with an increased likelihood of face-to-face contact. In order to explain the beneficial effects of clustering on innovation, the literature relies on the concept of localized knowledge spillovers (Döring and Schnellenbach, 2006; Feldman and Audretsch, 1999; Jaffe et al., 1993; Zucker et al., 1998). The existence of localized knowledge spillovers is strictly connected with the inventors' social and professional connections (Breschi and Lissoni, 2001; Powell et al., 1996). The concept of localized knowledge spillovers has been revisited by supporting the idea that a large part of the knowledge flowing among agents cannot be considered as a pure externality. On the contrary, flows are mainly regulated by economic transactions, such as work contracts, markets for technologies, and research collaborations among individuals, firms and institutions. The diffusion of knowledge through these mechanisms feeds the creativity of individuals and enhances innovation opportunities (Burt, 2004; Cowan and Jonard, 2004). However, it is difficult to think that knowledge networks, being social and not territorial constructs, are enclosed within regional borders (Ter Wal and Boschma, 2009; Asheim and Isaksen, 2002). Transcending cross-regional borders with external linkages brings new ideas, new information and fresh knowledge into the region (Breschi and Lenzi, 2012; Bresnahan et al., 2001; Bathelt et al., 2004; Grabher, 1993; Rosenkop and Nerkar, 2001). The lack of external linkages, and the consequent isolation of inventors within a region, might lead to a convergence toward homogenous, redundant knowledge circulating within the region and resulting in the decline of innovation (Bathelt et al., 2004; Burt, 2004; Neal, 2010; Uzzi, 1997). External linkages are not only intended in geographic terms, but are also related to the technology domain. A growing strand of literature currently considers a large part of new knowledge generation as the result of recombining existing knowledge from different fields (Antonelli et al., 2010; Kogut and Zander, 1993; Mccann and Ortega-Argilés, 2013; Youtie et al., 2008; Weitzman, 1998). In any case, it is difficult for focal firms to absorb and interpret knowledge from distant domains. For this reason, firms tend to explore only closely related technological domains and pursue incremental innovations (Rosenkopf and Nerkar, 2001). However, firms need to look for new knowledge in different technological domains in order to refresh existing information and develop new assets (Gavetti and Levinthal, 2000). In co-invention networks, inventors specialized in different technological domains are expected to have more chances to exchange knowledge when they are intensively connected. From the point-of-view of the analysis of regional innovative performance, a higher connectivity of inventors leads to higher chances of

contributing to regional knowledge recombination (Feldman and Audretsch, 1999). Moreover, the importance of the exchange of knowledge between complementary sectors has been emphasized by the concept of related variety. The fact that complementary technologies are accessible locally increases the probability of regional growth (Bishop and Gripaios, 2009; Boschma and Iammarino, 2009; Boschma et al. 2012; Frenken et al., 2007; Quatraro, 2010).

The importance of creating an intense regional network of collaborations, together with the insertion of cross-regional and cross-domain connections is the focus of my first study.

1.2.2 Technological spillovers and innovation

The second study of my dissertation goes more into the details in terms of the interaction of the medical device sector with other technologies. In the first section of the introduction, I argued how important precision mechanics were in building the first orthopedic tools. Nowadays, the technologies that help MedTech grow are not the same as in the 1960s. MedTech has evolved, as well as other technologies. From the beginning of the 21st century, MedTech and Information and Communication Technologies (ICTs) have shown very intense interaction in terms of technological knowledge exchange.

ICTs help MedTech in the creation of tools with completely new features. For instance, ICTs allow patients to save measurements, keep track of past values of their medical tests, and receive reminders for medications. All of the data collected are visible automatically by the physician, who can immediately intervene, if needed (Jog et al., 2015). Measurement devices can be implanted into the tissue (Yazdandoost and Kohno, 2007) and can transmit wireless data collected. ICTs can also be integrated into medical devices, such as infusion devices. In this case, the data of a patient are collected and aggregated in a dataset. The dataset is then put in a cloud that connects several hospitals. Taking the information anonymously, the software is able to compare the values related to different patients with similar conditions and provide suggestions on best practices. These are just some examples of the possible applications of ICTs in MedTech, but the advantages that the interaction of ICTs with MedTech has brought over the years are countless, particularly related to the level of the quality of health services at low cost.

In the literature, ICTs are recognized as General Purpose Technologies (GPTs). The central feature of a GPT is the horizontal propagation throughout the economy and the complementarity between its inventions and the development of related applications by other sectors. Most often, GPTs do not offer the complete innovative outcome, but the recombination of GPTs with complementary technology enables the creation of new innovative solutions (Bresnahan and Trajtenberg, 1995). The interesting effects of GPTs on the growth of the entire

economy have led scholars to look for ways to measure the process of knowledge flows. The willingness to capture technological knowledge spillovers dates back to 1979, when Griliches proposed one of the first attempts to build technological indicators using the indirect R&D of a sector to prove that it affects the cross-sectors' knowledge exchange.

The first method that uses patent data was proposed by Scherer (1982). He built a matrix that counts the exchanges of technologies between the producer and user sectors. He used patents, surveys and R&D data. Later, Putnam and Everson (1994) proposed a similar idea, the Yale matrix. A second method is the creation of a citation function. In the literature, there are different versions of the citation function. The very first one was proposed by Caballero and Jaffe (1993) and was partly redefined by other scholars in subsequent years (Hall et al., 2001; Jaffe and Trajtenberg, 1996; Popp, 2002). In general, the probability that a patent cites another patent is a function of three variables: the diffusion process, the obsolescence rate, and a parameter built on the characteristics of the two patents. The advantage related to this approach concerns the elimination of some of the noises affecting the citation probability (i.e., the examiner, the cohort effect, the country effect, etc.). Finally, another measure very frequently used is an index based on patent backward citations, which is the measure I try to improve with my study. A patent is a legal document that offers exclusive rights to the owner and to the inventors in exchange for public disclosure of the invention. In order to prove the novelty and non-obviousness of an invention, its technological content must be compared with previous existing knowledge. The applicant and the examiner list the existing literature (patent and non-patent literature) in order to have a benchmark to judge the effective novelty of the invention. In the literature, this measure is called the 'index of backward citations'. Many attempts have been developed to demonstrate that patent citations are a good measure of knowledge flow.

Jaffe, Trajtenberg, and Henderson (1993) describe the reasons for why patent citations are a good proxy to trace spillovers. Citations can be introduced either by the inventors or by the patent examiner. While the citations listed by the inventors should be an actual measure of the awareness of the knowledge owned, or at least of part of it, the citations added by the patent examiner are references to prior art that could be unknown by the inventors. Consequently, citations are a 'very noisy measure for spillovers'. However, at the same time, they are a conservative measure: if some significant results appear, they must be correct because they were able to emerge, despite the noise generated by the references added by the patent examiner. In the same vein, Hall et al. (2001) and Duguet and MacGarvie (2005) add empirical proof to the use of backward citations, undergoing surveys to explain the origins of the citations they insert in their patents. In both works, the authors find confirmation concerning the capability of

backward citations to reflect the inventors' knowledge, even if the validity changes with the source and the destination of the knowledge transmitted. Breschi and Lissoni (2004) explain that even if patent citations are added both by the inventor and the examiner, they are both valid. The reason is that inventors can have a strategical reason not to disclose the prior art, while examiners fill this gap. Recently, Jaffe and De Rassenfosse (2016) have proposed a comprehensive overview of the uses and pitfalls related to the measure of backward citations.

My work aims to propose a new version of the last measure, the backward citation. This analysis is inspired by the fact that different technologies require different time periods to be understood, and that this variance should be captured in the measure.

More specifically, I argue that the faster the adoption of a new technology z, the faster this new technology z becomes "common knowledge", and it is no longer cited. Consequently, it becomes invisible in terms of backward citations.

1.2.3 Regulations and innovation

The third study of the thesis analyzes the effect of the introduction of a regulation in a sector that was auto-regulated until the 1990s. As I mentioned in the first section of the introduction, when the revolution of the orthopedics sector started, there were no rules for setting a quality threshold for instruments, nor did any rules exist to assure safety for patients. Only few attempts had been conducted by the AO to ensure the standardization of materials. The situation changed at the beginning of the 1990s in Europe, with the introduction of a regulation that mandated the safety requirements to be fulfilled by any medical tool before entering into the market. This regulation, the "Council Directive 93/42/EEC on Medical devices", takes the place of all individual regulations existing at the national level (if any) and was recognized by all European countries. The effects of introducing this regulation are still the cause of significant debates (Ashford et al., 1985; Blind, 2008; Herzlinger, 2006; Rothwell, 1980; Stewart, 1981; Verhoeven et al., 2016). Some scholars see regulations as a barrier to evolution. Technological innovation positively contributes to economic growth. It represents the engine of the economic development process, proving new solutions and opportunities for industries and consumers. More broadly, it improves the social welfare by assuring greater consumer abundance and by providing new care for diseases. For these reasons, any limitations can only produce negative effects. Other scholars, instead, are more concerned about the side effects of technological innovation and argue that regulations are necessary to guarantee controlled development, which can also be seen as a stimulus for innovation (Porter and Linde, 1995).

Others are more inclined to understand "what tradeoff our society is willing to make" (Eads, 1980, p. 51) between social and economic benefits and the risk of an unconditional technological evolution. In fact, regulation has the difficult task of finding a trade-off between risks and benefits, and in doing so, it has to take into account the social and economic implications of its decisions. In the specificity of the medical device sector, it is particularly hard to understand the policy implications of innovation. In past years, the development and complexity of new devices have required a careful assessment of the quality and safeness of tools. This has led to the creation of connections among agents: public health, clinical specialties, epidemiology and academic disciplines, with the aim of producing evidence that a specific device is safe and efficient (Faulkner and Kent, 2001). However, regulations are seen by firms as one of the core factors that influence the innovation process. In particular, regulation can influence the degree of novelty in innovative outcomes. To measure the degree of novelty, innovation can be grouped into two types: incremental or radical.

An incremental or continuous innovation does not bring a fundamental change to the treatment, nor a crucial change to the product. It requires a short development cycle and, due to the very low degree of change, its acceptance by the market and by the regulation is almost sure. Radical innovations are generally defined as breakthroughs, compared to those inventions that do not depart from the traditional path, but simply add a few elements of novelty to the existing ones (Anderson and Tushman, 1990; Ashford and Hall, 2011). A radical innovation changes the treatment paradigm, with the consequence of providing a completely new product. Since this innovation is completely new, the reaction of the market is difficult to forecast, as well as the response of the regulatory pathway. Therefore, I argue that after the introduction of the regulation, MedTech firms feel more risk adverse and are less likely to put completely radical innovations on the market. It is likely that the biggest percentage of R&D expenses are used to modify and ameliorate existing tools, while only a smaller amount of resources is devoted to the invention of a new tool completely from scratch. This innovative behavior will protect firms from the rejection of tools by the regulation and will also promote easier acceptance by the market, due to the fact that the new tool is an amelioration of a previous one, already in use.

Nevertheless, the regulation also sets the standardization of requirements, where beforehand there were different rules (or none). This led to the second aspect of the analysis: the geographical extension of the inventions. I argue that the normalization of conditions to satisfy in order to introduce a tool to the market has led firms to be more open to foreign markets. Beforehand a company was focused only on its own country, because it was sure that its products could be sold there. Now the regulation "Council Directive 93/42/EEC" is the same

for all of Europe; thus, the firm can sell everywhere with the certainty of having fulfilled all of its requirements.

1.3 Thesis Contributions

The first work is positioned in the debate related to the importance of the co-location of innovative agents on the introduction of an innovation. Many scholars have stressed the importance of being in the same place in order to innovate. However, the mechanisms through which spillovers operate have remained a "black box" for a long time. A growing strand of literature has criticized the idea that agents belonging to the same spatial cluster benefit from costless knowledge externalities simply because they are there. Precisely, it has been shown that geographical proximity is not the only determinant of knowledge flows among agents, and its effect is largely reduced when other variables, such as co-invention network characteristics, are included in the analysis (Bettencourt et al., 2007; Breschi and Lissoni, 2001; Breschi and Lissoni, 2009).

My work aims to shed light on this argumentation. The results show that being located in the same place is not the only factor raising the chances of establishing a direct collaboration between MedTech inventors. The results also show that close collaborations are enhanced by the high intensity of their external linkages. This sheds new light on the importance of external linkages. In fact, the outcomes suggest that the capability of a region to benefit from cross-regional linkages is influenced by its internal network structure. The implications of this work are directed toward policy-makers aiming to enhance the regional innovation in a specific sector. These findings support the argument of smart specialization, in that a so-called "pipeline strategy", implemented to capture extra-regional knowledge, will not succeed if indigenous capabilities have not been formed. In other words, a pipeline strategy cannot be viewed as a substitute for internal capability failures (Foray, 2014).

The second work speaks to the literature on technological knowledge spillovers. The importance of knowledge spillovers for economic growth is universally recognized. The way in which technological knowledge spillovers can be measured has been a hot topic in the economic literature. The aim of this work is to propose a new method that can capture technological spillovers, taking into account the different speed of adoption for each technology. The results show how the speed of adoption of a technology can influence the measure of knowledge spillovers using backward citations. The implications of this work are relevant for the literature that aims to grasp technological spillovers between different fields. The results suggest that it is important to carefully analyze the dynamic behavior of different technologies in order to capture

the existing connections more precisely. The correct evaluation of the intensity of technological spillovers between sectors has implications for policy-makers whose intent is to understand the potential for modernization that would allow a traditional industry to improve its operational efficiency or product quality, as well as to experience a transitional move from traditional practices targeting old, declining markets to new technologies for entering new, emerging markets. The capability to grasp such a phenomenon in the most precise way enhances the possibility of having a policy that better fits the real needs of the society.

The third work adds new insights to the literature on the effects of social regulation on the innovation of the industrial sector. This literature claims that public intervention favors innovation activities (Porter and van der Linde, 1995), but extant empirical evidence provides contradictory results regarding the positive or negative effects of introducing new rules (Blind, 2012). One of the most difficult tasks of policy-makers is to propose a regulation that assures users' safety, and at the same time, minimizes the side effects on the economic outcomes of firms. Unique to this third study is the fact that, in considering the regulation effects on innovation activities, I look at the technical content of each invention. Specifically, I consider the technologies embodied in an invention. The results show that, after the regulation change, innovators tend to replicate extant technology combinations instead of introducing new ones. This result thus indicates that innovators become more risk adverse toward novelty. At the same time, a stringent regulation at the European level imposes the standardization of products to all European countries. If innovators can rely on uniform rules that their products have to satisfy, they are incentivized to extend their target markets. When policy-makers introduce a strict regulation, they think about the health and security of the final users. However, they should also consider the 'side-effects' for the economy. A more stringent regulation might discourage inventors from introducing new risky solutions.

Table 1.1 reports the overview of the thesis.

	First study	**Second study**	**Third study**
Empirical Context	Medical device sector in Switzerland	Medical device sector in Switzerland	Medical device sector in Europe
Referenced Literature	Network effects on innovation; Knowledge spillovers; Proximity effects	GPTs; Patent backward citations to measure technological spillovers	Effect of the regulation on innovation; Technology diffusion; Incremental vs. radical innovation
Research Question(s)	What is the best network structure to enhance regional innovation?	Are backward citations still the best measure to track knowledge spillovers?	What are the effects of introducing medical device regulation in Europe?
My Contributions	Results confirm the importance of the co-location of inventors for regional innovative performance. The positive effect of intense relationships within the region is enhanced by a few relationships outside of the region and with different sectors.	Introduction of a new measure of backward citations that is able to account for the differences in the adoption speed of different technologies	The results show the twofold effect of introducing the regulation on the performance of the sector. Innovators become less risk adverse and produce less radical innovations; at the same time, they have the possibility of opening their market beyond their national borders, thus exploiting common standards.

Table 1.1: Overview of the thesis

Chapter 2: Does the centrality of specialized inventors foster regional innovation? The case of the Swiss medical device sector

(with Dominique Foray and Michele Pezzoni)

2.1 Introduction

Empirical findings suggest that innovation exhibits a pronounced tendency to cluster spatially (Feldman and Kogler, 2010). During the 1990s, several works documented the importance of geographic proximity in fostering knowledge flows among co-located agents (Feldman and Audretsch, 1999; Jaffe et al., 1993). From this point of view, knowledge spills over among co-located firms or individuals simply because they are there, without being regulated by economic transactions or by formal contractual agreements among actors. The concept of localized knowledge spillovers, used to define the beneficial effect of co-location, has become popular and has served as a starting point, both for policymakers aiming to design regional innovation policies and for researchers aiming to combine geography and innovation.

Storper and Venables (2004) explain the beneficial effects of geographical proximity in knowledge exchanges between individuals with an increased likelihood of face-to-face contacts. According to the authors, face-to-face contacts facilitate the transmission of tacit and contextual knowledge among agents. Bathelt et al. (2004) use the term "buzz" to describe the beneficial co-presence of individuals in the same city or region.

However, the mechanisms through which spillovers operate have remained a "black box" for a long time. A growing stream of literature has criticized the idea that agents belonging to the same spatial cluster benefit from costless knowledge externalities simply because they are there. Precisely, it has been shown that geographical proximity is not the only determinant of knowledge flows among agents, and its effect is largely reduced when other variables, such as co-invention network characteristics, are included in the analysis (Bettencourt et al., 2007; Breschi and Lissoni, 2001; Breschi and Lissoni, 2009).

This paper aims to contribute to the current discussion by assessing how the regional level of connection regarding technologically specialized inventors and academic inventors impacts regional innovation outcomes. It focuses on the Swiss medical device sector (MedTech). The analysis considers both the structure of the network related to the regional community of inventors and the cross-regional linkages (Bathelt et al., 2004). The inventors are classified according to their technological specialization in the medical device technology sector, in

technologies complementary to medical devices, and academic inventors. The analysis considers two measures of the inventors' level of connection: degree centrality and the intensity of cross-regional collaborations calculated for each class of inventors.

The results show that the average degree centrality of the regional technological community specialized in the medical device sector positively correlates with regional innovation. Its effect is amplified when specialized inventors also have intense cross-regional collaborations. Moreover, regional innovation is affected by the position in the network of inventors specialized in complementary technologies that serve as the building blocks of medical device inventions, and by the cross-regional collaborations of the academic inventors.

These findings are relevant for the creation of regional innovation policies. This study shows that the level of connection, within and outside of the region, of different groups of inventors has different effects on the production of new knowledge in a specific technology. Precisely, this study suggests to policymakers which groups of inventors and which types of connections should be incentivized in order to foster regional innovative performance in the medical device sector.

This paper speaks to four streams of literature. The first stream of literature relies on the empirical works that have investigated the impact of network structure on regional innovation outcomes (Bettencourt et al., 2007; Lobo and Strumsky, 2008). Part of this literature has focused on the test of the "small world" hypothesis. The "small world" is a particular network structure characterized by an ecosystem of clusters connected by long ties (Newman, 2000). The results of these analyses are mixed (Breschi and Lenzi, 2012; Fleming et al., 2007).

A second stream of literature to which this paper speaks focuses on the importance of cross-regional collaborations, showing that their presence impacts the innovation activity of the local technological community (Bathelt et al., 2004; Owen-Smith and Powell, 2004).

A third stream of literature relies on the idea that innovation is the result of a recombination of existing knowledge in complementary domains (Kogut and Zander, 1993). Technological domains that are highly connected with other domains offer greater possibilities for innovation than less connected domains (Fleming, 2001; Galunic and Rodan, 1998; Mccann and Ortega-Argilés, 2013; Youtie et al., 2008).

Finally, the paper relies on the stream of literature studying the role of academic inventors in the co-invention network (Anselin et al., 2000; Balconi et al., 2004; Lissoni, 2010). The paper is organized as follows. Section 2 describes the theoretical framework and the contribution of this work to the existing literature. Section 3 provides details on the Swiss

medical device sector. Section 4 presents the methodology and the econometric model. Section 5 discusses the results. Section 6 concludes.

2.2 Theoretical framework and contribution

The spatial clustering of economic activities leads to several benefits such as increased trust bewteen actors, reduced costs, and higher efficiency of the labor market (Agrawal et al., 2006; Feldman and Kogler, 2010). In order to explain the beneficial effect of clustering on innovation, the literature relies on the concept of localized knowledge spillovers (Döring and Schnellenbach, 2006; Feldman and Audretsch., 1999; Jaffe et al., 1993; Zucker et al., 1998). The existence of localized knowledge spillovers is strictly connected with the inventors' social and professional connections (Breschi and Lissoni, 2001; Powell, 1996). The concept of localized knowledge spillovers has been revisited by supporting the idea that a large part of the knowledge flowing among agents cannot be considered as a pure externality. On the contrary, flows are mainly regulated by economic transactions, such as work contracts, markets for technologies, and research collaborations among individuals, firms and institutions. The diffusion of knowledge through these mechanisms feeds the creativity of individuals and enhances innovation opportunities (Burt, 2004; Cowan and Jonard, 2004).

In this framework, the co-invention network is a proxy for inventors' collaborations and possible contractual agreements among actors. The nodes in this network are the inventors who appear in the patent application documents, and two inventors are connected if their names appear in the same patent application. The idea that the properties of the co-invention network affect the diffusion of knowledge among inventors has already been investigated in several works (Ahuja, 2000; Boschma and Frenken, 2010; Breschi and Lissoni, 2009; Gomes-Casseres et al., 2006; Singh, 2005).

This paper highlights the characterization of the nodes of the co-invention network. Inventors are grouped along two dimensions: their technological specialization (Feldman and Audretsch, 1999) and their location, inside or outside of the focal region (Bathelt et al., 2004). The analysis starts by assessing the impact of the level of connection involving the inventors specialized in MedTech on regional innovation outcomes in the MedTech sector. A higher level of connection of the inventors specialized in MedTech is expected to enhance the probability of knowledge flows from other inventors, creating benefits for their innovative activity.

The connectivity of inventors in the regional technological community is measured according to two indices. The first index is membership to the largest connected component of the co-invention network. As discussed by Owen-Smith and Powell (2004), membership to the

largest connected component is a sufficient signal that allows members to benefit from access to the information available within the local technological community. This work relies on the same idea applied to membership to the largest connected component of the co-invention network of inventors specialized in MedTech.

The second index, degree centrality, measures the intensity of connection in the regional technological community (Miguélez and Moreno, 2013; Giuliani, 2005). Degree centrality consists of the count of direct connections from the focal inventor to the other inventors in the network. Direct connections are the most important channels of knowledge flows, considering that the probability of knowledge flows between two inventors decays sharply when their distance in the social network increases (Breschi and Lissoni, 2001; Vanhaverbeke et al., 2009).

The consequent hypothesis is that high levels of connectivity involving MedTech inventors might enhance regional inventive outcomes in the MedTech sector. This hypothesis is split into two subcomponents, according to the measures of connectivity used.

HP1a: An increased average degree centrality of MedTech inventors in the regional technological community correlates positively to the number of MedTech patent applications in the focal region.

HP1b: The presence of MedTech inventors in the principal component of the regional technological community correlates positively with the number of MedTech patent applications in the region.

It is difficult to think that knowledge networks, being social and not territorial constructs, are enclosed within regional borders (Ter Wal and Boschma, 2009; Asheim and Isaksen, 2002). Going through the cross-regional borders with external linkages brings new ideas, new information and fresh knowledge into the region (Breschi and Lenzi, 2012; Bresnahan et al., 2001; Bathelt et al., 2004; Grabher, 1993; Rosenkop and Nerkar, 2001). The lack of external linkages, and the consequent isolation of inventors within a region, might cause convergence toward homogenous redundant knowledge circulating within the region and leading to the decline of innovation (Bathelt et al., 2004; Burt, 2004; Neal, 2010; Uzzi, 1997;). Owen-Smith and Powell (2004) empirically test the impact of the presence of pipelines in the Boston biotechnology community. Ponds et al. (2010) and Maggioni et al. (2007) show the importance of cross-regional networks in the process of regional innovation. Miguélez and Moreno (2013) find that the more inventors within a region collaborate with inventors outside of the region, the greater the return on innovation.

Bathlet et al. (2004) propose a model of local-buzz and global pipelines, where they discuss the importance of external linkages for the local cluster. Following the same reasoning,

another hypothesis formulated in this paper is that cross-regional linkages do not suffice in introducing new knowledge that is beneficial for MedTech innovation outcomes. Inventors who are intensively connected with cross-regional collaborations also have to be central in the local community of inventors in order to foster the knowledge production process. They can absorb and interpret non-redundant knowledge from outside of the region, but they also benefit from intense connections within the regional technological community (Cohen and Levinthal, 1990). Inventors who are expected to foster the development of a technology within a region have to be both embedded in their local network and connected with long ties outside of the region. This idea is at the foundation of the smart specialization approach for regional innovation (Foray, 2014; Mccann and Ortega-Argilés, 2013; Miguélez and Moreno, 2013).

Thus, the second hypothesis follows:

HP2: Intense cross-regional linkages of MedTech inventors increase the number of MedTech patent applications in the region; however, the effect is amplified when it is combined with a high degree of centrality of MedTech inventors.

The third hypothesis formulated in this paper regards the role of academic inventors and the role of inventors specialized in technologies that are complementary to MedTech. Academics play a fundamental role, both in the production of basic research and in the production of applied research outcomes (Agrawal and Henderson, 2002). Empirical works have shown that academic inventors are frequently involved in collaboration with industry (Azoulay et al., 2009; Calderini et al., 2007). However, there are relevant differences between academic and industrial researchers. First, the research interests of academic inventors have a border scope when compared to industrial researchers (Fleming et al., 2001). Second, Balconi et al. (2004) show that academic inventors are more central and better connected than non-academic inventors. In particular, their role is to connect the non-academic communities of inventors that otherwise would be disconnected. In this sense, academic inventors act as brokers in the knowledge network (Lissoni, 2010). The presence of well-connected academic inventors in the regional network is expected to enhance inventive MedTech outcomes, increasing the probability that different technological communities are connected by academic inventors. Moreover, academic inventors might act as brokers in the geographical dimension, having more chances to generate new long-distance connections across regional borders. The nature of their professional activity favors the generation of cross-regional collaborations through participation in conferences, consulting activity, or collaborations with colleagues located in other universities (Lissoni and Sanditov, 2006). Academic inventors are particularly important in explaining

innovation outcomes in the medical device sector. This sector is characterised by strong interactions among different actors such as academics, surgeons and firms (Mina et al., 2007). This analysis includes the measures of academic inventors' degree centrality and cross-regional linkages.

A growing stream of literature currently considers a large part of new knowledge generation as the result of recombining existing knowledge (Antonelli et al., 2010; Kogut and Zander, 1993; Mccann and Ortega-Argilés, 2013; Youtie et al., 2008; Weitzman, 1998). It is difficult for focal firms to absorb and interpret knowledge from distant domains. For this reason, firms tend to explore only closely related technological domains and pursue incremental innovations (Rosenkopf and Nerkar, 2001). However, firms need to look for new knowledge in different technological domains in order to refresh existing information and develop new assets (Gavetti and Levinthal, 2000). In co-invention networks, inventors specialized in different technological domains are expected to have more chances to exchange knowledge when they are intensively connected. A higher connectivity of inventors leads to higher chances of contributing to regional knowledge recombination (Feldman and Audretsch, 1999). The importance of the exchange of knowledge with complementary sectors is the core aspect of the concept regarding related variety (Bishop and Gripaios, 2009; Boschma and Iammarino, 2009; Boschma et al. 2012; Frenken et al., 2007; Quatraro, 2010). The fact that complementary technologies are accessible locally increases the probability of regional growth.

The medical device sector involves a range of complementarity competencies and technologies (Ramlogan et al., 2007). The interdisciplinary nature of MedTech, as described by Rosenberg (1994), suggests that innovation in MedTech is the result of recombining knowledge flowing from the following technological domains: measurement instruments, pharmaceuticals, chemical engineering, machine tools and special machines. This analysis tests whether the degree centrality and cross-regional linkages of the inventors specialized in technologies, which are the building blocks of MedTech inventions, play a role in boosting regional innovation outcomes. The third hypothesis follows:

HP3: The average degree centrality and cross-regional linkages of academic inventors and inventors specialized in technologies complementary to MedTech affect positively regional innovation outcomes.

The relevant role played by academic inventors and inventors specialized in MedTech complementary technologies might affect HP2. Following the reasoning of HP2, the cross-regional linkages of academic inventors and inventors specialized in MedTech complementary technologies might substitute for the MedTech inventors' cross-regional linkages. As a result, academic inventors and inventors specialized in complementary technologies may be left with

the responsibility of connecting the local community of inventors to inventors outside of the region.

2.3 The Swiss medical device sector

This work focuses on the medical device sector in Switzerland. This sector is an exceptional success by any measures. It consist of 1,450 firms involved in the production and commercialization of medical devices (Swissmedic, 2014). The market of medical devices represents 2.3% of the Swiss GDP, with 14 billion CHF per year, accounting for 5.2% of Swiss exports. Six percent of Swiss firms have more than 250 employees, while half of them have fewer than 10 employees. The first 10 largest firms employ 14,017 workers. The whole sector consists of 52,000 full-time employees. The growth rate of sales ranged between 6% and 10% in the period 2011-1014 (Medical Cluster, 2014).

The literature identifies four main features of MedTech. First, MedTech depends on complementary technologies from other sectors (Ramlogan et al., 2007). Switzerland develops many types of medical devices such as robotics, ortho-dental, and orthopedics. There are 9 medical clusters in Switzerland. The Leman Lake cluster has relied on the mechanical precision and watch industries since 1700. The Neuchatel cluster benefits from the local competencies in the industries of precision mechanics and microelectronics. In the north of Switzerland is the cluster of Jura, where there is a business incubator for life science companies. The Basel cluster is the biggest European life-science cluster. In Solothurn, orthopedic devices are the core product. In Bern, medical device firms have the possibility to collaborate with universities of applied science, centers of biomedical engineering, and research centers. The cluster of Aargau is particularly attractive for the cheap-skilled labor market, and for this reason, the average percentage of people employed in R&D is more than the double the Swiss average. The Zurich cluster hosts the Swiss Federal Institute, a university, and a large number of successful spin-offs. Finally, Ticino hosts the headquarters of many multinational companies active in the MedTech sector.

Second, innovation in MedTech tends to be incremental due to the intrinsic uncertainty of the innovation process (Gelijns et al., 1998). MedTech is a sector regulated by strong directives that aim to maximize the safety and welfare of patients by minimizing the risk related to the use of new devices. Every new product must fulfill strict requirements, quality assessment, and clinical trials to enter the market (Chai, 2000).

Third, Rosenberg et al. (1995a, 1995b) show how applied research conducted in laboratories within firms is more relevant than basic research conducted in universities. On average, Swiss medical device companies spend more than 11% of their revenues on R&D.

Finally, MedTech innovation depends on the interaction of individuals, firms, and institutions. Companies need to collaborate with each other in order to develop new products, as shown in the Tuttlingen cluster by Halder (2002). Based on a survey conducted by the Swiss Cluster[2] in 2013, 70% of manufacturers engage in collaborations to develop new products. This evidence is supported by the Swissmedic Report, showing that 73% of collaborations are made directly with the buyer and can also involve suppliers, universities or other manufacturers in minor percentages (Swissmedic, 2014). In particular, academics and surgeons play a fundamental role as developers, since they are aware of the potential demand for new devices and the actual needs of the final users (Mina et al., 2007).

2.4 Data and Variables

The study sample includes 24 Swiss regions. Each region corresponds to a territorial unit identified by a NUTS3 code (Sonn and Storper, 2003). The dataset includes all patent applications to the European Patent Office (EPO) from 1985 to 2005, for which at least one of the inventors is located in a Swiss region. The MedTech applications are classified according to the technological classification adopted at EPO[3]. The study sample is a balanced panel of 504 observations, i.e., 24 regions observed for 21 years. A patent is assigned to a region if at least one of the inventors listed in the patent application reports an address located in that region. In case two inventors of the same patent report two addresses located in different regions, full credit of the patent is assigned to both regions.

The count of patent applications classified as MedTech is a proxy for innovative activity of the region in the MedTech sector (Ahuja, 2000). The source of patent data is the CRIOS-Patstat database, which provides a reclassification of patents, according to the disambiguated inventors' identity (Pezzoni et al., 2014; Tarasconi and Coffano, 2014). It relies on an elaboration of the Patstat dataset released by the EPO[4].

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[2] The Swiss Cluster is an organization that groups together all agents in the value chain of the network involving Swiss medical technology. The aim of the organization is to facilitate the creation of collaborations among its members. To find out more details about the Swiss Cluster, see: http://www.medical-cluster.ch/

[3] A medical device patent is defined as a patent that has the first four digits of the International Patent Classification (IPC) equal to: A61B, A61C, A61F, A61H, A61L, A61M, and A61N. Medical devices related to animals and to transport or accommodations are not considered. Moreover, the number of patents in these subcategories is negligible.

[4] The version of Patstat used for this work is Patstat October 2013.

The 24 regions included in our analysis include 38,041 distinct inventors, of which 3,196 are specialized in MedTech technology. These inventors filed 54,193 patent applications at EPO, 5,739 of which are classified as MedTech patent applications.

The inventors are classified into three groups, according to their technological specialization, and whether they are academics or not:

- inventors specialized in MedTech technologies (*MT*)
- inventors specialized in MedTech complementary technologies (*MCT*)
- Academic inventors (*ACAD*)

The specialization of each inventor is defined according to the predominance of specific technologies in the inventor's stock of patent applications. Precisely, an inventor is defined as specialized in MedTech technologies (*MT*) in year *t* if she invented at least one MedTech patent during the years from *t-1* to *t-5*. An inventor is defined as specialized in MedTech complementary technologies (*MCT*) if she is not specialized in MedTech, but she invented at least one patent in a technological domain complementary to MedTech. The definition of complementary technologies is based on an analysis of backward citations of MedTech patents. The backward citations of MedTech patents are considered during the time span *t-1* to *t-5*. Complementary technologies are all of the IPC classes of the patents cited by at least one MedTech patent. The most cited complementary technologies are: measurement, instruments, pharmaceuticals, chemical engineering, machine tools and other special machines (Schmoch, 2008). Not surprisingly, many of these technologies are both the building blocks of MedTech technology and the technologies in which Switzerland is historically specialized. Finally, the inventors not included in the two preceding categories are classified as inventors specialized in other technologies (*Other inv.*) not relevant for MedTech inventions.

An inventor is classified as an academic inventor (*ACAD*) if she has published one scientific article reporting an affiliation with a Swiss university. Academic inventors are identified using the approach proposed by Dornbusch et al. (2012). First, all of the publications attributed to authors with a Swiss university affiliation during the time span 1985-2005 have been collected from the Scopus database (a bibliographic database by Elsevier). The authors are selected based on their affiliation with university departments in scientific fields that are relevant for MedTech inventions, such as engineering, chemistry, biology, and medicine. Then, the names of the inventors are matched with those of the authors of the scientific articles[5]. Finally, the resulting

[5] The procedure applied allows to identify academic inventors who report on the patent document an address that is not the address of the university where they work, i.e. their personal address or the address

matches are filtered out in terms of whether the university of affiliation of the author is in a region different from the one reported on the patent application document. The result is a list of inventors who also appear as authors in published articles. Academic inventors are a subset of nodes in the co-invention network. Table 2.1 reports the average number of inventors in each class by year and region.

Variable	Obs	Mean	Std. Dev.	Min	Max
(1) n. of inventors specialized in MedTech technologies (MT)	504	29.38	43.69	0	321
(2) n. of inventors specialized in MedTech complementary technologies (MCT)	504	176.79	344.57	0	2415
(3) n. of inventors in other technologies (Other inv.)	504	181.31	168.83	0	1124
(1)+(2)+(3) n. of inventors	504	387.48	484.08	0	3254
n. of academic inventors (ACAD)	504	6.95	18.46	0	151

Table 2.1: Count of inventors in the four categories. The average is calculated by year-region. The 504 observations are the result of observing 24 regions for 21 years each.

The intensity of connections among inventors is measured by degree centrality (Freeman, 1978). Degree centrality is defined in two steps. First, for each focal inventor p_k all of the p_i inventors to which she is connected with a co-invention relationship are counted. More formally, the indicator function $a(p_k, p_i)$ in Equation 2.1 equals one if p_k and p_i are connected with a co-invention relationship, and zero otherwise. The measure of degree centrality ($C_t(p_k)$) in year *t* accounts for the co-invention relationships over the five-year window from *t-1* to *t-5* and n is the total number of inventors.

$$C_t(p_k) = \sum_{i=1}^{n} a(p_k, p_i) \quad \text{(Equation 2.1)}$$

Second, the average value of the index $C_t(p_k)$ is calculated for the inventors belonging to each of the three classes and for the focal region ($\overline{C}_{g,r,t}$). The index *g* in Equation 2.2 indicates each class of inventors: inventors specialized in MedTech (*g=MT*), inventors specialized in complementary technologies (*g=MCT*), and academic inventors (*g=ACAD*). $n_{g,r,t}$ indicates the total number of inventors of class *g*, in region *r*, in the time window from *t-1* to *t-5*.

$$\overline{C}_{g,r,t} = \frac{\sum_{k=1}^{n_{g,r,t}} C_t(p_k)}{n_{g,r,t}} \quad \text{(Equation 2.2)}$$

According to Owen-Smith and Powell (2004), belonging to the principal component in the regional network is a signal of membership to the regional technological community. In the

analysis, MedTech inventors are considered as members of the regional technological community if at least one inventor specialized in MedTech is part of the largest connected component of the regional network of inventors.

MedTech inventors' cross-region linkages are identified with the count of co-invention relationships between inventors located within the focal region and inventors located in other Swiss regions. The number of co-invention relationships for each focal inventor p_k is calculated as in Equation 2.1. However, different from Equation 2.1, the p_i inventors are all located outside of the focal region. Finally, the average number of cross-region linkages is calculated for each class of inventors (as in Equation 2.2). Average cross-region linkages are defined as $\overline{C}_{cross,g,r,t}$.

The empirical analysis consists of two regressions with different dependent variables explained by the same set of regressors. The first dependent variable is the count of MedTech patent applications attributed to the focal region in year t (count MT). The second variable is the count of all patent applications attributed to the region in year t, without any distinction based on their technological classification (Count ALL). The count of all patent applications is included in the analysis for the sake of comparison, in order to show that the results obtained for the MedTech sector are not accidental. In each Swiss region, on average, there are 116.5 patent applications per year, of which 12.6 are MedTech patent applications. The count of MedTech patent applications equals zero in 20% of the observations region-year.

Figure 2.1 shows the average degree centrality of the inventors specialized in MedTech ($\overline{C}_{MT}$), in MedTech complementary technologies ($\overline{C}_{MCT}$), and academic inventors ($\overline{C}_{ACAD}$). After the 1990s, academic inventors are systematically more central than the other two classes. This result confirms the empirical evidence in Balconi et al. (2004).

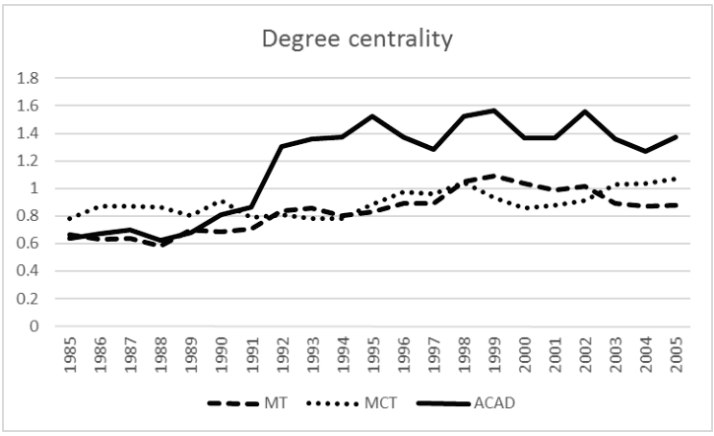

Figure 2.1: average degree centrality of the inventors

Two dummies control for cases when average degree centrality cannot be calculated or is equal to zero. When there are no inventors of class *g* in the region in the time span *t-1, t-5* degree centrality cannot be calculated. The dummy *n. g inv.>0* equals one if there is a positive number of inventors classified in class *g* within the region, and zero otherwise. When there are inventors of class *g* in the region, but none of them have co-invention relationships, the degree centrality equals zero. The dummy *Degree centrality g >0* equals one when the centrality index for class *g* has a positive value, and zero otherwise. Descriptive statistics are reported in Table 2.2.

Three variables $\overline{C}_{cross,MT}$, $\overline{C}_{cross,MCT}$, $\overline{C}_{cross,ACAD}$ represent the average cross-regional linkages, respectively, for MedTech inventors, inventors specialized in complementary technologies, and academic inventors.

Six dummy variables control for cases when there are no cross-regional linkages of inventors of class *g*. Descriptive statistics are reported in Table 2.2.

The variables *n. MT inv.*, *n. MCT inv.*, *n. ACAD inv.*, and *n. other inv.,* respectively represent the number of inventors specialized in MedTech, in MedTech complementary technologies, academic inventors, and the residual number of inventors specialized in other technologies within the region.

Another control included in the regressions is the market structure, as measured by the Herfindahl index (*H index*). A high value of the index means that a few applicants own the largest share of patents in region *i*. The index is calculated over a five-year window from t-1 to t-5. Moreover, a control for technological specialization is included in the regression, namely, the Herfindahl index of the technological classification of the patents applied for by inventors in the region (*H index technology*). Calendar-year dummies fixed effects are included in order to control for time-varying influences across regions. Regional fixed effects are included to control for the time-invariant characteristics of the region. Finally, basic statistics describing the network structure, namely, the share of isolated inventors in the network (*n. of isolated/(1+n. of inventors)*) and the share of inventors belonging to the largest connected component (*n. of inv. in pr. components/(1+n. of inventors)*) are included in the regression.

Variable	Obs	Mean	Std. Dev.	Min	Max
Inventors specialized in MedTech					
Degree centrality MT	504	0.57	0.57	0	2.67
Degree centrality MT >0	504	0.68	0.47	0	1
MT cross-regional linkages	504	0.90	1.02	0	11
MT cross-regional linkages >0	504	0.88	0.33	0	1
Degree centrality MT * MT cross-regional linkages	504	0.46	0.62	0	3.96
At least one MedTech inventor in the principal component	504	0.15	0.35	0	1
log(n. MT inv.)	504	2.55	1.37	0	5.77
n. MT inv.>0	504	0.95	0.21	0	1
Inventors specialized in MedTech complementary technologies					
Degree centrality MCT	504	0.60	0.59	0	3.25
Degree centrality MCT >0	504	0.65	0.48	0	1
MCT cross-regional linkages	504	0.60	0.63	0	3
MCT cross-regional linkages >0	504	0.70	0.46	0	1
Degree centrality MT * MCT cross-regional linkages	504	0.36	0.52	0	3.67
log(n. MCT inv.)	504	3.17	2.47	0	7.79
n. MCT inv.>0	504	0.73	0.45	0	1
Academic inventors					
Degree centrality ACADEMIC	504	0.37	0.79	0	5.45
Degree centrality ACADEMIC >0	504	0.31	0.46	0	1
ACADEMIC cross-regional linkages	504	0.32	0.58	0	3
ACADEMIC cross-regional linkages >0	504	0.33	0.47	0	1
Degree centrality MT * ACADEMIC cross-regional linkages	504	0.30	0.69	0	5.65
log(n. ACAD inv.)	504	0.80	1.29	0	5.02
n. ACAD inv.>0	504	0.42	0.49	0	1
Other controls					
log(n. other inv.)	504	4.77	1.09	0	7.02
n. other inv.>0	504	0.98	0.11	0	1
n. of isolated/(1+n. of inventors)	504	0.60	0.15	0	0.95
n. of inv. in pr. components/(1+n. of inventors)	504	0.06	0.06	0	0.37
H index technology	504	0.00	0.02	0	0.33
H index	504	0.07	0.08	0	0.51

Table 2.2: Descriptive statistics of the independent variables considered in the regression exercise. The 504 observations are the result of observing 24 regions for 21 years each.

2.5 Results

Table 2.3 shows the results of the regression exercise. Two Poisson models are estimated in order to account for the count nature of the dependent variables and for the non-negligible presence of zero values.

	(1)		(2)	
	count MedTech		**Count ALL**	
	Coeff.	Std.Err	Coeff.	Std.Err
VARIABLES				
Inventors specialized in MedTech (t-1, t-5)				
Degree centrality MT	0.34***	(0.090)	0.017	(0.028)
Degree centrality MT >0	0.049	(0.092)	0.034	(0.026)
MT cross-regional linkages	-0.018	(0.051)	-0.045***	(0.017)
MT cross-regional linkages >0	-0.43***	(0.16)	0.096**	(0.045)
Degree centrality MT * MT cross-regional linkages	0.18***	(0.058)	0.0092	(0.021)
At least one MedTech inventors in the principal component	0.21***	(0.043)	0.065***	(0.015)
log(n. MT inv.)	0.092	(0.080)	-0.032	(0.023)
n. MT inv.>0	0.61*	(0.34)	0.080	(0.078)
Inventors specialized in MedTech complementary technologies (t-1, t-5)				
Degree centrality MCT	0.14**	(0.070)	-0.028	(0.020)
Degree centrality MCT >0	0.32*	(0.17)	-0.068	(0.047)
MCT cross-regional linkages	-0.13	(0.084)	-0.066***	(0.022)
MCT cross-regional linkages >0	-0.35	(0.22)	0.012	(0.065)
Degree centrality MT * MCT cross-regional linkages	-0.12	(0.081)	0.026	(0.023)
log(n. MCT inv.)	-0.046	(0.037)	0.082***	(0.011)
n. MCT inv.>0	0.37**	(0.18)	-0.066	(0.054)
Academic inventors (t-1, t-5)				
Degree centrality ACADEMIC	0.015	(0.069)	0.023	(0.019)
Degree centrality ACADEMIC >0	0.0031	(0.14)	0.12***	(0.032)
ACADEMIC cross-regional linkages	0.22***	(0.076)	0.039*	(0.021)
ACADEMIC cross-regional linkages >0	-0.098	(0.15)	-0.23***	(0.034)
Degree centrality MT * ACADEMIC cross-regional linkages	-0.26***	(0.066)	-0.0099	(0.021)
log(n. ACAD inv.)	-0.098**	(0.044)	0.067***	(0.013)
n. ACAD inv.>0	-0.025	(0.084)	0.023	(0.026)
Other controls (t-1, t-5)				
log(n. other inv.)	-0.019	(0.042)	0.12***	(0.015)
n. other inv.>0	-1.42*	(0.73)	-0.077	(0.22)
n. of isolated/(1+n. of nodes)	0.61	(0.41)	-0.093	(0.13)
n. of inv. in pr. components/(1+n. of nodes)	-0.44	(0.53)	0.71***	(0.13)
H index technology	-0.69	(5.37)	-2.25	(1.70)
H index	0.20	(0.46)	-0.23**	(0.10)
Observations	504		504	
Number of id region	24		24	

Table 2.3: Regression table. Poisson estimations including fixed effects for each region. The 504 observations are the result of observing 24 regions for 21 years each.

The average degree centrality of inventors specialized in MedTech (*Degree centrality MT*) impacts positively on the number of MedTech patent applications: one more co-invention relationship for the average MedTech inventor increases the number of MedTech patents by

34%[6] (column 1). Thus, the empirical evidence confirms hypothesis HP1a. Column 2 shows that the centrality of inventors specialized in MedTech does not affect the number of patent applications in the focal region (*count ALL*).

Concerning hypothesis HP1b, the regression in column 1 shows that when at least one MedTech inventor belongs to the principal component (*at least one MedTech inventor in the principal component*), the number of MedTech patents in the region augments by 21%. Therefore, membership to the largest component of the co-invention network of inventors specialized in MedTech stimulates MedTech patent applications. The regression in column 2 shows a similar positive and significant effect, although the coefficient is smaller (+6.5%).

In order to test the second hypothesis (HP2), the analysis focuses on the sign and significance of the interaction between the degree centrality of MedTech inventors and the intensity of their cross-regional linkages (*Degree centrality MT * MT cross-regional linkages*). However, other actors, such as academics or inventors specialized in technologies complementary to MedTech, might act as cross-regional brokers. Then, two additional interactions are included in the regression, *Degree centrality MT * MCT cross-regional linkages* and *Degree centrality MT * ACAD cross-regional linkages*. The regression shows that the coefficient of the interaction term *Degree centrality MT * MT cross-regional linkages* is positive and significant, meaning that the impact of the centrality of MedTech inventors is amplified when the MedTech inventors have intense cross-regional linkages. Concerning the count of all patent applications in the region (Column 2), the presence of cross-regional linkages of inventors specialized in MedTech has a negative effect (-4.5%), and the interaction has no effect.

Finally, the third hypothesis (HP3) is confirmed. The centrality degree of inventors specialized in complementary technologies is positively and significantly correlated with the number of MedTech patent applications in the region. This result can be interpreted as the beneficial effect of the variety of MedTech complementary sectors in the Swiss regions. Moreover, cross-regional linkages of inventors specialized in complementary technologies have no impact on MedTech patent applications. The number of all patent applications in the region (Column 2) is not affected by the degree centrality of inventors specialized in complementary MedTech technologies or by their cross-regional linkages. However, the presence of inventors specialized in complementary MedTech technologies has a positive impact on the number of MedTech patent applications (*n. MCT inv.>0*).

[6] The coefficients of the Poisson estimations are interpreted as suggested by Wooldridge (2015).

Academic inventors' cross-regional linkages foster MedTech innovation (*ACADEMIC cross-regional linkages*); however, its interaction with the centrality of MedTech inventors shows a negative sign (*Degree centrality MT * ACADEMIC cross-regional linkages*). Precisely, the negative sign of the interaction means that when MedTech inventors are central in the network, the role of geographical brokerage played by academics is less beneficial for MedTech innovation. When focusing on column 2, the academic inventors' position in the network has some impact, especially their representativeness in the local community of inventors (*n. ACAD inv.*) and their connection to other inventors within the region (*Degree centrality ACADEMIC >0*).

Concerning the control variables, the technological specialization of the region (H index technology) has no impact on the number of patent applications (*count ALL*) or on the number of MedTech patent applications (*count MedTech*). The concentration of the sector has a negative impact only on the number of patent applications (*count ALL*).

The number of inventors not specialized in MedTech or in MedTech complementary technologies have a positive impact on the number of patent applications (*count ALL*), but not on the number of MedTech patent applications (*count MedTech*). Similarly, the size of the principal component has a positive impact on the number of patent applications (*count ALL*), but not on the number of MedTech patent applications (*count MedTech*).

2.6 Conclusions

This paper aims to contribute to the still mixed literature on the impact of structural properties regarding the network of collaborations on regional innovation performance.

This paper contributes to the previous literature by assessing the impact of structural properties involving the regional network of inventors on regional innovation in a specific sector: Swiss medical devices. The inventors are grouped according to their technological specialization, and whether or not they are academics. Following the methodologies used in prior studies, two types of relationships are considered: co-invention relationships within the local community of inventors, and cross-regional co-invention relationships.

The regression results show that the average degree centrality of inventors specialized in MedTech positively impacts regional innovative outcomes in the MedTech sector. Moreover, the degree centrality effect is enhanced by a high intensity of their cross-regional linkages. The interpretation is that cross-regional linkages are effective in bringing new knowledge to the region when MedTech inventors are able to benefit from strong connections with the local technological community. This sheds new light on the importance of external linkages. The results suggest that the capability of a region to benefit from cross-regional linkages is influenced

by its internal network structure. Moreover, the central position in the network of inventors specialized in technologies complementary to MedTech impacts positively on MedTech innovation, supporting the idea that interactions with complementary technologies are necessary in order to enhance innovation. Academic inventors act mainly as bridges outside of the region, favoring innovation creation. However, when MedTech inventors are central, the role of academic inventors as bridges outside of the region is less beneficial for regional MedTech innovation.

Moreover, this analysis shows that the determinants of the innovation outcomes of the region for the MedTech sector are different from the determinants of the total innovative outcome of the region, showing that the results concerning MedTech are not a pure artifact of the analysis.

The implications of this work are directed toward policymakers aiming to enhance regional innovation in a specific sector. This paper identifies which inventors' connections, local or cross-regional linkages, and which actors in the network are relevant in fostering regional innovation outcomes in the MedTech sector. These findings support the argument of smart specialization, in that a so-called "pipeline strategy", implemented to capture extra-regional knowledge, will not succeed if indigenous capabilities have not been formed. In other words, a pipeline strategy cannot be viewed as a substitute for internal capability failures (Foray, 2014).

This work contains three main limitations. The first limitation is related to the definition of MedTech patent applications. According to Directive 93/42/EEC, the MedTech sector includes several heterogeneous subgroups. However, in this work, MedTech has been considered as a homogenous sector, neglecting differences between subgroups. A second limitation regards the scope of the analysis, which is focused on Switzerland. An extension to other European countries, applying the same empirical framework, could generalize the results obtained. Finally, the last limitation regards the use of patent data. These data cannot cover the entire possible range of inventors' social and professional relationships or all of the innovative outcomes of the region. Nevertheless, patents are considered as a good proxy in those sectors, where intellectual property provides fairly strong protection for inventions, such as in the MedTech sector (Ahuja, 2000). Moreover, longitudinal network data are necessary to assess social network impact on innovation. The need for longitudinal data excludes the possible use of primary data (such as surveys or questionnaires provided to the inventors), due to the impossibility of asking respondents about their social connections in the remote past (Ter Wal and Boschma, 2009).

Chapter 3: How traditional medical technologies integrate ICT: A new methodological approach

(with Dominique Foray)

3.1 Introduction

One of the main questions for policymakers interested in the future of a traditional industry regards its potential for modernization. This potentiality would allow the industry to improve its operational efficiency or product quality, as well as to experience a transition from traditional practices targeting old declining markets to new technologies for entering new emerging markets[7].

The broad literature on the historical economics of technologies (David, 1990; David and Wright, 1999; Rosenberg and Trajtenberg, 2001) suggests that such a transformation potential is fundamentally determined by the capacity of traditional industries to recombine the existing knowledge base with new applications of a general purpose technology (such as steam power in the XVIII° century, electricity in the XIX° century, or information and communication technologies – ICTs - at the end of the XX° and the beginning of the XXI° centuries).

It is therefore important to develop adequate methodologies in order to capture such a dynamic of knowledge recombination or co-invention between the existing industrial technologies in a given sector and new ICT applications. Measuring this *knowledge recombination* should provide new insights into the dynamics of industrial change that an industry has experienced in the recent past and should help to predict its incipient future.

The usual empirical measure of knowledge recombination involves the use of patent backward citations[8]. However, such a measure has some drawbacks. When a new technology - say "easyT" - is "easy" to adopt and to be recombined with the existing knowledge base of industry I, there is a tendency from both inventors and patent examiners to bypass the backward citations to "easyT"; as a result, the dynamics of integrating "easyT" into the existing knowledge base of I becomes non-observable. We will show a concrete example of this problem. Our hypothesis is therefore that as a new technology is adopted quickly, it disappears as quickly from

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[7] Modernisation is manifest when the development of specific applications of a general purpose technology produces a significant impact on the efficiency and quality of an existing (often traditional) sector. Cases in point are the development of nanotechnology applications to improve the operational efficiency of the pulp & paper industry, or the integration of new information technologies into the footwear industry (Foray, 2014).

[8] See (Jaffe and de Rassenfosse, 2016) for an overview of patent citation data in social science research.

the citations' corpus. The point is that fast adoption makes the new technology quickly become "common knowledge"[9] for the inventors of industry I, and such "common knowledge" is not referred to as backward citations in the new patents of the industry. In such a case, it will be necessary to go to the second-stage citation - that is to say, to go deeper into the history of the integration of "easyT" - to be able to observe the presence of the new technology in the innovation dynamics in industry I.

In the next section, we recall the main characteristics of a general purpose technology, which makes it a key source or opportunity for generating innovation in any traditional sector, and in particular, in the sector of medical technologies. Section 3 discusses the data. Section 4 discusses the measure of "generality" as a proxy for the diffusion and adoption of general purpose technology. Section 5 presents our first round of results, based on the usual backward citation methodologies. The results are very much counter-intuitive with ICTs, which are almost absent in the medical device innovation picture. Section 6 develops a qualitative case to determine what the causes of this observation problem are, and discusses the "easy technology" hypothesis. Section 7 presents the current literature on new methods to calculate knowledge spillovers. Section 8 explains the different characteristics of technologies in terms of the speed of diffusion. Section 9 suggests a new method based on second-stage backward citations – in situations where the recombinant process involves an "easy technology." Section 10 concludes.

3.2 General Purpose Technologies and medical device innovations

A central feature of a general purpose technology (GPT) is horizontal propagation throughout the economy and the complementary nature between the invention of the GPT and the development of applications related to specific sectors. Most often, GPTs do not offer the complete innovative outcome, but the recombination of GPTs with complementary technology enables the creation of new innovative solutions (Bresnahan and Trajtenberg, 1995).

Expressed in the economist's jargon, the invention of a GPT extends the frontier of invention possibilities for the whole economy, while application development changes the production function of one particular sector. The basic GPT inventions generate new opportunities to develop applications, in particular, "user" sectors. Reciprocally, application co-invention increases the size of the general technology market and improves the economic return on invention activities related to it. The economic structure outlined by the presence of GPTs

[9] In this paper we use the term "common knowledge" always in brackets in order to avoid a misleading interpretation. In fact, a patent could not cite prior inventions but it does not mean that this invention in free and public.

and user sectors thus creates a round of positive externalities in the economic system. There are therefore dynamic feedback loops in accordance with which inventions give rise to the co-invention of applications, which in turn, increase the return on subsequent inventions. When things evolve favorably, a long-term dynamic develops, consisting of large-scale investments in R&D, whose social and private marginal rates of return attain high levels.

To be identified as GPT, a technology must, therefore, possess three characteristics: pervasiveness, an innovation-spawning effect and a scope for improvement (Helpman and Trajtenberg, 1994). The attribute of pervasiveness implies that GPTs have broad applicability, horizontal propagation, and therefore, economic-wide impact. The innovation-spawning effect captures the impact of the evolution and innovation of users' sectors on the growth of the "source" GPT. The mutual growth of the GPT, together with the users' sectors, creates some complementarities, which could increase R&D for both, which is the scope for improvement.

It is acknowledged that ICTs are currently a central GPT and represent the source of a great number of innovations in numerous user sectors (Bresnahan and Trajtenberg, 1995). Shin and Park (2007) conducted a network analysis on the interaction of ICT as GPTs and user sectors; they confirm a strong connection between ICT and other sectors, for example; the medical device sector.

Medical device innovations are characterized by interesting features, which make them a good case for studying and measuring the process of knowledge recombination and cumulativeness. As Gelijns and Rosenberg (1994) have observed, medical device innovations strongly rely on the transfer of knowledge and innovation already generated outside of the medical sector, and very often, generated in the industrial world. Thus, medical device innovations are not only "inherently interdisciplinary but also outward-looking by nature." This first feature points the centrality of transfer in the medicine of advances regarding electronics, optics, computers or material sciences. ICTs are, thus, an obvious source of innovation in medical technologies: the development of ICTs provides opportunities to increase productivity and improve the quality of a broad range of medical devices[10]. This happens through the so-called process of the co-invention of applications, which is the process by which new ICTs diffuse across a wide range of sectors, and specific applications are generated.

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[10] A few examples among many of the powerful combinations between ICT and MedTech include devices such as body scanners, magnetic resonance imaging and tele-surgery. Moreover, ICT helps the healthcare system in providing better quality of service at a lower cost, creating remote access to health services, allowing staff to save personal measurements on hospital platforms, and transforming devices for senior patients in user-friendly tools.

In the following sessions, we test empirically the interaction of ICTs with MedTech in the context of the Swiss medical device industry[11]. First, we apply the measures usually implemented to analyze a GPT and its horizontal propagation and innovativeness. Then, because of a few methodological problems that limit the standard method in tracking the dynamics of ICT integration in a user sector, we propose developing a new methodology that attempts to solve the problems identified.

3.3 The data

Medical devices comprise a complex sector, ranging from hospital beds to surgeon robots, along with prostheses and tubes for endoscopy. All of these inventions are built on different technologies. Given such huge heterogeneity, we decided to focus our work on a subgroup of medical devices: orthopedic medical devices. We have two reasons for this choice. First, the Swiss industry has a strong record in innovations within this domain of specialization. The traditional industrial strengths of Switzerland - precision mechanics and watches – provide strong inputs and an optimal environment for medical device firms to generate innovations in orthopedic instruments. Second, there is also good reason to expect that the last generation of innovation within this domain has been strongly based on the development of specific ICT applications, as proved by the numerous recent works on the interaction between these two sectors (Jog et al., 2015; Maulin P., and Wang J. 2010; Winters, J. M., and Wang, Y. 2003 ; Yazdandoost and Kohno, 2007)

We use patent data extracted from July 2015 PATSTAT[12] version.

We retrieve all of the patent applications belonging to Swiss applicants and Swiss inventors, applied under the Patent Cooperation Treaty (PCT), the Swiss national patent office, the European Patent Office, or at the US Patent office. The identification of the "orthopedics" International Patent Classifications (IPCs) was conducted, searching for keywords suggested by

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[11] Studying the dynamics of medical device innovation in Switzerland is motivated by the fact that the Swiss medical technology industry is a tremendous success, as documented in many books. By any measure (number of firms, employment, added value, number of global innovators, export performance), this industry is in a very high position in Switzerland and presents itself as a strong knowledge-driven industry, involving several global leaders. It is also a very innovative activity, characterized by a high density of inventors and innovators, as well as a high degree of innovativeness of the main customers, which are medical schools and hospitals. See, for instance, "Der diskrete Marsch der Schweizer Medizintechnik an die Weltspitze," in R.Breiding and G.Schwarz, *Wirtschaftswunder Schweiz*, Verlag NZZ, 2011.

[12] PATSTAT is the patent database provided by the European patent office. It contains information about patent applications in any national, European, and non-European patent office.

one of the experts[13] interviewed, inside the definition of each International patent classification code[14]. We identify 58 full-digit IPC codes. This leads to a sample of 9,300 patents from 1980 until 2013. In all of the results, we have converted the IPC to the TECHNICAL FIELD in order to make them more readable.

In terms of the definition of ICT, we base our decision on the sector description provided by Schmoch (2008) and the definition of ICT provided by Hall et al. (2001). Our definition of ICT includes four technology fields: Telecommunications, Digital communication, Basic communication processes, and Computer technology.

3.4 Measures of GPT propagation with the "Generality" index

A frequent indicator used by scholars to observe and measure the horizontal propagation of a GPT toward user sectors is the index of generality[15]. This index is based on an analysis of the list of references included in the patent legal document, the backward citations.

$$\text{Generality}=G_i=1-\sum_j^{n_i} s_{ij}^2 \qquad \text{(Equation 3.1)}$$

where i represents the focal patent, while s_{ij} represents "the percentage of citations received by patent i that belong to patent class j, out of n_i patent classes."

Thus, the expectation is that a GPT will receive a high number of citations from the users' sectors (i.e., pervasiveness, propagation). Given its other feature of "scope for improvement," the expectation is also that many citations will come from the same GPT.

Generality is the most frequent measure used to identify GPTs (Callaert et al., 2011; Hall and Trajtenberg, 2004; Moser and Tom, 2004; Youtie et al., 2008). However, other works (Helpman, 1998; Shin and Park, 2007) propose a different approach, based on network analysis to conduct empirical tests on GPTs. However, we do not replicate this procedure. Despite the fact that the discussion on the best measures for GPTs is very important when dealing with technologies not affected by "easy T", it is beyond the aim of this paper.

We calculate the "Generality" index for ICT related to the "Instrument" (Figure 3.1) in order to observe and document that ICT plays a central role in medical device innovations[16]. The results in Figure 3.1 show a very high value of the index. This means that ICT patents are cited

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[13] We interviewed three engineers working in three different medical device companies in order to have a more realistic and precise overview of the sector.
[14] For more details on the IPC and Technological fields, see Appendix 3.1
[15] For more details on the measure used to capture technological knowledge spillovers, see Appendix 3.2.
[16] See Appendix 3.1 for the definition of the "sector instrument" (WIPO classification).

by a broad range of different sectors. Nevertheless, the absolute number of citations from different technologies to ICT is actually low, comparing citations to patents of the same technological class.

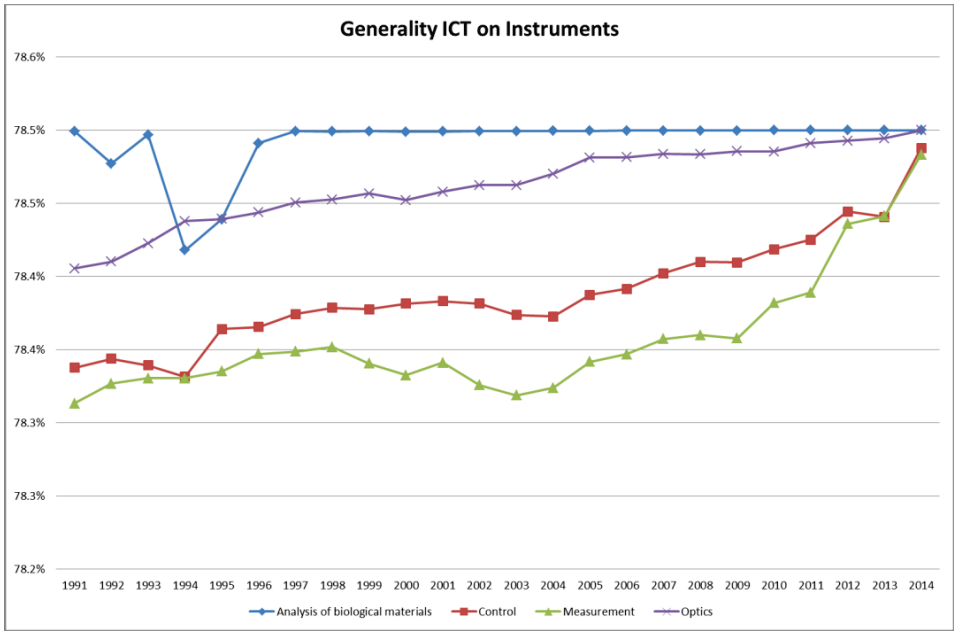


Figure 3.1: Generality index of ICT on the Instrument sector

The Generality index only tells that ICT is cited in many sectors, and as such, meets the criteria of horizontal propagation. Moreover, we still do not know whether ICT is an important GPT for the MedTech industry. To explore this point further, we need to check the backward citations of the MedTech sector to ICT.

3.5 It seems that ICT entered medical technologies at a glacial pace

We calculate all of the possible variations of the backward citation index listed and explained in Appendix 3.2. Initially, we compute the simple count of backward citations made by medical device patents, grouped by the application authority where the application was filed: the Swiss National Patent Office, the European Patent Office (EPO), the US Patent Office (USPTO) and the World International Property Rights Organization (WIPO). For purposes of simplicity and brevity, we present here only the results obtained with USPTO citation data.[17]

[17] The USPTO legislation, in particular, the "duty of candor," enhances the disclosure of prior art by inventors. See Appendix 3.2 for an overview of the differences in the application and granting processes between the various patent authorities. Our results obtained for IPI (Switzerland), EPO and WIPO are available upon request to the corresponding author of the paper.

The trend of the backward citations of the patents filed at the US Patent Office looks complete and seems to provide some information about the interaction between MedTech and other technologies.

In any of our initial estimations, the share of ICT never crosses a 1.5% threshold, nor does it appear before 1995. Furthermore Figure 3.2[18] shows a lack of citations to ICT, even in historical periods of great impetus of IC technologies. It seems that – contrary to a general feeling shared by both historians of technology and economists of innovation – ICTs entered medical technologies at a glacial pace, at least in Switzerland and in the domain of orthopedic medical devices.

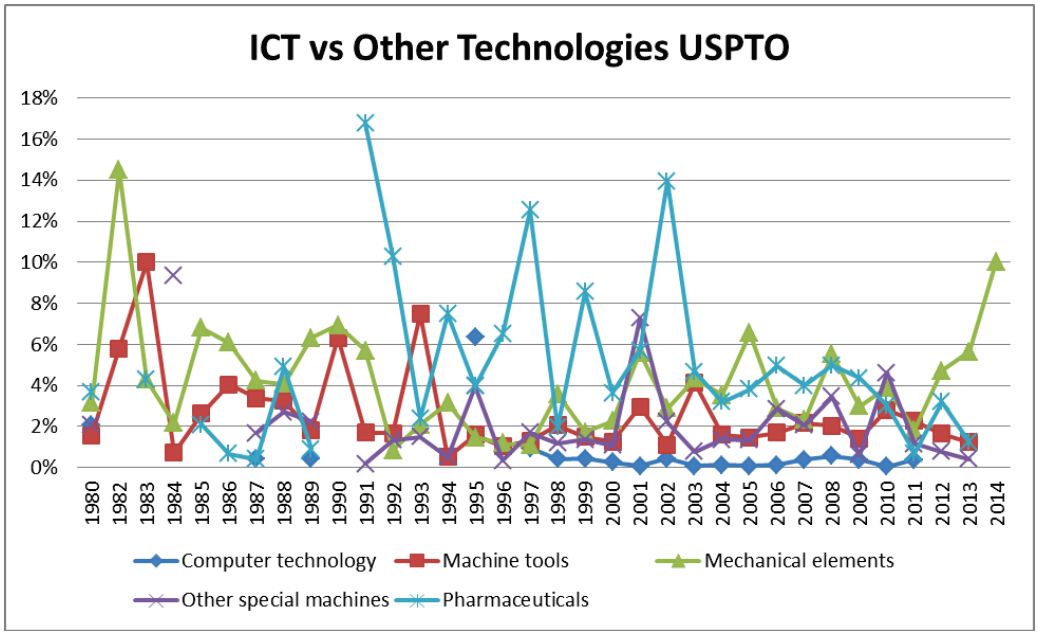


Figure 3.2: Percentage of US MedTech backward citations to ICT and the first 4 more cited technologies, over the total

These initial results are very surprising. The expectations were to find a quite high percentage of ICT technologies as anecdotal evidence, expert interviews, case studies, and historical analyses tend to show[19]. One central highlight from these various informative sources is the centrality of ICT integration as an engine for innovation and technological change in the medical device sector during the last 10 years. However, the figures above show how backward citations to ICT are very sparse. The technologies that appear to be important for medical device innovations are mostly the same in all of the three groups (but with different values).

[18] All the graphs related to the backward citations count are calculated as percentage of each technology, over the total amount of backward citations

[19] Transcripts of the interviews are available upon request (with undisclosed interviewee s names)

"Pharmaceuticals" began to be strongly present in the MedTech citations from the beginning of the 1990s. "Mechanical elements," "Machine tools," and "Other special machines" appear to be important technologies for MedTech in all of the three groups. A few other technologies have very low values (approximately 1.5%), such as "Electrical Machinery Apparatus and Energy," "Measurements," "Other Consumer Goods," and "Surface Technology, Coating." Using this method, the average percentage of citations involving MedTech to MedTech is 73%.

To explore these puzzling findings further, we calculate the backward citation index, grouping MedTech patents and their citations by family[20] (Figure 3.3).

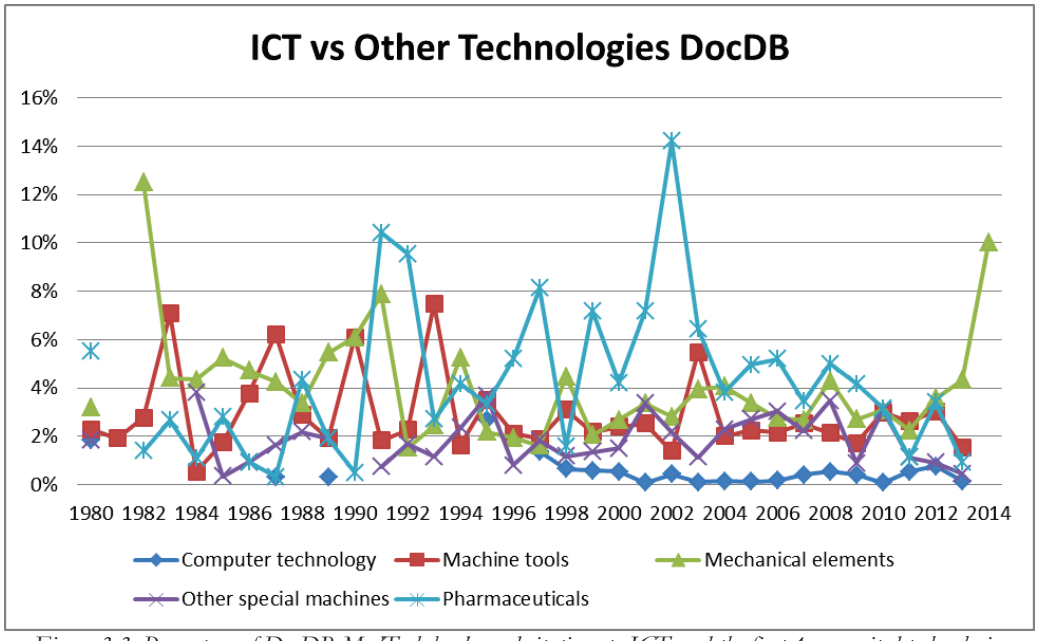


Figure 3.3: Percentage of DocDB MedTech backward citations to ICT and the first 4 more cited technologies

Using families, the amount of backward citations is higher than in previous exercises; therefore, it is less likely for us to find null values in the trends.

Despite the above finding, the new results do not add any information. The share of backward citations to ICT is less than 2.5%. This point coincides with the initial pick in 1995. After the pick, the trend stabilizes at around 0.5%. The most cited technologies are the same ones found in previous figures. There is slightly increasing importance of "Biotechnology," "Macromolecular Chemistry," "Electrical Machinery," "Measurement," and "Other Consumer

[20] Different approaches are possible for grouping patents and citations into families (Bakker et al., 2014). For our purposes, we decided to use the so-called DOCDB family method.

Goods," but their values are not high enough to overcome "Mechanical Elements," "Machine Tools," "Other Special Machines," and "Pharma."

Finally, we calculate backward citations using the citations' origins (Figure 3.4). We consider separately the citations that were referenced by the applicants and the ones referenced by the patent office, who applied at the US Patent Office[21], and we calculate the backward citations. With this method, the average percentage of MedTech to MedTech citations is 71%.

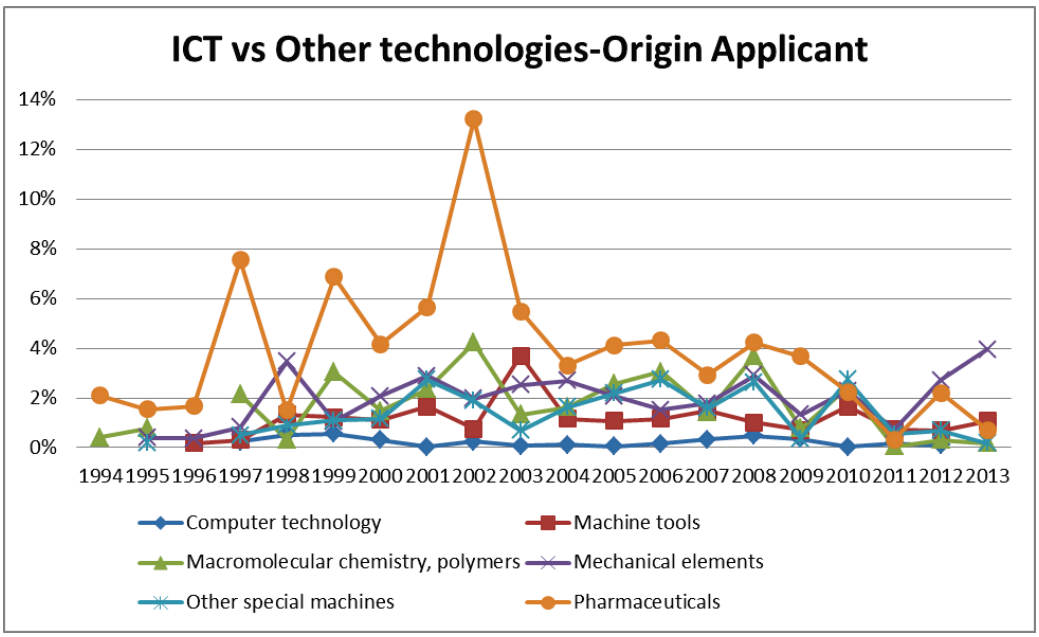


Figure 3.4: Percentage of MedTech backward citations originated by the applicant to ICT and the first 4 more cited technologies

In this case, the result changes significantly in terms of share values.

Looking at these results, Chemistry is the most-cited sector. The percentage of backward citations reached by "Pharma" is impressive, reaching 13% and with an average around 7%. The backward citations to Electrical Engineering, on the other hand, do not even reach 1%. In the Instruments sector, only citations to "Measurement" appear to have some impact in a short period of time, but with an average of less than 2%. As in previous results, the Mechanical Engineering sector, and in particular, "Mechanical Elements," "Other Special Machines," and "Machine Tools" has a strong presence in the citations. Other fields do not show particularly significant trends.

Based on these findings, the innovativeness of the medical device sector seems to rely truly on "traditional connections" such as Mechanics and Pharma. Table 3.1 suggests that the

[21] See Appendix 3.2 for more details.

potential of MedTech to regenerate through integrating new ICT applications is very low, and medical technology innovations seem to rely much more strongly on "non GPT" and more traditional technologies.

	Top ten cited Technologies
1	MedTech
2	Mechanical Elements
3	Pharmaceuticals
4	Machine Tools
5	Other Special Machines
6	Macromolecular Chemistry, Polymers
7	Materials, Metallurgy
8	Biotechnology
9	Surface Technology, Coating
10	Handling

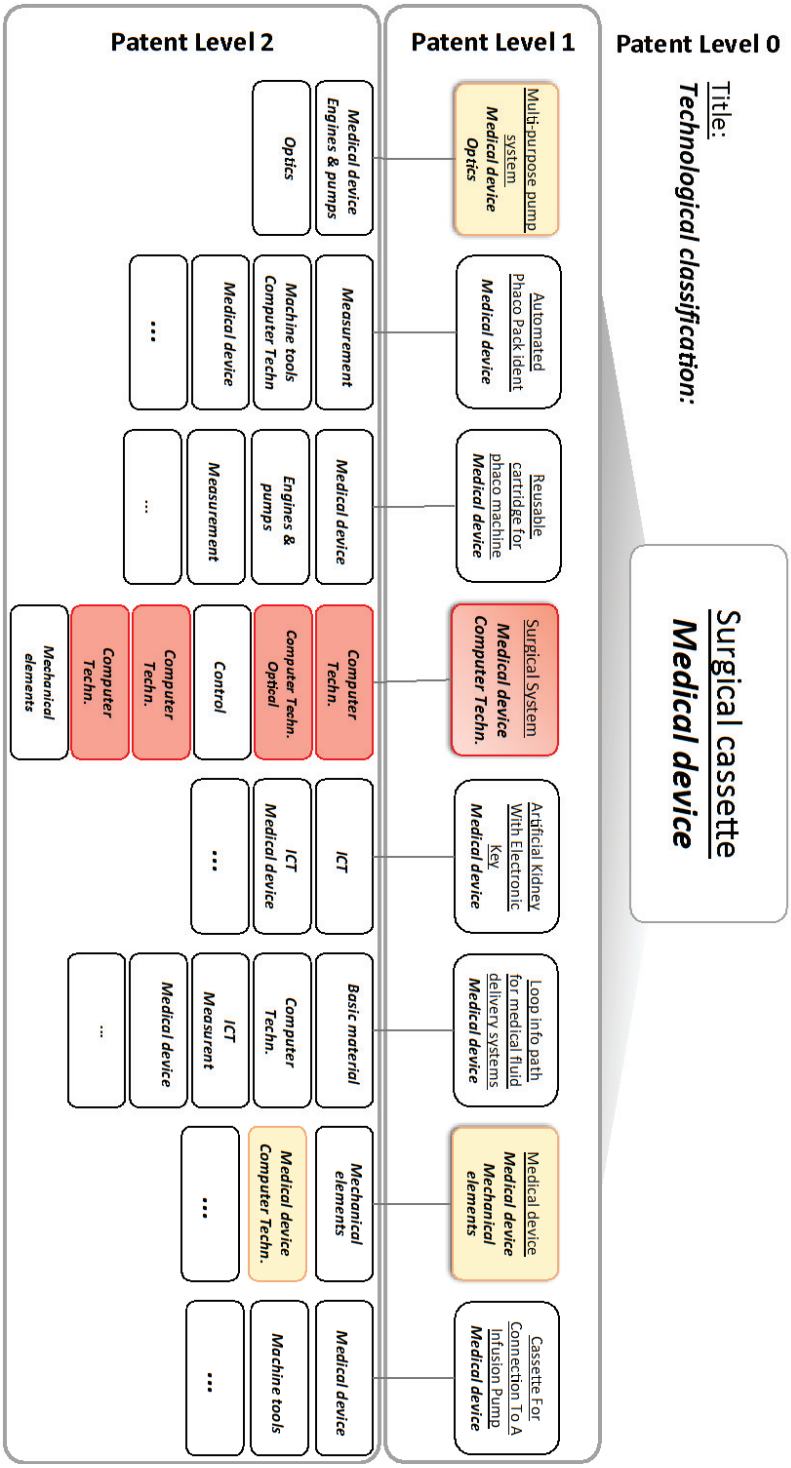
Table 3.1: Top ten technologies cited by Medtech

To summarize, we have used different methods of calculation regarding the backward citation index of MedTech in order to measure the dynamics of ICT integration. Our finding shows that ICTs do not play a central role. It seems to us that such a result is inconsistent with the massive (qualitative) literature and anecdotal evidence on this topic. In the next paragraph, we investigate more in-depth the reason for such a discrepancy between what the methods based on backward citation can demonstrate, and what the vast qualitative literature is telling us.

3.6 Qualitative overview of the problem

In order to better understand our results, we have randomly selected 10 patents within our sample, and we have analyzed their technological content, technological classification and backward citations. We chose for our qualitative example the EPO patent titled "Surgical Cassette"[22] (see Graphic 3.1).

[22] EP1787606A1



Graphic 3.1: Qualitative description of the problem: The Surgical Cassette patent

This patent has two IPCs, and both of them identify a medical device. Interestingly, in the abstract, the description of the invention states that it contains "Radio frequency identification…and pressure sensors, having a mean for automatically identifying unique information specific to an individual cassette which may affect operation of the surgical system…"

We expect to find at least some backward citations to ICT technologies. When we look at the backward citations, we find 8 patents. None of them has a classification (IPC) identifying technologies other than medical device technology. Just three out of the 8 patents have multiple IPCs – that is to say, they combine the medical device IPC with another IPC (see the three patents in color at level 1). The first one combines an IPC related to a medical device with other two IPCs: F04B43/12, defined as "Machine, pumps having flexible working members having peristaltic action *[Mechanical Elements]"* and F04B49/02, defined as "Control for machine pumps (stopping, starting, unloading) *[Mechanical Elements]."* The second patent combines the medical device IPC with G02B23/24, defined as "Fiberscope, instruments for viewing inside of hollow bodies *[Optics]."* The third patent combines the medical device IPC with G06K 7/10, "Methods or arrangements for sensing record carriers by electromagnetic radiation, e.g., optical sensing; by corpuscular radiation *[Computer Technology]"*.

Surprisingly, only one of the four "other" IPCs is related to ICT.

We decided to look more in detail at the three patents that exhibit a combination of different technologies in their classification. When we look at the backward citations of these three patents (level 2 in graphic 3.1, corresponding to the second stage of backward citations), we find that the technological classifications of the patent cited at level 2 describe in better detail the content of medical device innovation under consideration (the Surgical Cassette). [23]

The observation of second-level backward citations applies also to the other patents randomly selected.

In order to better understand the phenomenon observed, we interviewed two patent examiners currently working at WIPO. We showed them the patent on the "Surgical Cassette," and we asked them to tell us what kinds of citations they were expecting to find. Their answer was very straightforward: "We expect to find citations to previous medical devices using a similar technology." They confirm that patent examiners do not add references of what they view as

[23] In fact, we found patents whose aim is to identify drugs based on the barcode, or devices for conversion from a pharmaceutical identification number to a standardized number, or a peristaltic pump having the means for reducing flow pulsation.

"common knowledge," even if this "common knowledge" is still protected by a patent. Thus, in the specific case of the "Surgical Cassette" patent, ICTs were not included in the backward citations because, in the view of the examiners, those specific ICT components did not feature any impressive inventive step for the invention under consideration. It seems that if a technology has already been used to produce a new combination, the inventive step had already been recognized in former patents, and it is therefore not cited any more. It is treated by examiners as "common knowledge."

From this argumentation, we can argue that citations are inserted more in relation to the invention claims, than to the technological content of the application. MedTech' claims lays in sector such as Pharma, Mechanics and MedTech itself while all- purpose technologies, as ICT, are left out.

Consequently, we state that the problem in finding backward citations to ICT is twofold:

1) When the backward citation approach is reduced to the "first stage," a large part of the external knowledge that explains the focal invention (and that can be identified in the second stage) remains unobserved.

2) As the process of knowledge integration and recombination evolves, the knowledge used and absorbed at the early stages become invisible. It does not disappear as a substance, but it becomes invisible, or at least very hard to observe.

3.7 Are backward citations still the right method to measure GPTs, generality and knowledge spillovers?

Recently, scholars have started to discuss the validity of the backward citation index as a proxy for technological knowledge spillovers (Alcacer et al., 2009; Roach and Cohen, 2013). There is increasing awareness that the very way citations are inserted through an examiner's professional practices is neither systematic nor stable. The authors pointed out the potential mistakes generated by observation and measured those that are limited to first-stage backward citations. To identify the technological impact of a patent on another one, Trajtenberg et al. (1997) add to the classical count of citations a weighted count[24] of second-stage citations (strictly speaking, the backward citations of the patents cited by the focal patent). In this way, the authors aim to capture the technological impact of all previous knowledge regarding a specific patent. Frequently, patent citations are used additionally as a proxy for the value of a patent. With this

[24] The weight is fixed and equals 0.5.

aim, Von Wartburg et al. (2005) create a network of citations. The nodes of the network represent the patent applications, while the ties stand for the citations that connect the patents. The authors look not only at the direct ties of the network (the classic backward citations), but also at the second stage of citations, *namely* the indirect ties, weighted. Han and Park (2006) also propose a new method to measure knowledge flows between industries. Using patent data and citation data, they build a network of knowledge spillovers, represented by two matrices: the first one represents the amount of knowledge belonging to an industry, and the second one represents the degree of interaction between industries. Therefore, the knowledge flows are represented as the product of the two matrices. They show that the ICT-based sector turned out to be the most active actor in the network of knowledge flows. ICT both spreads and absorbs knowledge to and from other sectors. The authors also show the intense link between the ICT-based sector and more traditional ones such as manufacturing. Finally Jaffe and De Rassenfosse (2016) underline the lack of literature in regard to the process of citations across different sectors and hypothesize about the possibility of the existence of differences in the citing process.

In conclusion, the literature is starting to reveal the validity and robustness of the standard methods and seeks new methods for understanding knowledge spillovers. What emerges is that knowledge flows can be traced more properly and precisely while looking not only at the first stage of patent citations.

3.8 Our methodological proposition - 1: Measuring the speed of adoption

Our approach is based on the concept of "speed of adoption." Our hypothesis is the following: the faster the speed of adoption of a new technology z, the faster this new technology z becomes public knowledge, the faster it disappears from the first stage of backward citations, and consequently, it becomes invisible or unobservable. From an empirical point-of-view, this phenomenon leads to an underestimation of the knowledge recombination between the user sectors and the new technology z, which is rapidly adopted. In fact, if the new technology z is rapidly diffused in the user sectors, it will be massively included in the references of the first round of the patents of the user sectors using the new technology z. This will lead us to think about this technology z as "given," and it will not be necessary to cite it any more in subsequent inventions. We argue that the speed of adoption regarding a given new technology z may influence the capacity of the backward citation index to capture the real intensity of technological knowledge spillovers. For technologies with a high speed of adoption, the materialization of spillovers happens through the integration of public knowledge rather than of patented

technologies. This type of knowledge spillover is more difficult to measure by means of backward citations.

To calculate the speed of adoption, it is necessary to calculate the rate of adoption ($RA_{z,t}$). It is the percentage of firms that, at a certain point in time, decide to adopt a new technology over the total number of firms present in that moment on the market (Batz et al., 1999).

Thus, the speed and rate of adoption will be calculated as:

$$(1)\ \mathit{S}\text{peedAdoption}_{z,t} = \frac{RA_{z,t}}{t_z(t_1 \ldots T)} \qquad \text{(Equation 3.2)}$$

$$(2)\ \text{Rate adoption}_{z,t} = \left(\frac{N_{CA,\ z,t}}{N_{PA,\ z,t}} \right) \qquad \text{(Equation 3.3)}$$

where *t* is the year of the birth of a new technology, z is the technology, $N_{CA,z,t}$ is the number of firms adopting the new technology z, and $N_{PA,\ t,z}$ is the total number of potential adopters (including those who have already adopted z). $t_z(t_1 \ldots T)$ is the time occurring from the moment in which the new technology is available since the moment in which it was adopted.

We use both the standard IPC classification and the sector classification (technology field)[25], and we generalize the formula: instead of firms that adopt a technology, we calculate the numbers of sectors that adopt a technology. The technology z is identified as the first 4 digits of the IPC, and the time *t* is the priority date of the birth of the invention (priority date). $N_{CA,\ t,\ z}$ is the number of sectors adopting the new technology z and has been calculated as the number of cumulative distinct sectors who cite (backward) the technology z at time *T*. $N_{PA,\ t,z}$, the number of potential sectors adopting the new technology z at time *T,* has been calculated as the total number of distinct sectors that are present on the market at the time of the invention *t*[26]. We decide to take a fixed number of potential sectors in order to have the same "distance to walk" for all technologies; in this manner, different results will be comparable. Finally, $t_z(t_1 \ldots T)$, the time occurring from the moment in which the new technology is available since the moment in which it was adopted, is calculated as the lag of time between the priority date of the invention and the priority date of the patent of the user sector, accordingly (Criscuolo and Verspagen,

[25] See Appendix 3.1 for more details.
[26] The number of sectors present on the market is fixed and is 35, because the sectors in the PATSTAT technological classification are 35 in total.

2008; Gay et al., 2005)[27]. The calculation was computed on two different application authorities: USPTO and EPO. We obtained a random sample of patents, without caring about the specific country of origin, in order to have a sample as heterogeneous as possible. We choose 100 patents for each IPC (4 digits). The total amount of patents is 104963 for EPO and 125789 for USPTO. Then we look at the citations received by these patents up to this moment in time (2015). The aim of this exercise is examine, for each invention, how many sectors the invention was able to touch, and in how much time. Then, we compute an average speed of adoption per year, in order to see whether a particular technology has changed its speed of adoption over time.

The results show that, over time, the speed of adoption regarding different technologies remains quite constant. In order to make the results more readable, we translated the IPC into the sector classification[28], but only with the aim of understanding which kinds of technologies are represented by the IPC codes. Some technologies have a slightly increasing speed of adoption over time, such as technologies related to "Environmental Technology," "Nanotechnologies," "Basic Communication Processes," "Other Special Machines," or "Pharmaceuticals." Other technologies show a decreasing speed of adoption, such as those related with "Food Chemistry," "Machine Tools," or "Measurements." The technologies related to "Telecommunication" inventions represent an exception in terms of the constancy of the trend over time: they reached a peak in 2002, increasing six times its usual speed. The differences in the speed of adoption among the different technologies can also be quite large. In Table 3.2, we report the list of technologies grouped by the 35 sectors in order of decreasing speed of adoption. We see that the fastest technologies to be adopted are those in "Nanotechnology" and "Computer Science," followed by "Surface Technologies" and "Audio Visual Technology."

[27] Some authors argue about the validity in using the grant date instead of the priority date of the patent to calculate the citation lag (Metha et al., 2010). The reason is related to the different timing that passes between the application and the granting, which can be due to different reasons (patent offices, technology, complexity, and the patent examiner).

[28] The sector classification is provided by Table Tls 221 of PATSTAT. For more detailed information, please see Appendix 3.1.

Technologies	**Speed of adoption**
Micro-structural and Nano-technology	3.51278552
Computer Technology	3.29454233
Surface Technology, Coating	3.1737498
Audio-visual Technology	2.99461899
Optics	2.95263987
Measurement	2.95142554
Other Special Machines	2.75183467
Semiconductors	2.69498699
Telecommunications	2.6269757
Control	2.6219856
Chemical Engineering	2.56481576
Materials, Metallurgy	2.51757247
Other Consumer Goods	2.45011299
Thermal Processes and Apparatus	2.44560092
Analysis of Biological Materials	2.3537335
Environmental Technology	2.32940599
IT Methods for Management	2.30342264
Machine Tools	2.27040347
Textile and Paper Machines	2.23274166
Basic Communication Processes	2.17644449
Furniture, Games	2.15454082
Medical Technology	2.15130527
Handling	2.13123476
Macromolecular Chemistry, Polymers	2.11806198
Civil Engineering	2.11774589
Mechanical Elements	2.11421272
Transport	2.06314635
Basic Materials Chemistry	1.87971643
Engines, Pumps, Turbines	1.82687641
Electrical Machinery, Apparatus, Energy	1.68661383
Digital Communication	1.5747299
Biotechnology	1.43882896
Organic Fine Chemistry	1.40724125
Pharmaceuticals	1.20386883
Food Chemistry	0.04770575

Table 3.2: Absolute speed of adoption of different technologies

In Table 3.3, we show, for each technology, the average time after which a patent is not cited any more. This variable is calculated as the difference between the year of the last citation (priority year of the patent citing the patent in our sample) minus the year of the priority date of the focal patent. Not surprisingly, the technologies that disappear sooner are those with a higher speed of adoption.

Avg(time)	Technology field
4.9697	Micro-structural and Nano-technology
5.3671	Computer Technology
5.6977	Basic Communication Processes
6.1091	Optics
7.1202	Telecommunications
8.1267	Biotechnology
9.3368	Digital Communication
9.3485	Semiconductors
9.5807	Audio-visual Technology
10.3462	Measurement
10.3495	Surface Technology, Coating
10.477	Textile and Paper Machines
10.5313	Basic Materials Chemistry
10.566	Organic Fine Chemistry
10.6859	Other Special Machines
10.7518	Control
10.8847	Thermal Processes and Apparatus
11.2423	Mechanical Elements
11.2866	Handling
11.2868	Environmental Technology
11.2901	Macromolecular Chemistry, Polymers
11.3465	Chemical Engineering
11.3738	Materials, Metallurgy
11.43	Other Consumer Goods
11.4327	Engines, Pumps, Turbines
11.4358	Machine Tools
11.4726	Transport
11.7872	Analysis of Biological Materials
11.9011	Civil Engineering
12.0888	Pharmaceuticals
12.3832	Furniture, Games
12.4259	IT Methods for Management
12.9483	Food Chemistry
13.2367	Medical Technology
16.7391	Electrical Machinery, Apparatus, Energy

Table 3.3: Average time after which a patent is not cited any more

Thus, patents in technologies such as "Nanotechnologies" and "Computer Science" are the fastest to be adopted and the fastest to disappear from the citation references.

However, are they also the technologies that are able to reach a large amount of other sectors? In Table 3.4, we see that this is the case. Again, an invention in "Nanotechnologies" is able to be absorbed by, on average, 5 other sectors, while an innovation in "Computer Technologies" is able to reach 4 other sectors.

Avg(max_num)	Technology field
5.0152	Micro-Structural and Nano- technologies
4.91	Computer Technology
3.8328	IT Methods for Management
3.547	Macromolecular Chemistry
3.2422	Basic Materials Chemistry
3.2305	Surface Technology, Coating
3.155	Materials, Metallurgy
3.116	Environmental Technology
3.1155	Chemical Engineering
3.0888	Pharmaceuticals
3.049	Control
2.9167	Biotechnology
2.8918	Measurement
2.8897	Food Chemistry
2.7967	Semiconductors
2.7489	Optics
2.6892	Medical Technology
2.6827	Audio-visual Technology
2.6375	Telecommunications
2.6336	Other Consumer Goods
2.5842	Digital Communication
2.5757	Other Special Machines
2.5544	Thermal Processes and Apparatus
2.5535	Organic Fine Chemistry
2.5322	Textile and Paper Machines
2.5308	Analysis of Biological Materials
2.5261	Basic Communication Processes
2.5217	Electrical Machinery, Apparatus, Energy
2.4343	Machine Tools
2.2934	Mechanical Elements
2.2879	Engines, Pumps, Turbines
2.2859	Furniture, Games
2.2083	Handling
2.1462	Transport
2.1365	Civil Engineering

Table 3.4: Average number of sectors reached by any technology

These results suggest that technologies do not all behave in the same way when interacting with other sectors. As a consequence, the knowledge spillovers of different technologies cannot be expressed in their totality by using the backward citations of patent data. Some sectors such as "Computer Science" and "Micro-structural and Nano-technologies" are so fast in being adopted by other sectors that they also tend to disappear very quickly from the

history of prior art. These results are consistent with previous analyses (Hall et al. 2001; Metha et al., 2010). The findings of these analyses show that "Computer Science" is cited more quickly than any other sector, followed by "Electrical and Electronics" and "Chemicals."

If we come back to the results presented in Figure 3.2 on the backward citations of MedTech to 5 sectors, we can now observe that among the 5, Pharma technologies are both the most cited by MedTech and are also the slowest in terms of speed of adoption (Table 3.2).

Based on this qualitative and quantitative evidence, it seems clear that the usual method of backward citations to measure the integration of GPT into a given technological field is not very relevant, since the most powerful GPTs (in terms of speed of adoption) are also those that disappear from the citations and become public knowledge most quickly. We therefore propose a new method to calculate backward citations.

3.9 Our methodological proposition - 2: Application

In the example of the Surgical Cassette previously presented, we found that just three out of the eight cited patents have a medical technology IPC combined with some other technology. Thus, we look at our entire sample of medical device innovations in order to calculate how many patents have the same structure to see whether this technological structure stands. We find 1012 patents that have a combination of different IPCs[29], about 17% of the total patents in our dataset. When we look at the backward citations of our sample, we find that the total number of backward citations is 26467, of which 4194 are patents with a combination of different IPCs, 3601 are patents that belong entirely to another field, and the remaining 18672 are medical technology patents. When we look at the origin of the 3601 patents that belong to another field, we find that in 84% of the cases, these citations are made by medical device patents with a combined IPC. In only 16% of all cases, a patent classified entirely as "medical technology" cites a patent of another field. Consequently, we can differentiate two cases: the first one occurs when the focal patent is a pure medical technology invention (all of its IPCs are medical technology). The second one occurs when the focal patent has a combined IPC, so it has a medical technology IPC, combined with some IPCs of other sectors. When we find a patent that has a combination of IPCs, we proceed to the normal calculation of the backward citation measure. The novelty of our method relies on the treatment of those patents that are entirely classified as medical technology (such as the Surgical Cassette proposed in the qualitative

[29] With respect to a "combination of different IPCs," we mean those patents that have a combination of different technologies, for example, A61N (Electrotherapy…) and H02G (Installation of Electric Cables…).

example). In this case, the calculation of the first stage of backward citations is followed by the calculation of the second stage of backward citations. We perform the second stage citations only for the patents with pure MedTech classification, in order to avoid the overestimation of the count of backward citations to other technologies. In fact, as shown before, these patents count only for the 16% of the citations to other technologies, meaning that the technologies on which they are built are already had been used by other MedTech patents.

The second stage citation is then weighted by the size of their family in order to minimize the effect of big families. Thus, if a cited patent belongs to a family with 10 patents, its weight will be 0.1. The decision to use the inverse of family size is due to the fact that families have very different sizes, which has clear implications on the probability of being cited. In fact, if a patent belongs to a family with a size of 20, it is more likely to be cited by a patent that is part of a family of two patents.

The total number of backward citations will be calculated as:

$$\begin{aligned}&\text{Total backward citation patent}_i\text{to technology}_z\\&=\sum\Big(\sum \text{backward citation of all MedTech patents}\\&+\sum \text{weighted by family size 2nd stage backward citations of patent with"pure"MedTech IPC}\Big)\end{aligned}$$

(Equation 3.4)

We propose the calculation of a new method, grouping the focal patents by different application authorities, and we set the weight so that it reflects the family of the citing patent.

As in session 3.5, for purposes of simplicity and brevity, we present here only the results obtained with USPTO data[30]. The next figures present a comparison between the standard method of backward citation and our method for a range of technologies that MedTech patents are supposed to cite. We show successive citations to Chemistry, Electrical Engineering, ICT, Instruments and Mechanical Engineering.

In terms of Chemistry technologies (Figure 3.5), we see an increase of "Surface Technology, Coating," both in the absolute value of backward citations directly to this technology and in the consistency of the trend (there are no null values as before).

[30] Additional analyses are not reported, but are available upon request.

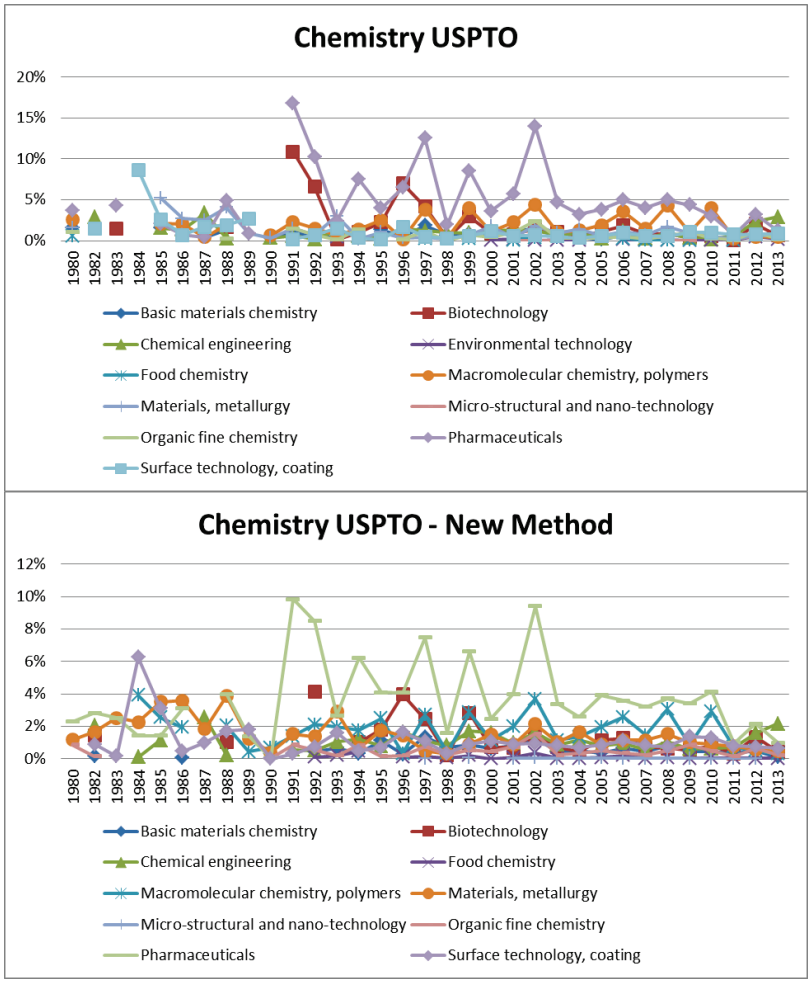


Figure 3.5: Comparison between MedTech backward citations to Chemistry; classical measure vs the new method – USPTO

With respect to the technologies grouped in Electrical Engineering, (Figure 3.6), "Electrical Machinery, Apparatus and Energy" gains a more stable trend, even if the values are still very low (average 1.2%).

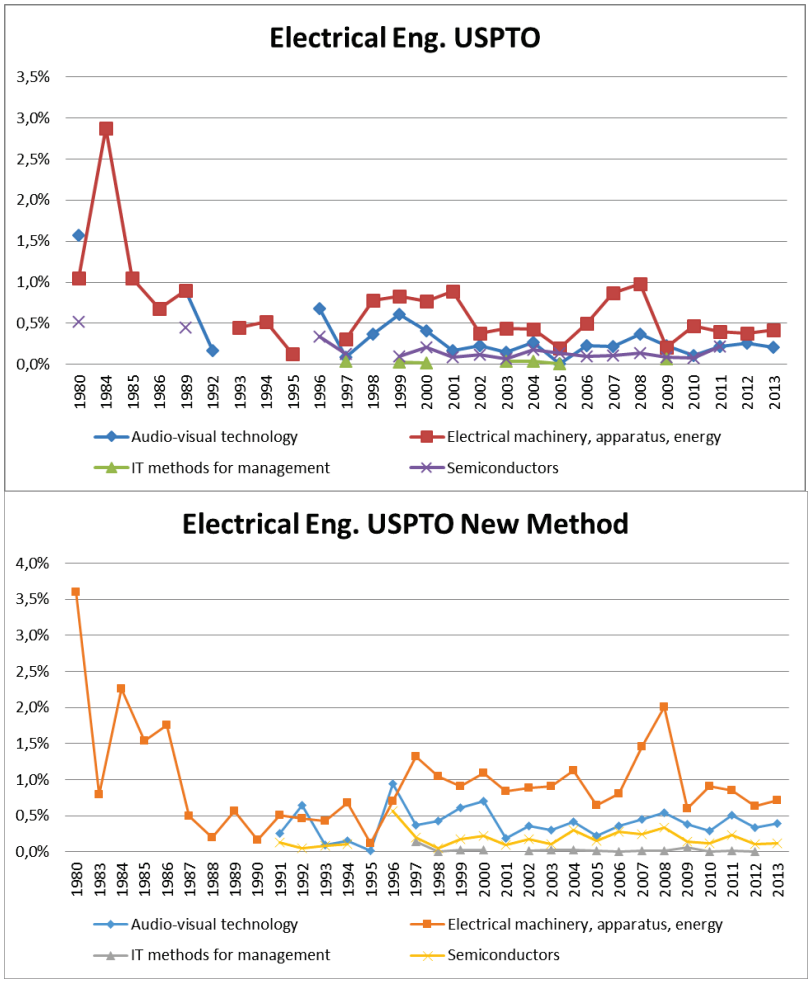


Figure 3.6: Comparison between MedTech backward citations to Electrical Engineering classical measure vs the new method – USPTO

Also, the technologies grouped in ICT gain a stronger trend. The effect of ICT on MedTech starts approximately in 1990 and, compared with the classical calculation, increases in its values (Figure 3.7). It is worth to notice that the classical measure shows in one period (1996) a high value of backward citations to ICT. It seems that in 1996, when ICTs began to be present in everyday life, MedTech started to interact intensively with for the first time.

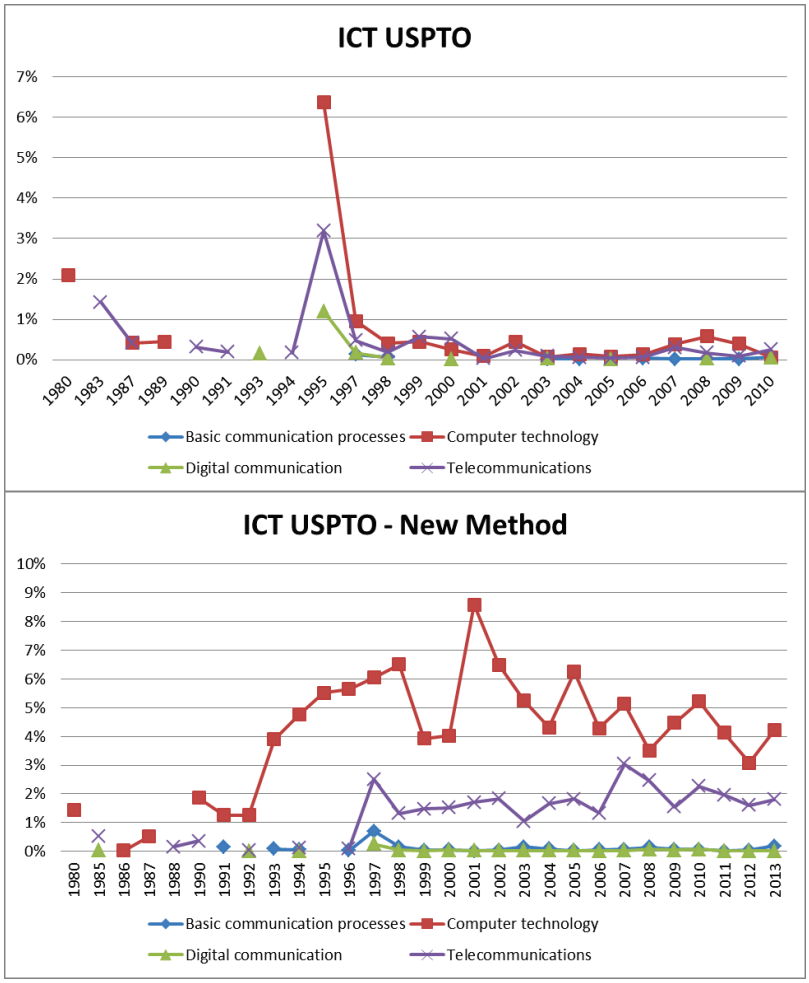


Figure 3.7: Comparison between MedTech backward citations to ICT; classical measure vs the new method – USPTO

Interestingly, in Instruments, "Measurements" gains a solid trend and increases significantly in its values (Figure 3.8). In the classical calculation, "Measurement" has never appeared to be important for MedTech, while now its values are high enough that it cannot be negligible.

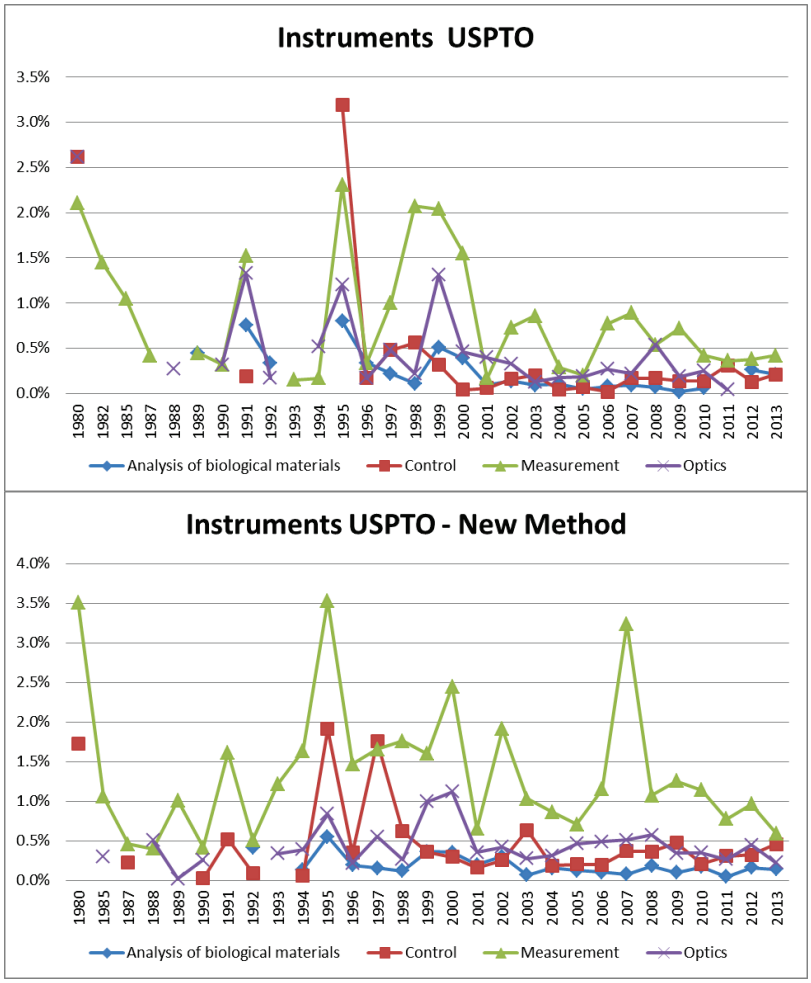


Figure 3.8: Comparison between MedTech backward citations to Instruments; classical measure vs the new method – USPTO

The impact of 'Mechanical Elements" and "Machine Tools" remains noteworthy (Figure 3.9). Moreover, the new figure better identifies the time periods in which "Mechanical Engineering" is crucial for MedTech, namely from the 1980s until the beginning of the 1990s to the present.

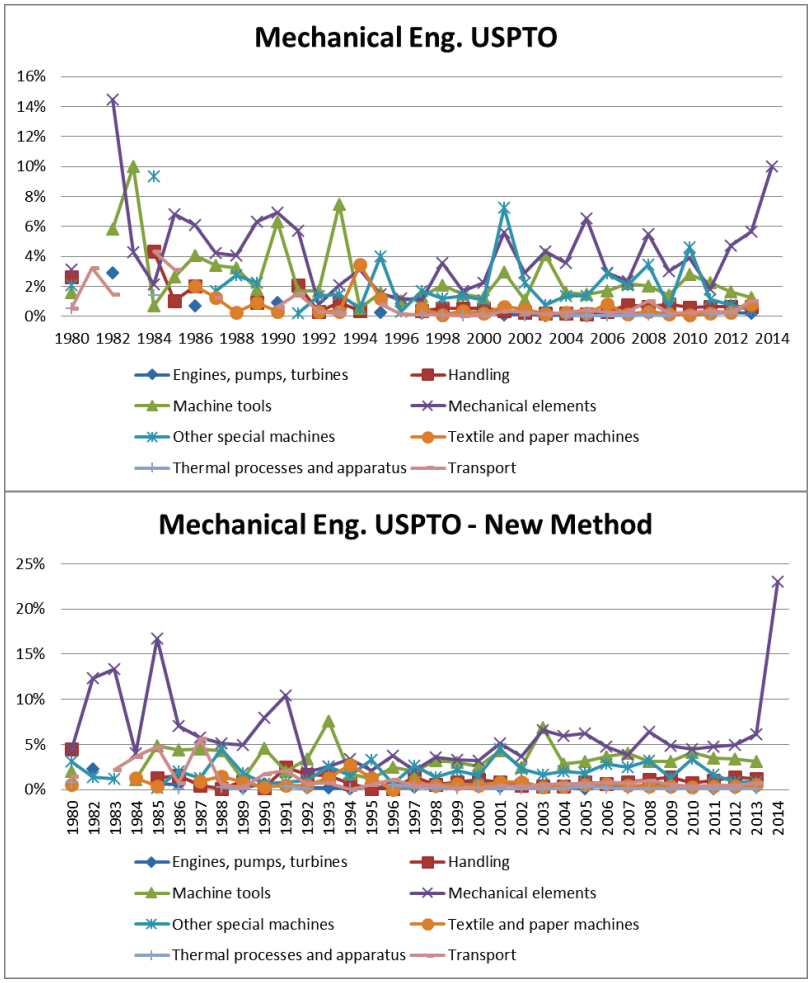


Figure 3.9: Comparison between MedTech backward citations to Mechanical Engineering; classical measure vs the new method – USPTO

As in Figure 3.10, the new index makes the effect of ICT comparable with that of the other strong technologies of MedTech.

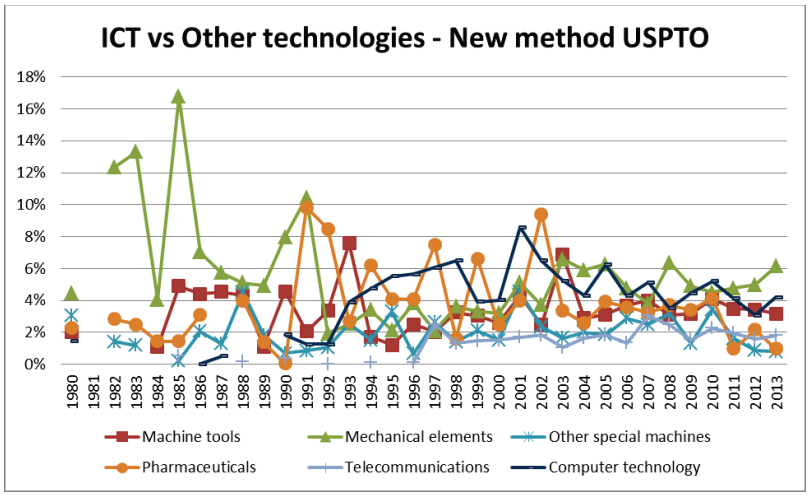


Figure 3.10: US MedTech backward citations to ICT and the first 4 more cited technologies- NEW METHOD

When we calculate the percentage points of variation between the classical calculation (we took the calculation by application authorities) and the new method, we see that the highest variation regards the technologies that were already very important for MedTech, namely "Pharma", "Mechanical Elements," "Machine Tools," and "Other Special Machines." "Measurements" goes together with "Computer Technology." This result is very important for the truthfulness of our measure. In fact, we were focusing on the behavior of ICT; however, our measure brings up all of the technologies important to MedTech that are so fast that they disappear more quickly than others. In fact, "Measurement," which together with ICT gains an important role in technological knowledge spillover activity, is in the 6th position in terms of adoption speed.

To further support the validation of the new measure, we observe that there are a few technologies (eight in total) that have negative variation. These technologies are the ones that also had a percentage below 1% (e.g., "Food Chemistry," "Environmental Technology," "IT Methods for Management") in the classical methods.

To conclude, we see that those technologies that were clearly identified as useful for the growth of MedTech innovation in the classical measures are confirmed with the new measure. The scope of the new measure is to add information that otherwise would be lost, due to the different adoption speeds of the technologies.

A final point to be discussed is related to the number of different stages to compute to obtain the complete information on knowledge spillovers. In order to understand until what stage of backward citations we have to calculate weighted citations, we try to go further in the calculation of the third stage. In Table 3.5, we report the results of the first three stages of the patent taken as an example, the Surgical Cassette.[31]

[31] The three stages are not weighted in Table 3.1.

First stage		Second stage		Third stage	
%	Field	%	Field	%	Field
5.56%	Computer technology	3.77%	Audio-visual tech.	0.23%	Analysis of biological materials
5.56%	Optics	13.21%	Computer tech.	2.53%	Audio-visual technology
83.33%	Medical technology	3.77%	Optics	0.12%	Basic communication processes
5.56%	Engines, pumps, turbines	1.89%	Measurement	0.12%	Basic materials chemistry
		5.66%	Control	0.35%	Biotechnology
		54.72%	Medical tech.	2.42%	Chemical engineering
		1.89%	Basic materials	10.24%	Computer technology
		1.89%	Machine tools	7.25%	Control
		9.43%	Engines, pumps, t.	1.04%	Digital communication
		3.77%	Mechanical elements	0.12%	Electrical machinery, apparatus, energy
				8.77%	Engines, pumps, turbines
				0.23%	Environmental technology
				0.81%	Furniture, games
				4.83%	Handling
				2.19%	IT methods for management
				1.15%	Machine tools
				0.12%	Macromolecular chemistry, polymers
				0.12%	Materials, metallurgy
				4.37%	Measurement
				2.65%	Mechanical elements
				36.82%	Medical technology
				0.58%	Optics

Table 3.5: First three stages of backward citations, "Surgical Cassette"

We can see how the second-stage citations capture the real nature of the invention more carefully. The share of backward citations to Computer Technology rises from 5.5% until 13%. Also, the percentage of Engines and Pumps rises by 4 points. Another important change is the slight decrease of Optics in favor of the adjunction of new technologies, such as "Audio Visual Technologies," "Measurement," and "Controls," which perfectly describe the invention, but which were not present in the first-stage citations. There is an addition of three other technologies cited, with a very low percentage: Basic Materials, Machine Tools and Mechanical Elements. Of these three technologies, all of them are actually the top 10 technologies cited by MedTech, so in any case, they reinforce a trend that was already very clear, and they cannot be considered as mere noise.

The third stage adds an incredible amount of other technologies, with a general decrease in the share of all technologies. We believe that the third stage, if taken into account, would not even add noise because the citations are spread over 22 technologies; moreover, considering that they would have been weighted even more strongly than the one in the first stage, their effect would disappear completely.

3.10 Conclusion

The importance of knowledge spillovers for economic growth is universally recognized. The way in which technological knowledge spillovers can be measured has been a hot topic in the economic literature. In this work, we attempt to track the technological knowledge spillovers from one of the recognized General Purpose Technologies, ICT, toward the medical device sector. In order to accomplish this task, we use patent data, and in particular, we propose a new formulation of the index of backward citations. From Hall et al. (2001), the calculation of patent backward citations has been the most popular way to capture knowledge displacements.

The aim of this work is to shed a light on the different behavior of the backward citations across technologies. We need to keep in mind that citations are inserted in order to explain the claims of a patent, in other word only the most innovative part. This brings already some issues for the scholars aiming to measure knowledge spillovers through citations. Backward citations do not reference to any technological details included in the new patent application. More than this, we notice that also the speed at which a technology is adopted can influence the measure of knowledge spillovers using backward citations. In order to test this idea, we conduct both a qualitative and a quantitative analysis on a sample of medical device patents. We argue that those technologies with a higher speed in being adopted are easier to understand and use, and for this reason, they are widely adopted from the first moment they appear on the market. The consequence is that they disappear faster from the list of references in the patent legal data because they become "common knowledge" more quickly. We calculate the speed of adoption of each technology, the time after which the technology has not been cited any more, and the amount of a sector that each technology is able to reach. The results show that technologies with a higher speed are also those with a higher capability of being adopted by different sectors, and those that disappear first from the list of patent backward citations. Our belief is that this dynamic introduces the difficulty of correctly tracing knowledge spillovers from the "fastest" technologies, such as ICT or Nanotechnologies.

We propose a modification of the original measure of backward citations that yields this new finding. It is based on the calculation of the weighed second degree of backward citations. When we add the second degree of backward citations to the classic one, we see how the percentage of the core technologies persists, with the addition of the technologies that were invisible beforehand, but that are actually important for innovation in the sector.

The implications of our work are significant for the literature that aims to grasp the technological spillovers between different fields. Our results suggest that it is important to

carefully analyze the dynamic behavior of different technologies in order to capture existing connections more precisely.

There are possible improvements related with this work. It would be interesting to study the speed at which a technology reaches a certain fixed number of sectors, to understand the probability of recombining a specific sector. This new measure offers the possibility of seeing a new emerging stream of technology recombination inside a sector that otherwise would remain too difficult to read.

Appendix

Appendix 3.1: The patent technological classifications

This paper is based on the July 2015 version of PATSTAT, which is the European Patent Office database containing information on patent data. Among the various types of information, PATSTAT contains data on the technological classification of patent data.

All of the analyses of this work are performed using International Patent Classification (IPC) codes. The IPC codes are used in PATSTAT to identify the technological classification of each patent application, and are contained in the PATSTAT table "tls_209_appln_ipc." The technological classification is a hierarchical system of codification. It provides a technological area correspondent to the new invention. It entered into enforcement in 1971 after the Strasbourg agreement. Since then, it is updated every January. An IPC code is composed of a mix of letters and numbers. The first position of the code is always a letter and identifies the section. Next, there are numbers and letters that explain in further detail the technological class to which the invention belongs. Technically, these subsequent numbers are defined as a class (letter of the session plus two digits), a subclass (a class plus a letter), and a group (a subclass plus two digits). The IPC divides technology into eight sections, with approximately 70,000 subdivisions. Each IPC code is clarified by a technical definition (i.e., "G11C 7/24" is "Memory cell safety or protection circuits, e.g., arrangements for preventing inadvertent reading or writing; Status cells; Test cells").

Since 2013, a new technological classification has been added. It has been created by Schmoch (2008), and it provides an industrial sector classification. In addition to the classical technological classification, it proposes a new level of grouping all patent applications into 5 sectors and 35 sub-fields. The 5 sectors are: Chemistry, Electrical Engineering, Mechanical

Engineering, Other Fields, and Instruments divided in 35 technological fields. Three columns, respectively named "TECHNICAL FIELD," "TECHNICAL FIELD NUMBER," and "TECHNICAL SECTOR," support the new classification, providing the names of the sectors, the names of the fields and the identification numbers of each field. They are contained in the PATSTAT table "tls_901_techn_field_ipc," together with the column of IPC codes that allow the user to complete the conversion between the two technological classifications. The connection between the two different methods is, in fact, possible by joining together IPC codes. For example, the sector Electrical Engineering includes the field "Computer technology," which has a "technology field number" equal to 6 and is associated with IPC codes G11C, G10L and all of G06#, with the exclusion of G06Q. If we match these IPC codes with those provided in table tls209_ipc_appln, we can retrieve all of the applications classified as "Computer Technology" and proceed, adding all of the useful information for the analysis.

We have decided to develop the analyses using IPC codes, but to present the results using sector classification because the latter classification is more readable than IPC codes (i.e., "Computer Technology" is easier to understand than "G11C 7/24").

In this work, we wish to track the interaction between Information and Communication Technology (ICT) and medical orthopedic devices. In sector classification, the category "ICT" does not exist. Based on the sector description provided by Schmoch (2008) and the definition of ICT provided by (Hall et al., 2001), we decided to create our definition of ICT, including four technology fields: Telecommunications, Digital Communications, Basic Communication Processes, and Computer Technology.

The identification of "orthopedic" medical devices was conducted via a search for keywords inside of each IPC definition. The keywords were suggested by one of the experts we interviewed in order to have a clearer view of the sector. We identify 58 IPC codes:

"A61F 2/00," "A61B 17/16," "A61B 17/56", "A61B 17/58," "A61B 17/60," "A61B 17/62," "A61B 17/64," "A61B 17/70," "A61B 17/72," "A61B 17/74," "A61B 17/80," "A61B 17/82," "A61B 17/92," "A61F 2/28," "A61F 2/30," "A61F 2/32," "A61F 2/34," "A61F 2/36," "A61F 2/38," "A61F 2/40," "A61F 2/42," "A61F 2/44," "A61F 2/46," "A61F 2/50," "A61F 2/54," "A61F 2/56," "A61F 2/58," "A61F 2/60," "A61F 2/62," "A61F 2/64," "A61F 2/66," "A61F 2/78," "A61F 2/80," "A61F 5/01," "A61F 5/02," "A61F 5/03," "A61F 5/04," "A61F 5/042," "A61F 5/045," "A61F 5/048," "A61F 5/05," "A61F 5/052," "A61F 5/055," "A61F 5/058," "A61F 5/08," "A61F 5/10," "A61F 5/11," "A61F 5/14," "A61F 5/24," "A61F 5/26," "A61F 5/28," "A61F 5/30," "A61F 5/32," "A61F 5/34," "A61F 5/37," "A61F 5/40," "A61G 1/052," "A61G 1/056"

Appendix 3.2: Existing measures for technological spillovers

In this Appendix, we wish to provide a brief overview of the different approaches existing in the literature to measure knowledge spillovers using patent data.

There are three different ways to measure knowledge spillovers using patent data: technology matrices, backward citations, and citation functions.

Matrices

The willingness to capture technological knowledge spillovers dates back to 1979, when Griliches (1979) proposed one of the first attempts to generate technological indicators using the indirect R&D of a sector to prove that it affects the cross-sector's knowledge exchange.

The first method using patent data was proposed by Scherer (1982). He built a matrix of technologies exchanges between the producer sector and the user sector. He used patent, survey, and R&D data.

Following the same idea, Putnam and Everson (1994) proposed the Yale matrix. They were able to build a matrix of technology exchanges between the producer and user sectors using patent data. The Canadian patent office is the only office that provides not only the IPC codes for each patent, but also the user sectors. This method has been used by many other authors, who investigated whether the Yale matrix was a correct indicator of technological knowledge spillovers (Keller, 1997; Kortum and Putnam, 1997; Meijl, 1997). The results show that there are two weaknesses related to the Yale matrices. The first one is related to the over- estimation of obvious relations, i.e., pharmaceutical products and the medical industry. The second weakness is related to the fact that this type of matrix does not measure pure technology knowledge spillovers. In fact, it is very likely that the user sector will be asked to pay a fee to use the technology covered by the granted patent.

Jaffe (1986) and Verspagen (1997) proposed two similar methods, based on the "technological perspective." The matrix is built based on the technological distance of firms, calculated using their technological patenting history. The technological spillovers between firms are weighted by their technological distance.

Function of citations

In the literature, there are different versions of the citation function. The very first one was proposed by Caballero and Jaffe (1993) and was partly redefined by other scholars in subsequent years (Hall et al., 2001; Jaffe and Trajtenberg, 1996; Popp, 2002). In general, the

probability that a patent cites another patent is a function of three variables: the diffusion process, the obsolescence rate, and a parameter based on the characteristics of the two patents.

The advantage related to this approach concerns the elimination of some of the noise that affects the citation probability (i.e., the examiner, the cohort effect, the country effect, etc.).

Backward citations

Another measure used very frequently is the index of patent backward citations. This is the measure we attempt to improve with our work.

A patent is a legal document that offers exclusive rights to the owner and to inventors in exchange for public disclosure of the invention. In order to prove the novelty and non-obviousness of any invention, its innovative content must be compared with previous existing knowledge. The applicant beforehand and the examiner afterwards list the existing literature (patent and non-patent literature) in order to have a benchmark to judge the effective novelty of the invention.

The existing literature is called the list of previous knowledge, i.e., "backward citations." Many attempts have been developed to demonstrate that patent citations are a good measure of knowledge flow.

Jaffe et al. (1993) describe the reason why patent citations are a good means of tracing spillovers. Citations can be introduced either by the applicant or by the patent examiner. While the citations listed by the applicant should be an actual measure of the awareness of the knowledge owned by the inventors, or at least part of it, the citations added by the patent examiner are references to prior art that could be unknown by the inventors. Consequently, citations are a "very noisy measure for spillovers," but they are also a very conservative measure, in the sense that if some significant results appear, then they must be correct because they were able to emerge despite the noise generated by the references added by the patent office. In the same vein, Hall et al. (2001) and Duguet and MacGarvie (2005) add empirical proof to the use of backward citations, undergoing surveys to explain the origin of the citations they insert into their patents. In both works, the authors find confirmation that backward citations reflect the inventors' knowledge, even if the validity changes with the source and the destination of the knowledge transmitted. Finally, Breschi and Lissoni (2001) explain that even if patent citations are added both by the inventor and the examiner, they are both valid. The reason is that inventors can have a strategic reason not to disclose the prior art, while examiners fill the gap.

A common method to calculate patent backward citations was simply to count the number of prior patents. For any focal patent, the references are counted. However, there are

many options that can be added to this simple count. The most common method has been to count the number of prior patents, weighed by the depreciation rate for the value of the patent (Hall et al., 2005). For each patent citation, much information can be added, such as the priority year, or the authority where the patent application was filed or the technological classification (IPC).

Thus, there are numerous choices that must be done in the calculation of the backward citation index, based on the information retrievable in PATSTAT.

In PATSTAT, it is possible to differentiate between the patent and non-patent literature. The non-patent literature includes articles, papers, academic works, and presentations; in short, everything that is not a patent. Also, the non-patent literature is used to decide the novelty of an invention, but in contrast to the patent literature, it does not have much information added to the exemption of a text description of the content. Despite this limitation, the non-patent literature has been used to measure the link between science and technology (Verbeek et al., 2002). In particular the non-patent literature has been used to measure the value of patents, but only in specific sectors, such as chemistry and pharma (Harhoff et al., 2003) and the depth and breadth of pharmaceutical research (Brusoni et al., 2005).

However, above the selection of the different variables requested for a specific analysis, "a thorough understanding of patenting practice is needed in order to interpret patent citations data properly" (Meyer, 2000). There are many differences in regulations between patent authorities that should be taken into account in developing a correct patent analysis. For our work, we analyze the differences between the European and US patent offices. The search report is the document written by the patent examiner that includes, among other information, the technological classification, the approval of the claims, and the missing references to prior art. In the US the "duty of candor" promotes the inclusion of as many citations as possible by the inventors. Consequently, in the US, two-thirds of the total citations are added by the inventor (Alcacer et al., 2009). At EPO, the duty of candor does not exist. On the contrary, the list of prior art is optional. An EPO examiner includes most of the citations. Also, the average citation count per patent changes between the two patent offices. The result is that the same measure computed from two different data sources can lead to very different results (Bakker et al., 2014).

Consequently, the origin of citations should also be taken into account. Since 2013, in PATSTAT it is possible to identify whether the citations come from the examiner or from the applicant. This information helps capture more accurately the cumulativeness of knowledge because it becomes possible to distinguish between the knowledge that was added by the inventor (or the applicant) from that added by the patent examiner for legal purposes, which can

be unascertained by the applicant of the patent (Alcacer et al., 2009; Criscuolo and Verspagen, 2008).

The last point to be discussed regards the level of analysis. Many works are limited to the patent level (more specifically, the patent application), counting the number of backward citations for each focal patent. Others prefer to look at families. There are two types of families: DOCDB and INPADOC. The DOCDB family groups all patents that share the same priority date; in other words, all of those patents that are exactly the same invention filed in different patent authorities. The INPADOC family, instead, has a less stringent definition and includes patents that are still protecting the same invention. However, they can also have a different priority application (Dernis and Khan, 2004). Again, in this situation, the count of citations can be different: one should count the total number of citations of the entire family in order to eliminate the risk of bias created by large patent families; otherwise, the count would not be at the level of application any more, but the family cited. There are many papers that discuss which of the two families is better to use (Bakker et al., 2014). This is not the aim of this paper, so we propose the two retrievable in PATSTAT. The count of citations per family can again be different: one could count the total number of citations of the entire family; otherwise, in order to eliminate the risk of bias created by large patent families, the count would no longer be at the level of application, but the family cited.

Chapter 4: The Effects of Regulation Change on Innovation: The Case of the European Medical Device Sector

(with Fabiana Visentin)

4.1 Introduction

According to common wisdom, technological innovation positively contributes to economic growth. It represents the engine of the economic development process, providing new solutions and opportunities for industries and consumers, and more broadly, improving social welfare, ensuring greater consumer abundance, and providing new medical interventions for diseases. However, this process is not immune to criticism. People have expressed concern for the side effects accompanying those innovations. Environmental problems caused by production procedures that do not respect nature, declining workplace conditions, and increased risk levels for final users are just some examples of the negative consequences of the frenetic search for new technological innovations (OECD, 2009).

In response to these concerns, since the mid-twentieth century, regulations have been introduced worldwide in all sectors to moderate the side effects of technological innovation. Economists' reactions to attempts to minimize the negative effects of technological evolution have varied. Some economists manifest their fear concerning the fact that regulations could deteriorate the natural technology growth trend. Others are more inclined to understand "what tradeoff our society is willing to make" (Eads, 1980, p. 51) between social and economic benefits and the risk of an unconditional technological evolution. The latter debate sheds light on other effects to which the regulation can lead, such as a new allocation of resources, risk reduction in R&D activities, commercialization of new products or a change in the type of institutions who carry out specific research.

There is little evidence concerning the impact of regulation on the ability of firms to innovate (Blind, 2012). Extant studies look at innovation in quantitative terms, e.g., examining the number of patent applications (Jaffe and Palmer, 1997; Golec et al. 2005; Popp, 2006) or the number of new products introduced (Nemet, 2009). We contribute to the existing literature by considering how regulation impacts the content of the innovation activity and the diffusion of an invention.

Our empirical strategy relies on comparing changes in innovative trends in two sectors with similar characteristics differing in the fact that one of them has been affected by a rigorous

regulation while the other not. In 1993, a stringent regulation, the Directive 93/42/EEC, affected the medical devices sector (MedTech) imposing the fulfillment of rigorous safety and quality requirements for the commercialization of any medical device. A similar sector in terms of patenting activity and actors involved, the mechanical sector, was not affected by any additional rules. Exploiting variations in sectorial regulation, we compute differences-in-differences estimates of the effects of the Directive. That is, we compare changes pre-1993 and post-1993 in the patenting behavior of the medical devices sector versus the mechanical sector.

For our analysis, we use a novel dataset of 543,667 inventions developed in the period 1980-2012 in Europe, 117,993 in the medical device sector and 425,674 in the mechanical sector, respectively. On one hand, the European medical device sector appears to be an ideal empirical setting to act as 'treated' in investigating the relationship between sector regulation and innovative dynamics. The sector has been affected by more stringent regulation over the years, since it includes tools that enter into direct contact with the human body. Nowadays, the actors involved in the sector have to fulfill clearly defined safety requirements and quality standards to market their products. However, back in the early 1990s, this same sector was mainly unregulated. On the other hand, the mechanical sector appears as an ideal 'counterfactual', since it remains unregulated. The comparison of the two sectors allows us to answer to the question "What have been the impacts of the regulation changes on innovation?"

This paper is part of a broader project investigating the evolution of the medical device sector in Europe. In the exploratory phase, which was oriented toward collecting qualitative evidence on the dynamics and mechanisms governing the sector, we interviewed the R&D personnel involving a random sample of medical device companies based in Europe[32]. When asked about the impact of rigorous rules on their activities, these sectoral actors were aligned in claiming that regulations limit the exploitation of their opportunities to introduce new devices.

> *"After the '90s, as manufacturers of medical devices, we need to conform to the directives and to prove that our products are safe and work properly… When I started to work here as Product Development Manager, I was pushing my team of engineers to do breakthrough research. I knew that it was easy to launch cutting-edge products on the market. Nowadays, we have to fight with a pile of papers… I asked to them to be conservative… if they work on improving the existent technologies, it is easier for me to convince the authorities that the device is safe. If I ask for the CE mark of a device that has never [been] seen before, it is a nightmare to find the appropriate clinical evidence! If I do not get the CE mark, I cannot commercialize the product, and all the investments will be lost. I cannot permit that! It's too risky! I prefer to stay on a safer side… Yes, we are still renewing our product portfolio; we are well-known as an innovative company, but we*

[32] For the interviews, we selected the representatives involving firms of different size and age located in Europe and specialized in various types of medical device production. Specifically, we conducted phone interviews with the CEOs of three multinational companies: the Product Development Managers at four small-medium enterprises and the founders of three start-ups. Our interviewees were based in Italy, Germany and France.

are not any more exploring the unknown as in the past." (Product Development Manager, small-medium French company)

"During my PhD studies, I developed a device – a sort of mask glasses – reproducing a virtual reality in 3D. My initial idea was to use the glasses as a medical tool to help patients who need help in rehabilitating from a stroke. These patients could have played in a virtual reality and, [in] doing so, their brain cells would have recovered their functions. I launched my own business on the medical direction, but soon after I realized that it was really difficult… too many rules! So I thought… What about selling the device as a game? This is what I am doing!" (Founder, German start-up)

According to the interviews, it is clear that regulations have been viewed as an obstacle for innovation. Inventing something from scratch has become too risky, and attempts to radically innovate are perceived as more likely to lead to "dud" inventions. As a consequence, incremental innovations appear more attractive to firms complying with regulations. In extreme cases, inventors have shifted their attention toward less regulated sectors. The first part of our work is dedicated to investigating whether the detrimental effects of regulation on innovation, anticipated by the qualitative evidence, are confirmed in the patenting process.

To comply with a regulation means following a set of rules that, in the case of the medical device sector, translates to fulfilling a set of safety standards. If that fulfillment is costly for inventors, we cannot ignore the benefits of standardization, once achieved. The regulation we are analyzing in this paper pertains to European coverage, i.e., countries belonging to the European Union are asked to satisfy the same standards in order to commercialize their products in the European market. It is clear that a European regulation is an important step to guaranteeing the acceptance of products in a broad geographical market. Therefore, we expect that this regulation would positively affect the diffusion of an innovation. The idea is that since inventors rely on standards that go beyond their national borders, they are incentivized to extend the protection of their inventions beyond the national level. The second part of our work is dedicated to investigating whether the patent data confirm the expected positive effect of regulation on the diffusion of inventions.

Our analysis shows that, the introduction of the European directive in 1993 induced a deviation in the medical devices sector patenting behavior with respect to what happened in the mechanical sector: (1) inventions were built on more familiar components; (2) at the same time, applicants filed their patents to a larger number of European patent offices than that in the pre-regulation period. Our results offer an important contribution to the policy debate on the consequences of regulation introduction.

The rest of this paper is organized as follows: Section 2 provides a brief overview of the effects of regulation on innovation; Section 3 describes the medical device sector and its

regulation; Section 4 provides an overview of our data; Section 5 presents our main analysis; Section 6 summarizes the empirical findings, and Section 7 concludes.

4.2 The effects of regulation on innovation

The Organization for Economic Co-operation and Development (OECD) defines a regulation as the "imposition of rules by government, backed by the use of penalties that are intended specifically to modify the economic behavior of individuals and firms in the private sector" (OECD, 1993, pg.73). The effect of regulation on technological change and innovation has been a hot topic in the literature for a long time (Ashford et al., 1985; Blind, 2008; Herzlinger, 2006; Rothwell, 1980; Stewart, 1981; Verhoeven et al., 2016). Regulations are seen by firms as one of the core factors influencing the innovation process. The OECD Directorate for Science, Technology and Industry (2009) highlights the direct relation that exists between regulation and innovation. Regulations can positively or negatively affect innovative outcomes.

According to Porter et al. (1995), a regulation can be considered to yield positive effects when it fulfills three characteristics: "It must create the maximum *opportunity* for innovation, leaving the approach to innovation to industry and not the standard-setting agency. Then, it should foster *continuous improvement*, rather than locking in any particular technology. Third, the regulatory process should leave as little room as possible for uncertainty at every stage" (pg. 100, italics is ours).

There are numerous cases in which regulations have been seen as an opportunity for innovation (Porter et al., 1995). Such regulations can be a stimulus for a breakthrough in the current technological trajectory. For instance, the introduction of a new regulation can enhance the creation of completely new processes or products because it may be too costly to fulfill the regulation requirements with the existing technology, and significant technological change is required. This was the case for the Act of the Consumer Product Safety Commission, which imposed the elimination of chlorofluorocarbons contained in aerosol devices. This imposition led to a radical transformation of the process and to a complete renewal of the product: a non-fluorocarbon propellant was developed to replace the existing technologies that were not fulfilling the recommended safety requirements. In other cases, the innovations introduced by regulations are less radical. The Clean Air Act, introduced in 1977, is an example of a regulation that led to simply incremental innovations. The Act established a daily threshold for mercury discharges per firm. Each firm complied with this regulation by slightly modifying their production processes and by putting in place solutions that were already known, but not used systematically.

There are cases for which regulation has been detrimental to innovation. Grabowski et al. (1978) showed how increased supervision of the pharmaceutical regulation in the U.S. had a negative effect on innovative activity in this sector. The redefinition of this regulation resulted in fewer radical products launched into the market by the pharmaceutical industry. The decreased creation of brand new products was accompanied by a high increment in the cost and time of R&D activities. Not only was the development of new products more costly, but firms perceived increased risk in developing brand new formulas: only one-seventh of the total products that had undergone clinical trials were admitted to the market. Similarly, Vernon (2003) found that the introduction of a price control policy, i.e., an economic regulation, resulted in decreased R&D intensity.

The above-mentioned examples provide evidence that regulations can have different consequences. The results are not generalizable; rather, they depend on the type of regulation, the type of industry affected by the regulation, and the availability of easy or existing technological solutions for the fulfillment of norms (Ambec et al., 2013).

OECD (1997) proposes a taxonomy of regulations in order to better understand their possible effects on innovation. Regulations, according to their scope, are classified as administrative, economic and social in nature. Administrative regulations have the aim of organizing the operational part of markets; economic regulations have the aim of favoring good organization of markets; and social regulations have the aim of safeguarding the welfare of society and minimizing negative externalities. The first two types of regulations lead to negative effects, such as increased barriers to entry and decreased investments in R&D, which are counterbalanced by positive effects, such as reduced risk in investments and minimized turnovers (Blind, 2012). In general, social regulations have negative consequences by reducing innovation due to the high costs of regulation compliance; nevertheless, they have positive effects in increasing the diffusion of new technologies.

Regulations in the medical device sector are classified as social regulations. In the medical device landscape, the policy implications of regulations on innovation are still controversial. In the past years, the development and complexity of new devices have required a careful assessment of their quality and safety. By staying at the technological frontier for medical devices, producers have benefitted patients in terms of bringing them relief, making disease treatment more effective, and improving their life quality. However, the introduction of completely new tools raises doubts related to their level of risk. Thus, for safety and health regulations, there is a trade-off between the possibilities of increasing the well-being of society and minimizing the side-effect risks of new products. A crucial point in this type of regulation

lies in its capability to minimize the information asymmetry existing between producers and final users, convincing the latter to use a new product that, fulfilling stringent requirements, is safe.

In this sector, regulators have acquired more and more importance in providing direction to innovative paths. Gelijns and Rosemberg (1994) claimed that "the preferences and rules of these various actors [including regulators] exert an important influence on which new technologies will be accepted into practice and how they will be used" (pg. 32).

> *"In the mid-1950s growing recognition that ischemic heart disease was becoming the leading cause of death, and a major cause of illness, stimulated the interest of the pharmaceutical (and medical devices) industry in developing new drugs (and devices). The first beta-blockers (and electrical cardio version devices) were introduced by cardiologists in the mid-1960s in Europe. U.S. regulatory policies toward beta-blockers (and electrical cardio version devices) were more stringent than in most European countries, and beta-blockers (medicines and devices) received approval for angina pectoris only in 1972. In effect, this meant that cardiac surgeons who developed new treatment procedures in the United States were able to obtain a competitive advantage over cardiologists because their surgical technology did not have to undergo regulatory approval."* (Gelijns and Rosenberg, 1994, pg. 41)

As reported in the quote, regulations can favor or hinder the development of new treatment procedures. In this study, we contribute to extant studies on the effect of regulation on innovation by analyzing the consequences of introducing Directive 93/42/EEC in the European medical device landscape. The next section is dedicated to provide a definition of the directive application context and a detailed description of its contents.

4.3 The Directive 93/42/ECC and its application context

The directive context of application: A brief overview of the medical device sector

Quoting the official definition offered by the European Commission, a medical device is "any instrument, apparatus, appliance, software, material or other article, whether used alone or in combination, including the software intended by its manufacturer to be used specifically for diagnostic and/or therapeutic purposes and necessary for its proper application, intended by the manufacturer to be used for human beings for the purpose of:

- Diagnosis, prevention, monitoring, treatment or alleviation of disease;
- Diagnosis, monitoring, treatment, alleviation of or compensation for an injury or handicap;
- Investigation, replacement or modification of the anatomy or of a physiological process;
- Control of conception;

and which does not achieve its principal intended action in or on the human body by pharmacological, immunological or metabolic means, but which may be assisted in its function by such means."[33]

Importantly, medical devices are classified according to their risk of use on the human body. The classification represents an easy way to distinguish devices, from those that are associated with a very high risk and that require very stringent regulations, to those that imply low risks and can be launched faster on the market. Classification rules are based on the duration of contact with the body (transient, short term, long term), on the degree of invasiveness (invasive device, body orifice, surgically invasive device), on the distinction between an active and non-active device, and on the type of tissue contact[34].

A peculiarity of this sector is related to the key role played by patients, who do not only enter into contact with medical devices during their therapies as users, but also actively participate in improving these tools[35]. The medical device sector is thus a very complex sector, and without any doubt, it requires strong regulations that are able to maximize the welfare produced by these devices and, at the same time, protect patients from the risk of their use.

Regulations on medical devices are very different across the world. Thirty percent of all countries have a structured framework for regulation; another 30% has partial regulation; and the remaining countries are in the process of developing a regulation framework or currently lack one (Lamph, 2000). Moreover, regulations also evolve at the same pace at which the complexity of the devices is increasing. So far, the literature on regulation in the medical device sector has focused on cross-country differences between U.S. regulation and European regulations (Chai, 2000 and Kramer et al., 2012). The two systems differ in a few aspects: for example, the U.S. system is highly centralized, i.e., the Food and Drug administration (FDA) has control of all procedures for the admission of a product to the market. On the contrary, European law on medical devices has "outsourced" the certification of safety criteria to external entities, called notified bodies. Moreover, U.S. regulation has been seen as more stringent, and sometimes this has been seen to have a negative effect on the speed of innovation. On the other side, European

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[33] For more details on the definition of a medical device, please refer to http://ec.europa.eu/growth/sectors/medical-devices/index_en.htm

[34] For more details on the classification of medical devices, please refer to http://ec.europa.eu/health/medical-devices/files/meddev/2_4_1_rev_9_classification_en.pdf

[35] Interesting examples of products developed with the active participation of patients are reported in Gelijns, Annetine, and Rosenberg. "From the scalpel to the scope: Endoscopic innovations in gastroenterology, gynecology, and surgery." Medical Innovation at the Crossroads 5 (1995): 67-96.

regulation is faster and less severe, even if some scholars are worried about patient safety (Lamph, 2000).

The directive content: 1993 as the breaking point year for the medical devices sector

In 1993, the European Union undertook new policies with the aim of opening national country borders to people and goods. This required the harmonization of different countries' laws involved in the union. On January 1, 1993, laws allowing the free circulation of goods entered into force. Together with all other goods, medical devices were included in this policy change with a specific European directive, called 93/42/EEC on medical devices.

Before 1993, Europe was very fragmented with respect to the regulation of medical devices. The majority of European countries did not have any specific regulations. In fact, only a few countries had written legislation suggesting requirements on how to put a device on the market. Only three countries, namely Germany, Luxemburg and Greece, had set up a national authority to control the market. The role of these organizations was to issue authorizations to introduce devices into the market.

In 1993, this regulation defined standards that all products must follow. First, the European Commission introduced the figure of the notified body. Conformity assessment of goods to the standards defined by the European Commission requires certification by a notified body. These notified bodies are third parties, firms or organizations that have the authority to release the EU certification for a product (CE mark), and consequently, its authorization to be sold within Europe. A firm can choose any European country to receive the CE mark. Each notified body is identified by a unique code, and the list of these notified bodies is published in the Official Journal of the European Commission. There could be two types of notified bodies: those working during the pre-market stage in order to certify conformity to the standards, and those working after the market stage, which have to assess whether a product is respecting the requirements once placed on the market. Should there be any breakdown in this process; the notified bodies also have the authority to revoke permission to circulate a specific product. These notified bodies frequently focus only on a specific class of devices[36].

The class to which a device belongs determines the rules to be applied for its approval. For this reason, the manufacturer should know from the very beginning of a product's developmental process the class to which it belongs in order to facilitate conformity assessment.

[36] Device classes are explained in the paragraph: "*The medical device sector: A highly regulated sector.*"

Independent of the device class, all products must fulfill these three conditions in order to be admitted into the market:

a. Meet all of the "essential requirements," including information on the product, which must be provided by the manufacturer;

b. Fulfill the reporting requirements of the vigilance system; and

c. Obtain the CE mark.

Harmonization of the "essential requirements" represents the main change introduced by Directive 93/42/EEC. "Essential requirements" are related to the introduction of a clinical evaluation, the introduction of a standardized quality system and of technical files that must be provided together with the device (see Annex I Part I, 6a of 93/42/EEC). The evaluation provides clinical data related to the characteristics and operation of the device under normal circumstances and a description of the possible side effects. The data can be based on clinical investigations or published or unpublished reports on other clinical experiences. The evaluation of the data must follow a specific procedure, which is crucial for an assessment of the conformity of the device. With respect to the introduction of an efficient quality system, it must be related as much as possible to the type of product developed. There is no imposition on the type of quality system to adopt, but the manufacturer is required to keep track via written documentation of all elements, modifications and provisions of the quality system. This quality system must also manage the risk analysis, preparation of instructions for use, post-market surveillance and reporting to the vigilance system. The notified bodies will control and certify that the quality system has fulfilled all of the previous requirements. Another element introduced by the regulation is related to technical documentation, which must be provided together with the device by the manufacturer. There is a long list of elements that must be included in the technical documentation[37], and among them are the results of the risk analysis conducted by the quality system, evidence of requirement fulfillment and clinical data. The technical documentation must be sent to the notified body for conformity assessment. Compared to previous national regulations, requests for a formal risk assessment heavily increase the responsibility of the manufacturer. For this reason, the European Commission specifies a particular harmonized standard in order to develop the risk analysis (see the EN 14971). The manufacturer must also supervise the after-market period, maintaining up-to-date information

[37] Please refer to Directive 93/42/EEC for details.

about user experiences; moreover, it is obliged to immediately report any deviation from previous documentation to the vigilance system.

During subsequent years, new directives were added to the 93/42/EEC with the aim of refining the criteria of safety that medical devices must attain. For example, the In Vitro Diagnostic Device Directive 98/79/EC details the criteria that in Vitro devices must satisfy in order to enter the market. At the end of 1998, the mutual recognition agreement (MRA) entered into force. This agreement was written with the specific aim of promoting market access and fostering the trade of goods between the European Union and other countries such as Australia, Canada, Israel, Japan, New Zealand, Switzerland and the USA. The MRA concerns six sectors, namely medical devices, electromagnetic compatibility, telecommunications equipment, electrical safety, recreational craft, and pharmaceuticals. The MRA was supposed to guide the convergence of regulatory frameworks and the harmonization of safety requirements and quality systems. However, the MRA has still kept the regulations separate from one another. This means that there is no automatic approval of European medical devices in external countries, but there is a recommendation by the notified bodies to accept the device. The same applies for external medical devices in Europe. Finally, in 2014, after the scandal of the French counterfeit breast implants, the EU regulation has become stricter. Despite these additional refinements, Directive 93/42/EEC marks a watershed in the European context for the medical device sector, delineating the boundaries between the period when there was a patchwork of national regulatory systems (pre-1993 period) and the period when the regulatory system was harmonized across European state members (post-1993 period). For this reason, we decided to focus our attention on the 1993 regulation.

4.4 Data

In our study, we use patent data in order to trace innovative activities. There are some concerns associated with the use of intellectual property files as a proxy for innovative activities, especially with respect to the fact that not all inventions are patented; moreover, at the same time, there is no one-to-one relationship between a patent document and a marketable product. However, patents are still the most common data used to trace innovation (Acs et al., 2002; Bettencourt et al., 2009; Hall et al., 2001). In our case, patent data appear as ideal data for two main reasons. First, patents allow us to explore the technical content of an invention (Fleming, 2001; Dahlin and Behrens, 2005). Patent documentation contains detailed information on the technical building blocks of each invention. As we describe in the following section, we use the technological classification to evaluate the novelty content of each patent. Second, patents can be

used to trace extensions of geographical protection involving an invention. We use information about patent offices receiving patent applications in order to retrieve the market extension protection that an applicant intends to provide for her invention, which we refer to as diffusion of the innovation.

Data for this study come from the July 2015 version of PATSTAT. To gather the data, we proceed in three steps. First, we extract the entire list of patent applications filed in the medical device sector to the European Patents Office (EPO) or to a national patent office of one of the EU 15 state members[38] in the period 1980-2012. To identify the patents classified as medical devices, we collect the International Patent Classification (IPC) codes associated with the corresponding sectorial code[39]. In the same way, having identified the mechanical tools sector as the appropriate unregulated sector to compute differences-in-differences estimates of the effects of the Directive introduction, we proceed with the extraction of all the corresponding patents[40]. Second, we assign to each patent the nation corresponding to the first inventor address[41]. We kept a patent in our sample if that address was located in one of the European state members. The choice to refer to inventors' address in assigning a nationality to a patent responds to our attempt to minimize the noise generated by ownership changes[42]. Third, we group together patent applications that refer to the same invention according to their DOCDB family[43], "the set of applications filed in several countries which are related to each other by one or several common priority filings" (Zunica et al., 2009). In this way, our final database results as a dataset at an invention (patent family) level that comprises 543,667 observations spitted between the medical device sector (117,993 observations) and the mechanics sector (425,674 observations).

For our analysis, we use a novel dataset of 543,667 inventions developed in the period 1980-2012 in Europe, 117,993 in the medical device sector and 425,674 in the mechanical tools sector, respectively.

Before entering in the details of the analysis, in the following section we provide an overview of the key features of the medical device and mechanics sectors to guide the reader in understanding the choice of two sectors as ideal empirical setting for our analysis.

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[38] We consider as state members the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, The Netherlands, Portugal, The United Kingdom, Spain and Sweden.
[39] Specifically, we use the sectorial codes proposed by Ulrich Schmoch (2008).
[40] For the extraction of mechanical patents we refer to the sectorial code 26, Machine tools.
[41] We replicate the same method used by Almeida and Kogut (1999) in assigning a patent to a specific region.
[42] PATSTAT reports for each patent the *current* applicant at time *t*, as it is not possible to easily retrieve if the current applicant corresponds to the original one. Data on ownership changes are available in separate documentation, but do not cover the entire database.
[43] As a reference family, we used the DOCDB family listed by PATSTAT (for further details on family definitions, please refer to Martinez, 2010).

The medical device and mechanics sectors: A comparison of their key features

Even if the first medical devices were built hundreds years ago, the real explosion of the sector in Europe happened around the 50's when the society started to flourish after the two World Wars. The vibrant economic growth of the post-war period let many people to afford items that before were exclusively accessible to rich people such as cars, ski, motor sports. The increased demand for new medical devices was driven by the drastic augmentation of fractures due to the use of these items but, more in general, to the diffuse eagerness to ameliorate the life conditions. Thus, while pharma conducted impressive discoveries for what concerns antibacterial and antihypertensive drugs, the medical device sector was able to develop new devices thanks to its unique openness to other fields of discovery (Rosenberg, 1994). Very often, the idea of a new device was conceived by surgeons, since they were the ones that first perceive the need (Chatterji et al., 2008). Surgeons did not possess the technical competencies to operationalize their ideas, and they started to collaborate with mechanical companies capable to transform ideas into prototypes. In this way mechanical companies entered the medical device sector. Among other, Siemens is an example of company that shifted part of its production toward the medical device sector. Table 4.1 reports the main actors active in the two sectors in term of patenting activity and show that Siemens is still among the top-10 companies in the medical device sector as well as in the mechanics sector.

Mechanics sector			**Medical device sector**		
Top-10 company	Company Mechanics	Country of Origin	Top-10 company	Company MedTech	Country of Origin
1	Robert Bosch Gmbh	DE	1	Philips Electronics	NL
2	Siemens Ag	AT	2	Siemens Ag	GB
3	Telefonaktiebolaget Lm Ericsson	SE	3	Procter & Gamble Company	US
4	Nokia	AT	4	Sanofi- Aventis	DE
5	Regie Nationale Des Usines Renault S.A.	FR	5	SCA Hygiene products	DE
6	France Telecom	FR	6	Aesculap & Company	DE
7	Astrazeneca AB	SE	7	Karlstorz & Company	DE
8	British Telecommunications Public Limited Company	GB	8	Fresenius Medical Care	DE
9	Peugeot Citroen Automobiles S.A.	FR	9	Novo Nordisk	DK
10	Infineon Technologies Ag	DE	10	St. Jude Medical	SE

Table 4.1: The top-10 most patenting active companies in the mechanics and medical device sector

The similarities between the two sectors traced back to the origins of the medical device sector and remains over time.

For what concerns the composition of the applicants by age, we can see that the applicants of the medical device sector are relatively "young." The 16% are less than 10 old, the 37% are from 10 to 20 years old, the 43% are between 20 to 50 years old and the remaining 2% is older than 50 years. We see a very similar composition for what concerns the age of the applicants for mechanics. The 24% have less than 10 years, the 27% is between 10 and 20 years old, the 47% is between 20-50 years old, and the remaining 2% is older than 50 years.

If we look at the distribution of the innovative actors of the two sectors by country across Europe (see Figure 4.1), we see that the top-three countries are Germany, Great Britain, and France, while the countries that are poorly innovative in one sector are poorly innovative also in the other.

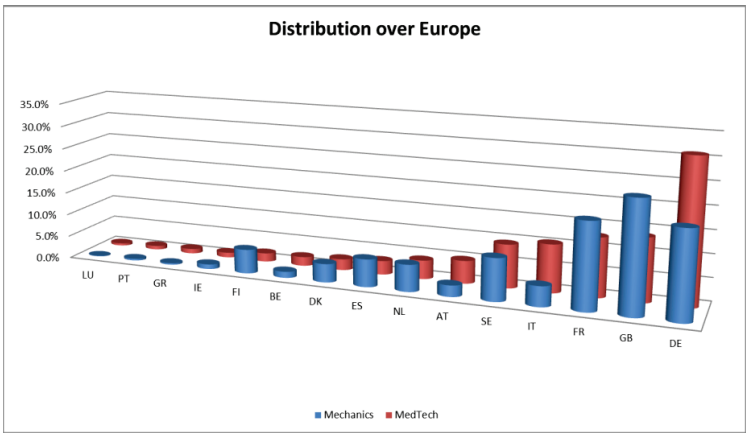

Figure 4.1: Applicants' distribution by country across Europe

Looking at the legal status, the applicants of the two sectors are assigned to five distinct categories: companies, government institutions, universities, hospitals and individuals. Overall, approximately 70% of the applicants are individuals followed by companies that represent about 25%, and government institutions and universities represent the residual categories (see Figure 4.2).

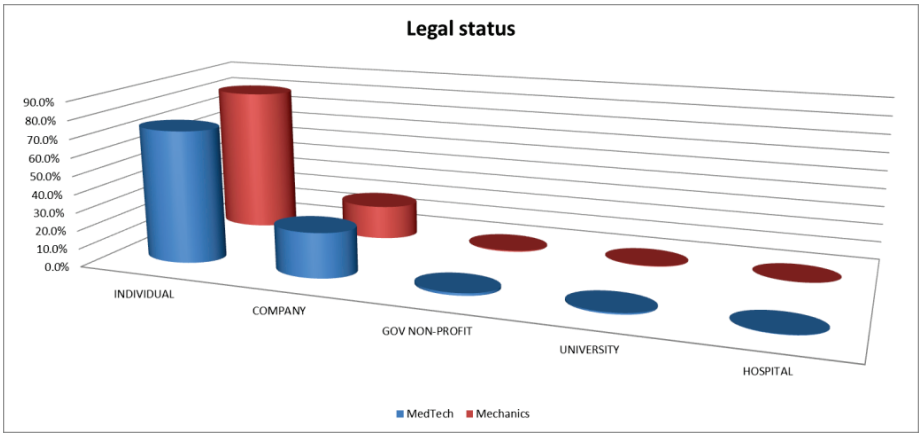

Figure 4.2: Applicants' distribution by legal status

Looking at the specialization of the innovative actors of the two sectors, we observe that the majority of applicants are fully specialized in their technology. In other words, they have 100% of their patent portfolio composed only by patents of their own technology. The applicants with a mixed fifty-fifty composition of technologies in their patent portfolio follow in terms of importance (see Figure 4.3).

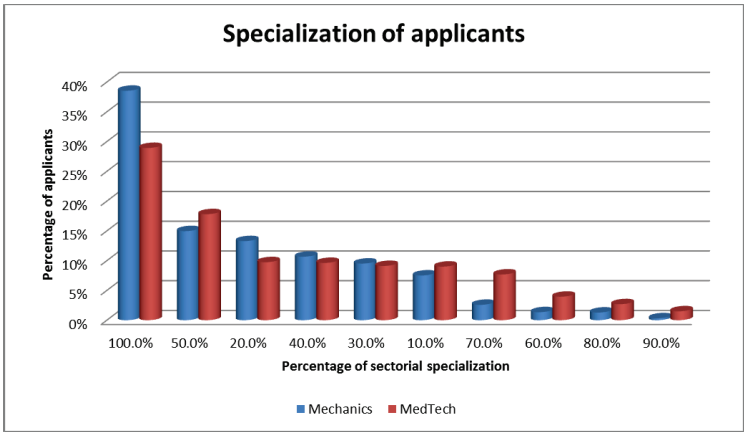

Fig 4.3: Specialization of Mechanics applicants vs. Medical Device applicants

While the sectors show a very similar innovative trend pre-1993, they have started to differ soon after. For what concerns the evolution over time of the number of innovative actors we notice that the two sectors have a very similar trend until 1992. After that, mechanics had a huge boom, redoubling the amount of companies active in patenting while the medical device sector growth rate remains much smaller (see Figure 4.4).

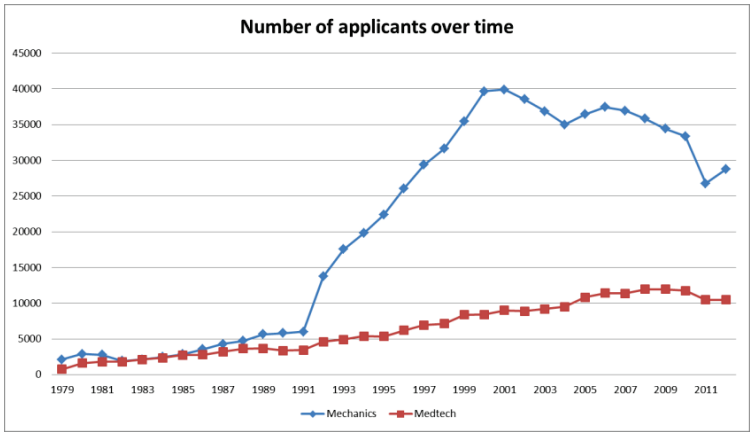

Figure 4.4: Comparison between the number of applicants per year per medical devices and mechanics

This trend is reflected in the patenting activity of the two sectors. Figure 4.5 shows that the two sectors have an identical trend before 1993 and then the medical devices sector deviated from mechanics.

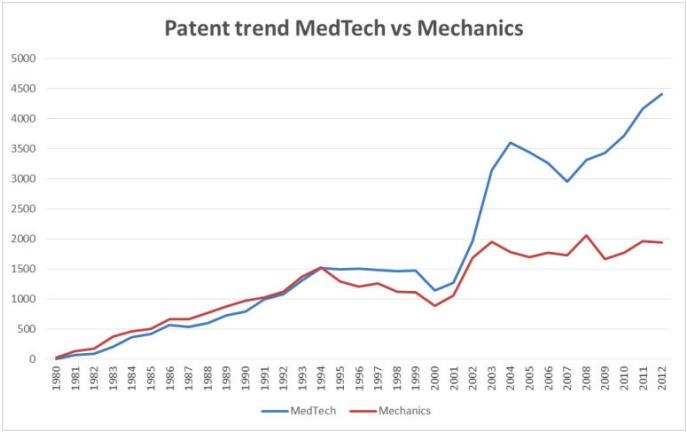

Fig 4.5: Patent trend of the medical device sector vs. the mechanics sector

The remarked deviations in the innovative trend of the medical device sector with respect to the trend followed by the mechanics sector after 1993 informed us about the effects of regulation that are analytically explored in the next section.

4.5 Analysis

Following the arguments delineated in the Introduction Section, we test two hypotheses:

1. *Regulation has a detrimental effect on the innovative content of an invention;*
2. *Regulation stimulates the geographical diffusion of an invention.*

In order to assess whether the introduction of Directive 93/42/EEC in 1993 has affected 1) innovative content and 2) the diffusion of an invention, we perform difference-in-differences regressions that compare changes in the patenting behavior of medical device inventors with changes in the patenting behavior of mechanics inventors. In all our regressions the unit of analysis is a European invention patented in the medical device and mechanics sector during the observation period (1980-2012).

In this section, we illustrate our dependent variables (sub-section 4.5.1), the econometric specifications used for the analyses (sub-section 4.5.2) and finally, the controls included in the econometric exercises (sub-section 4.5.3).

4.5.1 Dependent variables for innovative content and the geographical diffusion of an invention

Innovative content of an invention

The innovative content of an invention can be evaluated along a continuum, between being incremental and being radical, with respect to the extant inventions.

An incremental innovation does not bring any fundamental change in a treatment, nor does it bring about a crucial change in the product (Schumpeter, 1942). It requires a short development cycle and, due to the very low degree of change, its acceptance by the market and the regulation is almost a certainty. An example of this innovation could be an instrument to check for glycaemia, to be used by people suffering from diabetes. Over the years, this device has become smaller, lighter, with a bigger memory to save historical data, and with a clearer screen. However, it has not significantly changed in terms of how patients use it. They still need to insert into the device a strip containing a drop of blood in order to know their blood sugar level.

Radical innovations are generally defined as breakthroughs, compared to inventions that do not depart from the traditional path, but simply add a few elements of novelty to the existing ones (Anderson and Tushman, 1990; Ashford and Hall, 2011). However, there is no agreement in terms of a formal definition and measure of a radical innovation. Some scholars identify radical innovations by looking at technology trajectories. For instance, Dosi (1982) and Anderson and Tushman (1990) consider an innovation to be radical if it creates discontinuity in the technology trajectory, and if it destroys the existing equilibria. In line with these authors, Henderson (1993) develops the idea of a radical innovation as an instrument to enhance or destroy competencies. Other scholars examine the value of an invention and claim that it is

radical if consumers are willing to pay a higher price for it (Tirole, 1988). These approaches match the radical nature of an innovation with its impact on an industry, and on the market in terms of its ability to break with tradition in the field and to record commercial success. In the medical device sector, a radical innovation changes the therapy paradigm, with the consequence of providing a completely new product. Since this innovation is completely new, the reaction of the market is difficult to forecast. An example of this type of innovation is the balloon catheter. It is a small balloon used to open up a closed artery narrowed by plaque. Before this invention, artery occlusions were treated with a much more invasive operation.

The debate on where radical innovations originate is still open. Some scholars state that radical innovations are the result of a recombination of existing knowledge (Cohen and Levinthal, 1990; Fleming, 2001; Von Wartburg et al., 2005). In this case, existing technologies are seen as blocks that can be combined to create something new. Alternatively, the creation of radical innovations could be based on completely new knowledge (Poel, 2003). For instance, following this line of thought, Arthur (2009) and Christensen (2013) affirm that new technologies may appear without having any clear or major precedent. One mixed view is that of scholars such as Ahuja and Lampert (2001) and Boyd et al. (2011), who argue that a radical invention could use old technologies or emerging ones, or a combination of both.

In our study, in order to evaluate the innovative content of an innovation, we refer to Fleming's "component familiarity" index (2001), which proxies for the level of familiarity that inventors have with the components of their inventions. Our dependent variable, *Familiarity*, is based on the idea that each IPC code is a distinct knowledge component of an invention (Dosi, 1982; Fleming and Sorenson, 2001; Strumsky and Lobo, 2015). Therefore, a radical invention is built on new combinations of IPC codes, whereas an incremental invention replicates the combinations of IPC codes used by extant inventions. To construct our *Familiarity* measure, we proceed in two steps. First, we list the combination of IPC codes to which the focal invention is assigned. Then, we look back in time to see whether this combination has already been assigned to other inventions. If this is the case, an indicator function assumes the value of 1, and 0 otherwise. Then, we multiply the indicator function by an exponential function, where the exponent is the ratio between the priority application date of the two patents and a time constant of knowledge loss[44]. Finally, the components are summed. The *Familiarity* measure for the focal patent i is summarized by the following formula:

[44] Following Fleming (2001), we assume that there is a yearly knowledge loss of 18%.

$$\boldsymbol{Familiarity}_i = \sum_{all\ patents\ k\ granted\ before\ patent\ i} 1\{patents\ k\ using\ the\ same\ IPC\ code\ combination\ as\ patent\ i\} \times e^{\frac{(application\ date\ of\ patent\ i - application\ date\ patents\ k)}{time\ constant\ of\ knowledge\ loss}}$$

(Equation 4.1)

When the focal invention has a unique IPC codes combination with respect to *all* previous inventions, the index is equal to 0, i.e., the invention is radical in nature because inventors have no familiarity at all with the specific code combination. The value of the index increases when the focal invention replicates existing IPC codes combinations. Therefore high values indicate that the invention is incremental in nature.

The *Familiarity* measure is computed using a 4 IPC code digit level of precision, corresponding to the definition of a subclass (example A61F). In Appendix 4.2, we report an illustration of how to compute a single component of the sum reported in Equation 4.1.

The geographical diffusion of an invention

The geographical diffusion of an invention is the second aspect of the innovation dynamics that we analyze. We use the geographical protection of an invention as proxy for its geographical diffusion.

Patents give to its owners the exclusive right to use and produce an invention; however, this right is limited in space. This spatial limitation is related to the specific country where the patent application has been filed. When an applicant decides to apply for a patent, she can choose to protect it in just a few countries, or she can choose to have protection in all of the countries covered by the European Patent Office (EPO) contracting states[45]. In the first case, the applicant follows the national procedure of the state where the applicant intends to protect her invention. In the second case, the applicant guarantees to the patent broader protection, i.e., the patent, once granted, provides protection in all of the contracting states, even if only a unique application has been filed. The national and EPO procedures are not mutually exclusive. A patent application could be filed first to a national patent office, and later, within twelve months, the applicant can ask for an extension at the EPO [46] (Archibugi, 1988; Gay et al. 2005).

Our measure of diffusion, *Geo Diffusion*, is a variable that counts the number of national patent offices where a patent has been filed. In the case of an EPO application, the number of

[45] An applicant can also decide to go through USPTO or other patent offices external to Europe. However, this procedure is beyond the aim of this paper, since we are focusing our attention on Europe.
[46] See Euro-PCT guide, point 449 ff (January 2016).

patent offices where the protection of a patent has been extended is not available. In order to overcome this problem, we decided to count for 18 countries, corresponding to the number of members states in 1993. In constructing this variable, we have taken into account only patent offices in Europe because we are interested in studying the diffusion of an innovation within Europe.

4.5.2 Econometric specifications

The innovative content of an invention

Figure 4.6 reports a graphical illustration of how the content of an invention, measured by our *Familiarity* measure, changed over time in Europe for the medical device sector and mechanics.

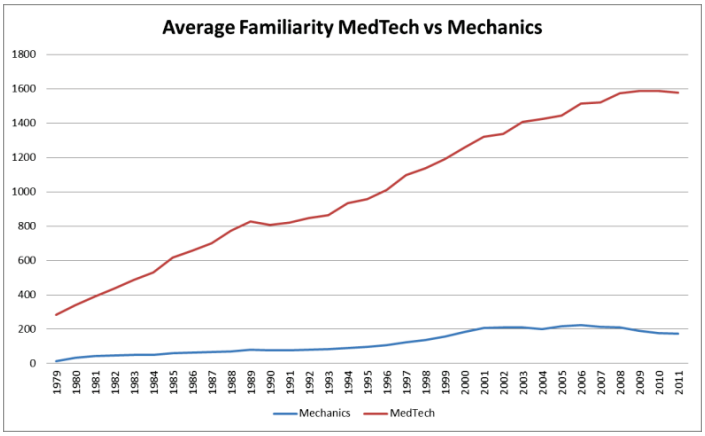

Figure 4.6 – Comparison of the familiarity index between the Medical device sector and Mechanics.

This graphical evidence shows that, the degree of innovative content of Mechanics patents remains quite constant over time. On the contrary, with the introduction of a strict regulation, medical devices inventors became risk adverse toward novelty.

To formally evaluate whether the introduction of the EU regulation in 1993 had an impact on the *Familiarity* of subsequent inventions, we estimate an Ordinary Least Squares (OLS) model for the following equation

$$Familiarity_i = \beta_0 + \beta_1 Regulation + \beta_3 MD + \beta_4 (Regulation * MD) + \beta_2 CInvention_i + \beta_3 CApplicant_i + \varepsilon_i$$

(Equation 4.2)

where *MD* is a dummy that equals 1 for inventions in the medical device sector and equals 0 for inventions in the mechanics sector. *Regulation* is a time-related dummy that takes a

value of 0 if the invention was filed before 1993, and a value of 1 in the following years (that is, after the introduction of Directive 93/42/EEC). The interaction term *Regulation*MD* marks observations from the medical device sector after the Directive introduction. After the introduction of the regulation, incremental innovations became more attractive for medical device inventors with respect to radical ones. For mechanical inventors the incentive to implement radical innovations remains the same. Thus, we expect the coefficient of the interaction term to have a positive sign.

In addition to the absence/presence of a regulation at the European level, we expect the absence/presence of a national regulatory authority to affect the innovative content of an invention. To control for this aspect, we add *National Office,* a dummy that is equal to 1 if the invention was realized in a country where there was a National Agency for Heath Safety in the invention application year. Furthermore, we include two types of controls. The variables in $CInvention_i$ measure the characteristics of invention *i*, and those in $CApplicant_j$ measure the characteristics of the invention applicant/s. Finally, we add the country fixed effects to control for local characteristics of the country where the invention is realized and the cumulative number of patents to control for the innovative trend path.

The geographical diffusion of an invention

Figure 4.7 reports a graphical illustration of how an invention's degree of diffusion changed over time in Europe in the two sectors. The figure shows that around 1993 medical device inventions diffuse more than mechanics inventions that remain stable and in certain years diffuse less.

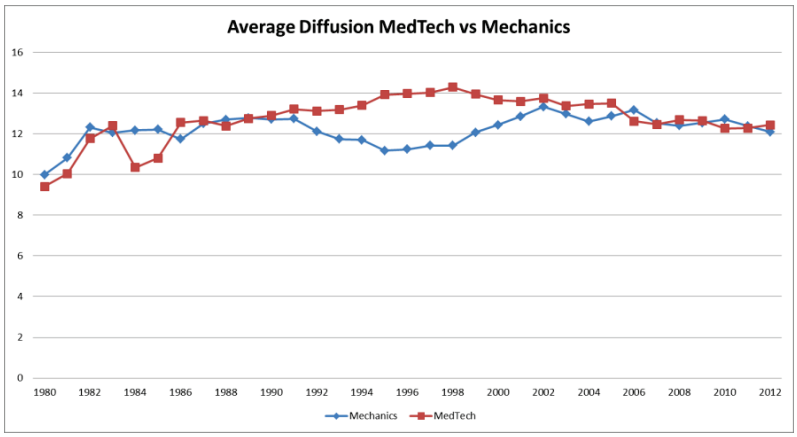

Figure 4.7 – Comparison of the geographical diffusion between the Medical device sector and Mechanics

To formally evaluate whether the introduction of Directive 93/42/EEC impacts the *Geo diffusion* of a specific invention, we estimate a count regression model that accounts for the

fact that our dependent variable can only take positive integer values, i.e., the number of national patent offices where a patent has been filed.

The conditional expectation of invention *i*'s number of national patent offices can then be expressed as follows:

$$\mu_i = exp(\beta_1 Regulation + \beta_3 MD + \beta_4 (Regulation*MD) + \beta_2 CInvention_i + \beta_3 CApplicant_i)$$

(Equation 4.3)

where the interaction *Regulation*MD* is expected to have a positive effect on *Geo diffusion*. In other words, inventions affected by the regulation are expected to diffuse more than the inventions in the control group since the standardization guaranteed by the regulation stimulates inventors to submit their patents to a greater number of patent offices. For invention and applicants' characteristics, we used the same ones listed in the analysis of the technological content of an invention. The controls mentioned are described in the next sub-section.

4.5.3 Controls included in the econometric exercises

National Agency for Heath Safety

Each EU state member has established, at different moments in time, a national authority that is responsible for the quality, safety and efficacy of medicine and health products. The majority of them have a specific section that monitors medical devices in the country. In our study, we construct a dummy variable, *National Agency,* which assumes a value of 1 if the invention is filed after the country has established its national agency[47]. Table 4.2 reports the list of EU National Agencies for Health Safety with their corresponding established year.

Country	Agency	Established year
Austria	Austrian Agency for Health and Food Safety	2002
Belgium	Federal Agency for Medicine and Health Products	2007
Denmark	Danish Medicine Agency	2015
Finland	Finnish Medicine Agency	2009
France	National Agency for the Safety of Medicine and Health Products	2011
Germany	Federal Institute for Drugs and Medical Devices	1975
Greece	National Organization for Medicine	1983
Ireland	Health Product Regulatory Authority (HPRA)	1996
Italy	Italian Medicine Agency	2003

[47] Each patent is assigned to the country corresponding to the first inventor address (see the "Data" section).

Country	Agency	Established year
Luxembourg	Ministry of Health	1980
Netherland	Medicine Evaluation Board	1995
Portugal	National Authority of Medicine and Health Products	1993
Spain	Spanish Agency for Medicine and Health Products	1999
Sweden	Medical Product Agency	1994
United Kingdom	Medicine and Healthcare Product Regulatory Agency	2003

Table 4.2 – List of EU National Agencies for Health Safety with their corresponding established year.

Invention characteristics (CInvention$_i$)

CInvention$_i$ is a vector of controls related to invention *i*. The included variables are standard controls considered in the patent literature. The patent documentation keeps track of "prior art." Scholars have used the *Forward citations count*– citations to the focal patent received by later patents – and *Backward citations count*– citations to previous patents made by the focal patent- to measure the value and the technical content of an innovation, respectively.

Harhoff et al. (1999) explain the logic behind the use of forward citations as a measure of a patent's value. They show that the economic value is proportional to the amount of forward citations received. Many works rely on the belief that receiving a large amount of citations is a proxy for identifying a radical patent, due to the fact that radical inventions establish the technical basis for subsequent inventions (Trajtenberg, 1990; Dahlin and Behrens, 2005; Schoenmakers and Duysters, 2010). Katila's work (2000) criticizes the positive correlation between forward citations and patent value. She proves that patents referred to as radical innovations are less cited than non-radical ones. This can be due to difficulties in understanding the new technology, the impossibility of embedding it directly into the existing process, or simply to a time lag in recognizing the innovative value of the invention.

Backward citations map the knowledge upon which an invention relies (Jaffe, 1986; Reitzig, 2003; Rosenkopf and Nerkar, 2001). We interpret the variable *Backward citations count* as the amount of knowledge that has been necessary to realize the invention *i*. We argue that an invention that is more incremental needs less prior knowledge than a radical one. A possible concern might be that the *Backward citations count* could be consider as a measure of how knowledge has been recombined (Fleming, 2001) and to evaluate if new elements have been introduced to the extant ones (Hargadon et al., 1997). However there is not common consensus in looking at backward citations as a proxy for the novel content of an invention (Ahuja and Lampert, 2001; Rosenkopf and Nerkar, 2001; Shane, 2001; Stuart and Podolny, 1995). Moreover

in our dataset the correlation between our measure of innovative content, *Familiarity*, and *Backward citations count* is very low (2%). This result reassures us in keeping *Backward citations count* as control in our estimated models.

Additionally, we use the *Backward citations average age* in order to capture the time lag window, where the invention draws its technological references. The assumption is that inventors are more familiar with technology components that have been recently used (Fleming, 2001). The *Forward citations average age* proxies for the time lag period that the invention requires to be absorbed and applied by others. Radical inventions might require more time to be understood (Katila, 2000). Finally, we introduce the *Count of citations to non-patent literature*. Previous studies have found that references to scientific literature denote greater closeness to a breakthrough than to an established technology, i.e., a great degree of novelty (Carpenter et al., 1981). Additionally, in the case of a medical device, references to scientific literature are required so as to add clinical data support as proof of the invention's reliability.

Applicants' characteristic (CApplicant $_j$)

CApplicant $_j$ is a vector of controls related to the applicants' characteristics. Over the past century, the process of knowledge creation has fundamentally changed. Nowadays, collaborative models have mainly replaced the individualistic-based model of discovering activities (Wuchty et al., 2007). Previous studies have shown a positive impact of collaboration on the inventions' impact (Jones et al., 2008). Consistent with these studies, we include the collaboration dimension as the number of applicants, *Count of applicants*. The *Applicants' Age* is an indication of the average age of the applicants. Finally *Applicants' Specialization* is an indication of the average technological specialization of the applicants. It is calculated as the average of the patent portfolio specialization in the focal sector (medical device or mechanics) of all the applicants involved in invention *i*.

Other controls

As an additional control, we include the number of cumulative active patents at time *t-1, Number of cumulative patents,* as a proxy for the innovative trend.

Variable	Mean	Std. Dev.	Min	Max
Familiarity index	374.83	729.20	0.00	7541.58
Geographical diffusion	12.56	9.44	0.00	49.00
Regulation	0.83	0.37	0.00	1.00
MD	0.22	0.41	0.00	1.00
National Agency	0.62	0.49	0.00	1.00
Invention characteristics				
Backward citations count	8.58	10.49	0.00	339
Forward citations count	11.41	51.93	0.00	3598.00
Backward citations average age	9.95	7.90	0.00	108.00
Forward citations average age	4.19	4.34	0.00	49.88
Count of citation to non-patent literature	39.41	218.43	0.00	21060.00
Applicant's characteristics				
Count of applicants	2.12	1.63	1.00	28
Applicants' Age	11.78	17.41	0	128
Applicants' Specialization	44.36	31.47	0.00	100
Other controls				
Number of cumulated patents	160981.30	94311.92	3954.00	285173.00

Table 4.3 - Descriptive statistics[48].

Descriptive statistics are reported in Table 4.3.

4.6 Results

Innovative content of an invention

The regression results from estimating equation 4.2 are presented in Tables 4.4 [49].

[48] *Notes:* Number of observations= 543,667 (unit of analysis: invention)

[49] For all the tables robust standard errors are in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The unit of analysis is the invention *i*.

Variables	I		II	
	Coeff.	**Std. Err**	**Coeff.**	**Std. Err**
Regulation	-84.844***	(22.627)	-84.767***	(22.977)
MD	670.146***	(14.667)	664.681***	(16.038)
Regulation*MD	678.331***	(55.140)	677.488***	(56.867)
National Agency			20.025	(11.778)
Invention characteristics				
Backward citations count	-1.554***	(0.363)	-1.533***	(0.364)
Forward citations count	-0.368***	(0.058)	-0.357***	(0.064)
Backward citations average age	-4.597***	(0.638)	-4.584***	(0.653)
Forward citations average age	-3.778***	(0.611)	-3.548***	(0.792)
Count of citations to non-patent literature	0.103***	(0.031)	0.103***	(0.032)
Applicant's characteristics				
Count of applicants	5.573**	(2.095)	6.191***	(2.035)
Applicants' Age	-0.152	(0.446)	-0.214	(0.418)
Applicants' Specialization	-1.186**	(0.437)	-1.168**	(0.432)
Other controls				
Cumulative number of patents	0.001***	(0.000)	0.001***	(0.000)
Constant	163.567***	(29.092)	154.065***	(28.047)
Country FE			YES	
Observations	543,667		543,667	
R-squared	0.424		0.424	

Table 4.4 - OLS estimation results for Familiarity.

Table 4.4 reports the results of our econometric exercise. We consider two specifications. In column I, we consider only the effect of Directive 93/42/EEC; in column II, we add a control for the presence of a national authority, *National Agency*, which regulates the sector in the country where the invention was filed.

In Table 4.4, as expected, the interaction term *Regulation*MD* has a positive effect on the *Familiarity* index, i.e., inventions filed after the introduction of Directive 93/42/EEC by medical device inventors are more incremental with respect to the ones filed by mechanical inventors. These findings prove that Directive 93/42/EEC was one of history's great watersheds for the medical device sector.

We would like to highlight some remarkable results regarding the other controls. The coefficient of *Backward citation count* is significant and negatively correlated with the level of familiarity of an invention. Thus, incremental innovations need less amount of previous knowledge in order to be developed with respect to radical innovations. The coefficient of

Forward citation count is significant and negatively correlated with the level of familiarity of an invention. This result is in line with the idea of the scholars arguing that radical innovations are associated with a higher value and are consequently cited more often than incremental innovations. The coefficient of the average age of backward citations, *Backward citation average age*, is negative correlated with invention familiarity level. Inventions with a greater level of novelty draw their technological references far back in time. It seems that in order to develop radical innovations, companies need to look further in time and maybe to forgotten technologies. The coefficient of the average age of forward citations, *Forward citation average age*, is negatively correlated with the invention familiarity level. Thus, inventions with a greater level of novelty are cited in the short run.

Regarding applicants' controls, the coefficient of the *Count of applicants* has a positive sign. This means that larger teams realize inventions with a greater level of familiarity. This result suggests the idea that the creation of radical innovation is more likely to happen within smaller teams. The coefficient *Applicants' Specialization* is negatively correlated with the incremental level of the innovation. This result suggests that companies with a deep sectorial knowledge are more likely to realize radical inventions. Similarly, the coefficient *Applicants' Age* is negatively correlated with the invention familiarity level suggesting that younger firms are more willing to produce radical inventions.

The coefficient of the number of references to non-patent literature, *Count of citation to non-patent literature,* is positively and significantly correlated with the invention familiarity level. This could be related to the nature of a medical device invention that requires the demonstration of clinical trials in order to be marketable. Finally, also the coefficient *Cumulative number of patents* is positively correlated with the invention familiarity level, underlining a correlation between the trend of patenting and a higher probability for an innovation to be incremental.

When we add the control for the presence of a national agency in the country, *National Agency*, the results remain stable across the specifications. Moreover, the coefficient of the dummy *National Agency* has no correlation with the innovative content of inventions.

Geographical diffusion of an invention

The regression results from estimating equation 4.3 are presented in Tables 4.5.

Variables	I		II	
	Coeff.	**Std. Err**	**Coeff.**	**Std. Err**
Regulation	-0.044***	(0.005)	-0.042***	(0.005)
MD	0.032***	(0.007)	0.056***	(0.006)
Regulation*MD	0.040***	(0.009)	0.067***	(0.009)
National Agency			-0.183***	(0.004)
Invention characteristics				
Backward citations count	0.011***	(0.000)	0.011***	(0.000)
Forward citations count	0.001***	(0.000)	0.001***	(0.000)
Backward citations average age	0.005***	(0.000)	0.005***	(0.000)
Forward citations average age	0.009***	(0.002)	0.009***	(0.002)
Count of citations to non-patent literature	-0.000***	(0.000)	-0.000***	(0.000)
Applicant's characteristics				
Count of applicants	0.065***	(0.001)	0.063***	(0.001)
Applicants' Age	0.003***	(0.000)	0.003***	(0.000)
Applicants' Specialization	-0.003***	(0.000)	-0.003***	(0.000)
Other controls				
Cumulative number of patents	-0.000***	(0.000)	0.000***	(0.000)
Constant	2.434***	(0.016)	2.452***	(0.017)
Country FE	YES		YES	
Observations	543,667		543,667	
Pseudo R-squared	0.086		0.089	

Table 4.5 – Poisson Estimations for number of patent offices where an invention i is filed.

To analyze how Directive 93/42/EEC affects the diffusion of an invention, we perform an econometric exercise that replicates the same specifications used in Tables 4.4. We present in column I the baseline model, and in column II, we add the *National Agency* variable.

Our results show that after the introduction of Directive 93/42/EEC, medical device inventions are filed to a greater number of patent offices with respect to mechanical inventions. In other words, a medical device applicant is stimulated to invest in broader geographical protection than a mechanical one, since, having fulfilled the standard of a European regulation, she is more confident that her invention will be accepted beyond her national borders.

Regarding the controls, the coefficient of *Backward citation count* is significant and positively correlated with the diffusion of an invention. We have seen in the previous paragraph that radical innovations are characterized by referencing a higher number of citations. Thus, it seems that radical innovations diffuse broader than incremental innovations. The coefficient of

Forward citation count is significant and positively correlated with the diffusion of an invention. As before, we have seen that radical inventions are cited more than incremental. Thus, we can argue that radical innovations diffuse more than incremental. The coefficient of the average age of backward citations, *Backward citation average age*, is positively correlated with diffusion. Inventions that, on average, cite older prior art diffuse broadly. This result supports the results presented in discussing the relationship between age of the prior art cited and invention familiarity level. The coefficient of the average age of forward citations, *Forward citation average age*, is positively correlated with the diffusion of an invention. Thus, an invention that, on average, receives citations several years after its publication diffuses broadly.

Regarding applicants' controls, the coefficient of the *Count of applicants* has a positive sign. This means that the invention developed by larger teams diffuse largely. The coefficient *Applicants' Specialization* is negatively correlated with the diffusion of the innovation. This result shows that inventions developed by companies with a deep sectorial knowledge are less capable to diffuse their inventions. The coefficient *Applicants' Age* is positively correlated with diffusion suggesting that the innovations developed by older firms circulate more than the ones developed by younger companies.

The coefficient of the number of references to non-patent literature, *Count of citation to non-patent literature,* is negatively and significantly correlated with diffusion. This result seems to suggest that inventions that refer less to non-patent literature diffuse more. Finally, the coefficient *Cumulative number of patents* is positively correlated with the invention diffusion, underlining a correlation between the trend of patenting and a higher probability of circulation.

In the specification that adds the dummy *National Agency* the results are consistent. The coefficient of *National Agency* has a negative correlation with the diffusion rate of inventions. This suggests that those inventions in countries where there is an agency which control the innovative output diffuse less than the ones where there is no control.

4.7 Conclusions

We evaluate the impact of the introduction of a regulation on (1) the technological content; and (2) the geographical diffusion of an innovation. We create a novel dataset of 543,667 inventions introduced in the European medical device and mechanical sectors in the period 1980-2012. We find that innovative content for invention in MedTech decreased significantly after 1993 with respect to inventions in mechanics. Moreover, after 1993, MedTech applicants tended to file their inventions more broadly, assuring an extension of the geographical protection to their invention.

Unique to our study is the fact that, in considering regulation effects on innovation activities, we look at the technical content of each invention. Specifically, we consider the technologies embodied in an invention. We find that, after the regulation change, MedTech innovators tend to replicate extant technology combinations instead of introducing new ones. This result indicates that MedTech innovators became more risk adverse toward novelty. At the same time, a stringent regulation at the European level imposes the standardization of products to all European countries. If patent applicants can rely on uniform rules that their products have to satisfy, they are incentivized to file their applications broadly. In other words, moving from a defragmented combination of different rules to a uniform set of rules with broad coverage, leads MedTech applicants to extend their targeted markets, while for Mechanics ones things remain unchanged.

The results have direct implications for the literature on the impact of social regulations on innovation. This literature claims that public intervention favors innovation activities (Porter et al., 1995), but the extant empirical evidence provides contradictory results (Blind, 2012). While previous studies measure innovative dynamics as patent applications or firm performance, our study explores invention characteristics in terms of content and geographical extension protection. Going beyond the simple patent counts and firm balance sheet accounts allows us to investigate how regulation affects the nature of an innovation. Specifically, we find that regulation discourages radical innovations. Products based on existing technologies are easier to be accepted as safe than products that break with the past. If a regulation appears to downsize the invention innovative content, on the other side, it seems to guarantee a wide market to an invention for its commercialization. The existence of a common set of rules in a large economic space such as that of the EU assures standardization and limits the negative effects of a patchwork of national norms.

Although our analysis provides interesting results, it is not exempt from limitations. First, the use of patent data includes some limitations as a no one-to-one correspondence with a device. Moreover not all the inventions are patented. We try to overcome one of the limitations in the use of patent data, the overestimation of the count of patent data. For this reason we use patent families that group in one single observation all the applications that identify a unique innovation. Second, an alternative explanation could apply for the decline of the innovative activities observed. Innovative activities might decline because inventors became more reluctant to exploit opportunities at the technological frontier, even in the absence of a specific regulation because they do not want to incur the risk of harming patients by experimenting with unknown techniques. However, we cannot ignore than in the last decade, a large number of original

medical devices have been introduced. The bio-artificial liver that was listed by the *Times* as one of the most important inventions of 2001 is just an example. The bionic contact lens, mind-reading, and eye-wither devices provide other examples of the most innovative efforts in the medical device sector. For this reason, we refrain to formulate any consideration regarding the value of individual innovation.

Our results have important implications for policymakers. When policymakers introduce a strict regulation, they think about the health and security for the final users. However, they should also consider the "side-effects" for the economy. A more stringent regulation might discourage inventors from introducing new risky solutions. In response to this, we believe that, in planning their interventions, regulators should listen to the opinions of small companies and medical device experts in order to introduce norms that guarantee patient safety, but at the same time, meet the needs of the sectorial operators. Of course, we do not want to make general statements, and we are aware that our study is limited to a specific sector.

Appendixes

Appendix 4.1

Applicants' name harmonization

In order to retrieve applicants' names, we relied on the PATSTAT Person Augmented Table (EEE-PPAT). Specifically, we used the PATSTAT Table TLS206_PERSON & TLS906_PERSON (December 2014), which includes patentees' harmonized names and classifies assignees by organizational type.

This table is the result of a project launched in 2006 by EUROSTAT in collaboration with EPO, ECOOM (KU Leuven) and Sogeti. In this appendix, we provide an overview of the method they applied for name harmonization and organizational type assignment in order to clarify the data- cleaning procedures behind our data sources. Interested readers can find a detailed explanation of the method leading to the table creation in Du Plessis et al. (2009), Magerman et al. (2009), and Peeters et al. (2009).

The name harmonization and patent application assignment is a three-step process. First, applicants' row names undergo a pre-cleaning standardization procedure, where spaces and all non-alphabetical characters are deleted, and characters and punctuation are standardized. Also, the applicants' legal form is treated so as to appear normalized. Second, strings are compared to find word similarities, based on spelling variations. Finally, cleaned names are

matched with the original ones and grouped, and patent applications are reassigned to the harmonized names.

The applicants' organizational type classification considers the following categories: private business enterprises, universities/higher education institutions, governmental agencies and individuals. The first step of the algorithm regards the automatic research into the name string of some "clues" that help in identifying to which sector a name belongs, such as legal forms for companies or governmental agencies, or educational status for individuals, i.e., Doc., Eng.… Due to the difficulties in connecting a "clue" to a unique sector, an additional validation step is included. This leads to the creation of a set of rules specific for each case and raises the quality of the result. The final quality level of the final dataset is 99%. This means that 99% of the records have a sector assigned, and vice versa; 99% of the records are assigned to just one sector.

Appendix 4.2

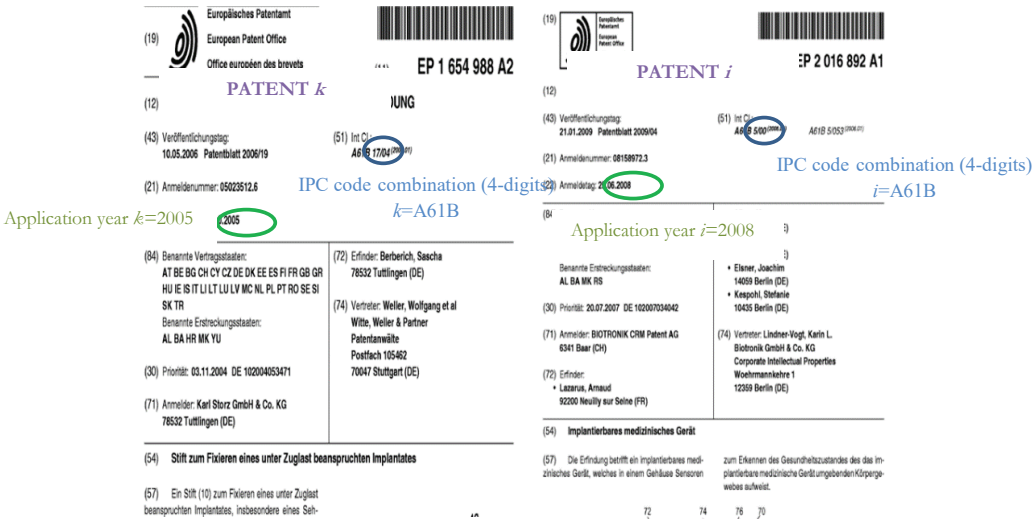

Figure 4.8: Illustration of how to compute a single component of the sum supported in equation 4.1.

Patent *i* uses the same IPC code combinations of patent *k* that was submitted 3 years before. The *Familiarity* index for patent *i* above is:

$$Familiarity_i = 1 * e^{\frac{2008-2005}{3}} = 1.8$$

Figure 4.9: Illustration of how to compute a single component of the sum supported in equation 4.1.

Patent *i* does not use the *same* IPC code combination of patent *k* that was submitted 2 years before. The *Familiarity* index for patent *i* above is:

$$Familiarity_i = 0 * e^{\frac{2007-2005}{2}} = 0$$

Appendix 4.3

In this appendix we report the results of an econometric exercise to test the robustness of the results reported in the main text. The analysis reported exploits a variation in the legislative status of each European country. We compute differences-in-differences estimates of the effects of the Directive for countries with a national agency and countries without a national agency. In order to perform this exercise, we add to equation 4.2 and 4.3 the interaction between the dummy *Regulation* and the dummy *National Agency*, *Regulation*National Agency*. This interaction term takes value 1 if an invention has been developed after 1993 in a country with a National Agency. The idea behind this specification is that the Regulation became effective only if combined with the presence of a National Agency that monitors the application of the Regulation. Having introduced the presence of a national agency as source of variability among country, we can apply differences-in-differences where we limit our empirical setting to the inventions in the medical device sector (117,993 observations).

Table 4.6 shows that the first hypothesis, *Regulation has a detrimental effect on the innovative content of an invention,* is confirmed. *Regulation* has a positive effect on the *Familiarity* index, showing that invention after 1993 are incremental and not radical. The coefficient of the interaction term *Regulation*National Agency* does not have any effect on the innovative content. The results on the controls remain similar to the one presented in the main text with

the exception for two coefficient, *Forward citation average age* and *Count of applicants*. *Forward citation average age* is now negatively correlated with invention familiarity, whereas *Count of applicants* has now a negative sign. This could be interpreted as the fact that larger teams realize inventions with a greater level of novelty.

The second hypothesis, *Regulation stimulates the geographical diffusion of an invention,* is confirmed. The coefficient *Regulation*National Agency* has a positive effect on the diffusion of the innovations. It seems that only countries with an active national agency are stimulated to diffuse more their inventions. The results on the controls remain similar to the one presented in the main text with the exception for two coefficient, *Applicants' Specialization* and *Count of applicants*.

Applicants' Specialization is now positively correlated with invention diffusion and *Count of applicants* has now a negative sign. This means that smaller teams realize inventions with a greater potential of diffusion.

The limitation of the use of this setting, compared with the one presented in the main text, is the impossibility to disentangle the effect of the Directive 93/42/EEC and the one related to the creation of the common market.

Variables	**OLS Model**		**Poisson Model**	
	DV Familiarity		**DV Geo Diffusion**	
	Coeff.	**Std. Err**	**Coeff.**	**Std. Err**
Regulation	157.680**	(55.403)	-0.026***	(0.008)
National Agency	-24.253	(29.689)	-0.288***	(0.011)
Regulation*National Agency	61.822	(47.037)	0.215***	(0.011)
Invention characteristics				
Backward citations count	-2.447**	(0.883)	0.007***	(0.000)
Forward citations count	-0.159***	(0.042)	0.001***	(0.000)
Backward citations average age	-12.444***	(1.552)	0.010***	(0.000)
Forward citations average age	6.732***	(1.191)	0.045***	(0.001)
Count of citations to non-patent literature	0.673**	(0.299)	-0.002***	(0.000)
Applicant's characteristics				
Count of applicants	-43.783**	(16.114)	-0.072***	(0.006)
Applicants' Age	-1.167*	(0.611)	0.011***	(0.000)
Applicants' Specialization	-3.807***	(0.689)	0.004***	(0.000)
Other controls				
Cumulative number of patents	0.010***	(0.001)	0.000***	(0.000)
Constant	864.738***	(42.556)	1.867***	(0.018)
Country FE	YES		YES	
Observations	117,993		117,993	
R-squared	0.106		0.19	

*Table 4.6 – OLS and Poisson Estimations including the interaction term Regulation*National Agency.*

Chapter 5: Conclusions

The medical device sector is nowadays an industry of tremendous success. By any measure, whether it be the number of firms, employment, number of global innovators, or export performance, this industry stands in a very high position. The sector presents itself as a very innovative business, characterized by a high density of innovators and a high degree of originality, thanks to its strong interaction with other fields, despite strict control on new products imposed by the regulatory framework.

Since the beginning of its existence in the 1960s, the medical device sector has in its collaborative nature the driving force of its growth. As a matter of fact, everything began as a result of a joint effort of six Swiss surgeons who aimed to create an organization that could teach new techniques for orthopedic surgery. Very soon thereafter, this organization expanded and became an association that involved not only doctors, but also companies and medical schools. The companies who joined the association were not specialized in medical equipment; however, they were specialized in precision mechanics. Their technical competencies were central to helping doctors develop new devices. The creation of new tools soon became an interesting business opportunity. Suddenly other mechanical companies wished to take advantage of the new market and started to collaborate with surgeons. The problem was that at that time, there was no regulation to control the quality or safety of a device. Thus, in order to earn more money, companies used scarce materials, different from the ones agreed upon by doctors, causing serious illness in the patients using such devices. The need for control was so urgent that the AO surgeons established an internal quality check so as to assure high-quality tools.

This thesis proposes three studies, providing novel empirical evidence related to the three main characteristics of the medical device sector: the network, knowledge spillovers and regulation, at the present.

The second chapter of this thesis aims to understand the importance of the collaborative network of inventors for regional innovation. Previous literature has offered heterogeneous answers to the question: What is the best network structure to adopt in order to enhance innovative activities? Some scholars suggest the importance of proximity and co-location of innovators in order to boost innovation. Others worry that a closed cluster could limit creativity and cause the circulation of redundant knowledge. In my first work, I analyze what the network structure that enhances regional innovative activity in the medical device sector. The results show that the ideal network structure is composed of intense internal connections between MedTech inventors, supported by external linkages. The results become

even stronger when well-connected MedTech inventors are linked with inventors specialized in other technologies. These findings highlight the importance of the combined effect of "home" connections, together with external linkages. The capacity of a region to benefit from external knowledge is determined by its internal connectivity.

The third chapter extends the analysis concerning the importance of the knowledge exchanges between MedTech and other sectors. All scholars agree on the crucial role played by knoweldge spillovers for economic growth. For this reason, a hot topic in the literature regards the definition of a measure capable of tracking knowledge flows. The most frequently used measures are three: technological matrices, the Yale matrix, and patent backward citations. The dabate related to the degree of precision at which these measures actually estimate knowledge spillovers, especially when they occur across sectors, is still open. My study proposes a new definition of the measure of backward citations. In the analysis, I show how technologies are different in terms of the speed at which other sectors are capable of understanding, absorbing and using them. My hypothesis is that the existence of different adoption speeds should have an impact on the number of citations received by each technology from other sectors. When I compare the classical measure of backward citations with my new results, I show: *i)* the technologies that were heavily cited before are still the most important, meaning that the new measure does not change the basic idea of the classical measure; *ii)* the technologies that were neglected before, but with a high adoption speed, start to appear as relevant. The aim of this study is therefore to carefully interpret the measure of backward citations when applied across sectors.

In the fourth chapter, I analyze the effect of introducing the European regulation on medical devices in 1993 on the innovative performance of the sector. In recent years, strict social regulations have been introduced with the intent of guaranteeing consumers' safety and health. The literature is mixed regarding the effects of regulation on innovation. Some scholars perceive the regulation as a limitation of natural technological evolution. Others see the regulation as an incentive for innovation. In order to study the effect of medical device regulation on the innovation of the sector, I create a novel dataset of European patents. The results show that the regulation has a negative effect on the radical nature of inventions. New medical device patents are built on more familiar component combinations in order to increase the odds of being accepted. At the same time, the regulation has the positive effect of opening the market and increasing the diffusion of the innovations. The existence of a common set of rules in a large economic space such as that of the EU assures standardization and limits the negative effects of a patchwork of national norms.

References

Acs, Z. J., Anselin L., and Varga, A. 2002. Patents and Innovation Counts as Measures of Regional Production of New Knowledge. *Research Policy,* 31(7), pp. 1069–85.

Agrawal, A. and Henderson, R. 2002. Putting Patents in Context: Exploring Knowledge Transfer from MIT. *Management Science*, 48(1), pp. 44-60.

Agrawal A., Cockburn, I., and Michale J. 2006. Gone but Not Forgotten: Knowledge Flows, Labor Mobility, and Enduring Social Relationships. *Journal of Economic Geography,* 6(5), pp.571–91.

Ahuja, G. 2000. Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study. *Administrative Science Quarterly,* 45(3), pp. 425–55.

Ahuja, G., and Lampert, C.M. 2001. Entrepreneurship in the Large Corporation: A Longitudinal Study of How Established Firms Create Breakthrough Inventions. *Strategic Management Journa,l* 22(6-7), pp. 521–43.

Alcacer, J., Gittelman, M., and Sampat, B. 2009. Applicant and examiner citations in U.S. patents: An overview and analysis. *Research Policy*, 38, pp. 415–427.

Almeida, P., & Kogut, B. 1999. Localization of knowledge and the mobility of engineers in regional networks. *Management science*, 45(7), 905-917.

Ambec, S., Cohen, M. A., Elgie, S., and Lanoie, P. 2013. The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness? *Review of Environmental Economics and Policy,* 7(1), pp. 2–22.

Anderson, P., and Tushman, M.L. 1990. Technological Discontin- Uities and Dominant De- Signs : A Cyclical Model of Technological Change. *Administrative Science Quarterly,* 35(4), pp. 604–33.

Anselin L., Varga A., and Zoltan, J. 2000. Geographic and Sectoral Characteristics of Academic Knowledge Externalities. *Papers in Regional Science,* 79(4), pp. 435–43.

Antonelli C., Krafft J., and Quatraro F. 2010. Recombinant Knowledge and Growth: The Case Of Icts. *Structural Change and Economic Dynamics,* 21(1), pp. 50–69.

Archibugi, D. 1988. In Search of a Useful Measure of Technological Innovation (to Make Economists Happy withou Discontenting Technologists). *Technological Forecasting and Social Change,* 34, pp. 253–77.

Arthur, W. B. 2009. The nature of technology: What it is and how it evolves. *Simon and Schuster*.

Asheim, B. T., and Isaksen, A. 2002. Regional Innovation Systems: The Integration of Local 'Sticky' and

Global 'Ubiquitous' Knowledge. *The Journal of Technology Transfer,* 27.1, pp. 77-86.

Ashford, N. A., Ayers, C., and Stone, R.F. 1985. Using Regulation to Change the Market for Innovation. *Harvard Environmental Law Review,* 9(2), pp. 419–66.

Ashford, N. A., and Hall, R.P. 2011. The Importance of Regulation-Induced Innovation for Sustainable Development. *Sustainability,* 3(12), pp. 270–92.

Azoulay, P., Ding, W. and Stuart, T. 2009. The Impact of Academic Patenting On The Rate, Quality And Direction Of (Public) Research Output. *The Journal of Industrial Economics*, 57(4), pp.637-676.

Balconi M., Breschi, S., and Lissoni, F. 2004. Networks of Inventors and The Role Of Academia: An Exploration Of Italian Patent Data. *Research Policy,* 33(1), pp.127–145.

Bakker, J., Verhoeven, D., Zhang, L., and Van Looy, B. 2014. Patent Citation Indicators : One Size Fits All ? *Scientometrics,* 106(1), pp. 187-211

Bathelt, H., Malmberg, A., and Maskell, P. 2004. Clusters and Knowledge: Local Buzz, Global Pipelines And The Process Of Knowledge Creation. *Progress in Human Geography,* 28(1), pp.31–56.

Batz, F.J., Peters, K.J., and Janssen, W. 1999. The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics*, 21(2), pp. 121–130.

Bettencourt, L. M., Kaiser D.I., and Kaur, J. 2009. Scientific Discovery and Topological Transitions in Collaboration Networks. *Journal of Informetrics,* 3(3), pp. 210–21.

Bettencourt, L. M. A., Lobo, J. and Strumsky, D. 2007. Invention in The City: Increasing Returns to Patenting as a Scaling Function Of Metropolitan Size. *Research Policy* 36(1): Pp.107–120.

Bishop, P., and Gripaios, P. 2010. Spatial Externalities, Relatedness and Sector Employment Growth In

Great Britain. *Regional Studies,* 44 pp. 443-454.

Blind, K. 2008. Regulatory Foresight: Methodologies and Selected Applications. *Technological Forecasting and Social Change,* 75(4), pp. 496–516.

Blind, K. 2012. The Influence of Regulations on Innovation: A Quantitative Assessment for OECD Countries. *Research Policy,* 41(2), pp. 391–400.

Boschma, R.A., and Frenken, K. 2010. The Spatial Evolution Of Innovation Networks. A Proximity Perspective. *The Handbook of Evolutionary Economic Geography,* pp.120-135.

Boschma, R.A., and Iammarino, S. 2009. Related Variety, Trade Linkages, and Regional Growth in Italy. *Economic Geography,* 85, pp. 289-311.

Boschma, R., A., Minondo, A., and Navarro, M. 2012. Related Variety and Economic Growth In Spain. *Regional Science* 91, pp 241-256.

Boyd, R., Richerson, P.J., and Henrich, J. 2011. The Cultural Niche: Why Social Learning Is Essential for Human Adaptation. *Proceedings of the National Academy of Sciences of the United States of America,* 108 Suppl, pp. 10918–25.

Breschi, S., and Lenzi, C. 2012. Net City: How Co-Invention Networks Shape Inventive Productivity in Us Cities. pp.1–32.

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

Breschi, S., and Lissoni, F. 2004. Knowledge networks from patent data. *In Handbook of quantitative science and technology research*, pp. 613-643, Springer Netherlands.

Breschi, S., and Lissoni, F. 2009. Mobility of Skilled Workers And Co-Invention Networks: An Anatomy of Localized Knowledge Flows. *Journal of Economic Geography,* 9(4), pp.439–468.

Bresnahan, T., Gambardella, A., and Saxenian, A. 2001. Old Economy' Inputs For 'New Economy' Outcomes: Cluster Formation in The New Silicon Valleys. *Industrial and Corporate Change,* 10(4), pp.835–860.

Bresnahan, T.F., and Trajtenberg, M., 1995. General purpose technologies "Engines of growth"? *Journal of Econometrics,* 65(1), pp. 83–108.

Brusoni, S., Criscuolo, P., and Geuna, A. 2005. The knowledge bases of the world's largest pharmaceutical groups: what do patent citations to non-patent literature reveal? *Economics of Innovation and New Technology*, 14(5), pp. 395–415.

Burt, R., 2004. Structural Holes and Good Ideas, *American Journal Of Sociology,* 110(2), pp.349–399.

Calderini, M., Franzoni, C., and Vezzulli, A. 2007. If Star Scientists Do Not Patent: The Effect Of Productivity, Basicness and Impact On the Decision to Patent in the Academic World. *Research Policy,* 36(3), pp. 303–319.

Caballero, R., and Jaffe, A. 1993. How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth. *NBER Macroeconomics Annual 1993*, 8, pp. 15–86.

Callaert, J., Du Plessiss, M., Grouwels, J., Leococq, C., Magerman, T., Peeters, B., Song, X., Van Looy, B., and Vereyen, C. 2011. Patent Statistics at Eurostat: Methods for Regionalisation, Sector Allocation and Name Harmonisation.

Carpenter, M. P., Narin, F., and Woolf, P. 1981. Citation Rates to Technologically Important Patents. *World Patent Information,* 3(4), pp. 160–63.

Chai, J. 2000. Regulation of medical devices in the European Union. *Journal of Legal Medicine*, 21(4), pp. 537-556.

Christensen, C. 2013. The innovator's dilemma: when new technologies cause great firms to fail. *Harvard Business Review Press.*

Cohen, W. M., and Levinthal, D.A. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*, pp.128–152.

Cowan R., and Jonard, N. 2004. Network Structure and The Diffusion Of Knowledge. *Journal of Economic Dynamics and Control,* 28(8), pp.1557–1575.

Criscuolo, P., and Verspagen, B. 2008. Does it matter where patent citations come from? Inventor vs. examiner citations in European patents. *Research Policy,* 37(10), pp. 1892–1908.

Dahlin, K. B., and Behrens, D.M. 2005. When Is an Invention Really Radical? *Research Policy,* 34(5), pp. 717–37.

David, P.A. 1990. The Dynamo and the Computer : An Historical Perspective on the Modern Productivity Paradox. *The American Economic Review*, 80(2), pp. 355–361.

David, P.A., and Wright, G. 1999. General Purpose Technologies and Surges in Productivity: Historical reflections on the future of the ICT revolution. *Discussion papers in Economic and Sociology*. University of Oxford

Dernis, H., and Khan, M. 2004. Triadic Patent Families Methodology. *OECD Science, Technology and Industry Working Papers.*

Döring, T., and Schnellenbach, J. 2006. What Do We Know About Geographical Knowledge Spillovers and Regional Growth? A Survey of the Literature. *Regional Studies*, 40(3), pp.375-395.

Dornbusch, F., Schmoch, U., Schulze, N., and Bethke, N. 2012. Identification of University-Based Patents: A New Large-Scale Approach. *Research Evaluation*, November, Rvs 033.

Dosi, G. 1982. Technological Paradigms and Technological Trajectories. *Research Policy,* 11(3), pp. 147–62.

Duguet, E., and MacGarvie, M. 2005. How well do patent citations measure flows of technology? Evidence from French innovation surveys. *Econonomics of Innovation and New Technology,* 14(5), pp. 375–393.

Du Plessis, M., Van Looy, B., Song, X., and Magerman, T. 2009. Data production methods for harmonized patent indicators: Assignee sector allocation. *Luxembourg: EUROSTAT Working Paper and Studies.*

Eads, G. C. 1980. Regulation and Technical Change: Some Largely Unexplored Influences. *American Economic Review,* 70(2), pp. 50–54.

Faulkner, A., and Kent, J. 2001. Innovation and regulation in human implant technologies: developing comparative approaches. *Social science & medicine*, 53(7), pp. 895-913.

Feldman, M. P., and Audretsch, D.B. 1999. Innovation In Cities: Science-Based Diversity, Specialization and Localized Competition. *European Economic Review,* 43 (2), pp.409–29.

Feldman, M. P., and Kogler, D.F. 2010. Chapter 8 - Stylized Facts in the Geography of Innovation. *Handbook Of The Economics of Innovation*, Edited By Bronwyn H. Hall and Nathan Rosenberg, 1, pp.381–410, Vol. 1, North-Holland.

Fleming, L. 2001. Recombinant Uncertainty in Technological Search. *Management Science*, 47(1), pp.117-132.

Fleming L., King, C., and Juda, A.I. 2007. Small Worlds and Regional Innovation. *Organization Science,* 18(6), pp.938–954.

Fleming, L., and Sorenson, O. 2001. Technology as a Complex Adaptive System: Evidence from Patent Data. *Research Policy,* 30(7), pp. 1019–39.

Foray, D. 2014. Smart Specialisation: Opportunities and Challenges for Regional Innovation Policy. 1st Edition. New York: Routledge.

Freeman, L. C. 1978. Centrality in Social Networks Conceptual Clarification. *Social Networks*, 1(3), pp.215–239.

Frenken, K., Van Oort, F.G., and Verburg, T. 2007. Related Variety, Unrelated Variety and Regional

Economic Growth. *Regional Studies* 41(5), pp. 685-697.

Galunic, C., and Rodan, S. 1998. Resource Recombinations in the Firm: Knowledge Structures and the Potential for Schumpeterian Innovation. *Strategic Management Journal,* 19(12).

Gavetti, G., and Levinthal, D. 2000. Looking Forward and Looking Backward: Cognitive And

Experiential Search, *Administrative Science Quarterly* 45(1), pp.113-137.

Gay, C., Le Bas, C., Patel, P., and Touach, K. 2005. The determinants of patent citations: an empirical

analysis of French and British patents in the US. *Econonomics of Innovation and New Technology*. 14(5), pp. 339–350.

Gelijns, A., and Rosenberg, N. 1994. The dynamics of technological change in medicine. *Health Affairs,* 13(3), pp. 28–46.

Gelijns, A. C., Rosenberg, N., and Moskowitz, A.J. 1998. Capturing the Unexpected Benefits of Medical Research. *The New England Journal of Medicine,* 339(10), pp.693-698.

Giuliani, E. 2005. Cluster Absorptive Capacity: Why Do Some Clusters Forge Ahead And Others Lag Behind? *European Urban and Regional Studies,* 12 (3), pp.269–288.

Golec, J., Hegde, S., and Vernon, J. 2005. Pharmaceutical R&D Spending and Threats of Price Regulation. Working paper. *National Bureau of Economic Research*, Cambridge, MA

Gomes-Casseres, B., Hagedoorn, J. and Jaffe, A.B. 2006. Do Alliances Promote Knowledge Flows? *Journal of Financial Economics,* 80(1), pp.5–33.

Grabher, G. 1993. The Weakness of Strong Ties: The Lock-In of Regional Development in the Ruhr Area. *The Embedded Firm: On the Socioeconomics of Industrial Networks*, pp.255–277.

Grabowski, H. G., Vernon, J. M., and Thomas, L. G. 1978. Estimating the Effects of Regulation on Innovation: An International Comparative Analysis of the Pharmaceutical Industry. *The Journal of Law & Economics,* 21(1), pp. 133–65.

Griliches, Z. 1979. Issues in Assessing the Contribution of R&D to Productivity Growth. *The Bell Journal of Economics,* pp. 92–116.

Halder, G. 2002. How Does Globalisation Affect Local Production and Knowledge Systems? The Surgical Instrument Cluster of Tuttlingen, Germany. *INEF-Report* 57, Duisburg, 53 pages.

Hall, B., Jaffe, A., and Trajtenberg, M. 2001. The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools. *National Bureau of Economic Research*, No. W8498.

Hall, B.H., Jaffe, and A., Trajtenberg, M. 2005. Market Value and Patent Citations. *RAND Journal of Econonomics*, pp. 16–38.

Hall, B.H., and Trajtenberg, M. 2004. Uncovering GPTS eith patent data. *National Bureau of Economic Research,* No. W10901.

Han, Y.J., and Park, Y. 2006. Patent network analysis of inter-industrial knowledge flows: The case of Korea between traditional and emerging industries. World Pat. Inf. 28, 235–247.

Hargadon,C., Andrew, B., and Sutton, R. I.. 1997. Technology Brokering And Innovation In A Product Development Firm. *Administrative science quarterly,* 42(4), pp. 716–49.

Harhoff, D., Narin, F., Scherer, F. M., and Vopel, K. 1999. Citation Frequency and the Value of Patented Inventions. *Review of Economics and Statistics,* 81(3), pp. 511–15.

Harhoff, D., Scherer, F.M., and Vopel, K. 2003. Citations, family size, opposition and the value of patent rights. *Research Policy*, 32(8), pp. 1343–1363.

Helpman, E. 1998. General purpose technologies and economic growth. *MIT press*.

Helpman, E., and Trajtenberg, M. 1994. A Time to Sow and a Time to Reap: Growth Based on General Purpose Technology. *National Bureau of Economic Research,* No. W4854.

Henderson, R. 1993. Underinvestment and incompetence as responses to radical innovation: Evidence from the photolithographic alignment equipment industry. *The RAND Journal of Economics*, pp. 248-270.

Herzlinger, R. E. 2006. Why Innovation in Health Care Is so Hard. *Harvard Business Review,* 84(5), pp. 58–66.

Jaffe, A.B. 1986. Technological Opportunity and Spillovers of R & D : Evidence from Firms ' Patents , Profits and Market Value. *National Bureau of Economic Research.*

Jaffe, A. B., and Palmer, K. 1997. Environmental Regulation and Innovation: A Panel Data Study. *The Review of Economics and Statistics,* 79(4), pp. 610–19.

Jaffe, A.B., and Rassenfosse, G. De. 2016. Patent citation data in social science research: Overview and best practices. *National Bureau of Economic Research,* No. W21868.

Jaffe, A.B., and Trajtenberg, M. 1996. Flows of knowledge from universities and federal laboratories : Modeling the flow of patent citations over time and across institutional and geographic boundaries. *Proceedings of the National Academy of Sciences*, 93(23), pp. 12671-12677.

Jaffe, A. B., Trajtenberg M., and Henderson, R. 1993. Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *The Quarterly Journal of Economics,* 108(3), pp.577–598.

Jog, Y., Sharma, A., Mhatre, K., Abhishek, A., 2015. Internet of Things As A Solution Enabler In Health Sector. *International Journal of Bio-Science & Bio-Technology,* 7(2), pp. 9–24.

Jones, B. F., Wuchty, S., and Uzzi, B. 2008. Multi-university research teams: Shifting impact, geography, and stratification in science. *Science*, *322*(5905), pp. 1259-1262.

Katila, R. 2000. Measuring Innovation Performance. *International journal of Business performance measurement,* 2(512), pp. 180–93.

Keller, W. 1997. Technology Flows Between Industries: Identification and Productivity Effects. *Economic Systems Research,* 9(2), pp. 213-219.

Kogut, B., and Zander, U. 1993. Knowledge of the Firm and the Evolutionary Theory of the Multinational Corporation. *Journal of International Business Studies* 24(4), pp.625–45.

Kortum, S., and Putnam, J. 1997. Assigning Patents to Industries: Tests of the Yale Technology Concordance. *Economic Systems Research*, 9(2), 161–176.

Kramer, D. B., Xu, S., and Kesselheim, A.S. 2012. How Does Medical Device Regulation Perform in the United States and the European Union? A Systematic Review. *PLoS Medicine,* 9(7), e1001276.

Lamph, S. 2000. Regulation of Medical Devices in the European Union. *The Journal of legal medicine,* 21(4), pp. 537–56.

Lissoni, F. 2010. Academic Inventors as Brokers. *Research Policy,* 39(7), pp.843–857.

Lissoni, F., and Sanditov, B. 2006. Networks of Inventors and Academics in France, Italy and Sweden: evidence from the Keins Database. *Working paper series Crios.*

Lobo, J., and Strumsky, D. 2008. Metropolitan Patenting, Inventor Agglomeration and Social Networks: A Tale of Two Effects. *Journal of Urban Economics,* 63(3), pp.871–884.

Magerman T, Grouwels J., Song X. and Van Looy B. 2009. Data Production Methods for Harmonized

Patent Indicators: Patentee Name Harmonization. *EUROSTAT Working Paper and Studies, Luxembourg*

Maggioni, M. A., Nosvelli, M., and Uberti, T.E. 2007. Space Versus Networks in the Geography of Innovation: A European Analysis. *Papers in Regional Science,* 86(3), pp. 471-493.

Martínez, C. 2011. Patent families: when do different definitions really matter?. *Scientometrics,* 86(1), pp. 39-63.

Maulin, P., and Wang J. 2010. Applications, challenges, and prospective in emerging body area networking technologies. IEEE Wireless Communications Magazine 17, no. 1, pp. 80-88.

Mccann, P., and Ortega-Argilés, R. 2013. Smart Specialization, Regional Growth and Applications to European Union Cohesion Policy. *Regional Studies*, June, pp.1–12.

Medical Cluster. 2014. *Swiss MedTech Report*, Bern www.medtech-switzerland.com

Meijl, H. Van. 1997. Measuring the Impact of Direct and Indirect R&D on the Productivity Growth of Industries: Using the Yale Technology Concordance. *Economic Systems Research*, 9(2), pp. 205–211.

Meyer, M. 2000. What is special about patent citations? Differences between scientific and patent citations. *Scientometrics*, *49*(1), 93-123.

Metha, A., Rysman, M., and Simcoe, T. 2010. Identifying the age profile of patent citations: new estimates of knowledge diffusion. *Journal of Applied Econometrics,* 25(7), pp. 1179–1204.

Miguélez, E., and Moreno, R. 2013. Skilled Labour Mobility, Networks and Knowledge Creation in Regions: A Panel Data Approach. *The Annals of Regional Science,* 51(1), pp. 191–212.

Mina, A., Ramlogan, R., Tampubolon, G., and Metcalfe, J. S. 2007. Mapping Evolutionary Trajectories: Applications to the Growth and Transformation of Medical Knowledge. *Research Policy,* 36(5), pp. 789–806.

Moser, P., and Tom, N. 2004. Was electricity a general purpose technology? *The American Economic Review, Papers and Proceedings*. 94(2), pp. 1–16.

Neal, Z. P. 2010. From Central Places To Network Bases: A Transition In The U.S. Urban Hierarchy, 1900-2000. *City & Community,* 10 (1), pp.49–74.

Nemet, G. F. 2009. Demand-pull, technology-push, and government-led incentives for non-incremental technical change. *Research Policy*, *38*(5), pp. 700-709.

Newman, M. E. 2000. Models of the Small World. *Journal of Statistical Physics,* 101(3-4), pp.819–841.

OECD. 1993. Glossary of Industrial Organization Economics and Competition Law, compiled by, commissioned by the Directorate for Financial, Fiscal and Enterprise Affairs.

OECD. 2009. Directorate for Science, Technology and Industry. *Innovation.*

Owen-Smith, J., and Powell, W.W. 2004. Knowledge Networks as Channels and Conduits: The Effects of Spillovers in the Boston Biotechnology Community. *Organization Science,* 15(1), pp.5–21.

Peeters B., Song X., Callaert J., Grouwels J., Van Looy B. (2009). Harmonizing harmonized patentee names: an exploratory assessment of top patentees. *EUROSTAT working paper and Studies, Luxembourg*

Pezzoni, M., Lissoni, F., and Tarasconi, G. 2014. How to Kill Inventors: Testing the Massacrator© Algorithm for Inventor Disambiguation, *Scientometrics,* 101(1), pp.477–504.

Podolny, J. M., and Stuart, T. E.1996. Local Search and the Evolution of Technological Capabilities. *Strategic Management Journal,*17, pp. 21–38.

Poel, I. Van De. 2003. The Transformation of Technological Regimes. *Research Policy,* 32(1), pp. 49–68.

Ponds, R., Van Oort, F., and Frenken, K. 2010. Innovation, Spillovers and University–Industry Collaboration: an Extended Knowledge Production Function Approach. *Journal of Economic Geography,* 10(2), pp. 231-255.

Popp, D. 2002. Induced Innovation and Energy Prices. *The American Economic Review,* 92(1), pp. 160–180.

Popp, D. 2006. International Innovation and Diffusion of Air Pollution Control Technologies: The Effects of NOX and SO2 Regulation in the US, Japan, and Germany. *Journal of Environmental Economics and Management,* 51(1), pp. 46–71.

Porter, M. E., and Linde, C. Van Der. 1995. Toward a New Conception of the Environment-Competitiveness Relationship. *American Economic Association,* 9(4), pp. 97–118.

Powell, W. W. 1996. Inter-organizational collaboration in the biotechnology industry. *Journal of Institutional and Theoretical Economics* (JITE)/Zeitschrift für die gesamte Staatswissenschaft, pp. 197-215.

Putnam, J., and Evenson, R. E. 1994. Inter-sectoral technology flows: Estimates from a patent concordance with an application to Italy. *Mimeograph*, Yale University, New Haven, CT.

Quatraro, F. 2010. Knowledge Coherence, Variety and Economic Growth: Manufacturing Evidence

From Italian Regions, *Research Policy,* 39(10), pp. 1289-1302.

Ramlogan, R., Mina, A., Tampubolon, G., and Metcalfe, J.S. 2007. Networks of Knowledge: The Distributed Nature of Medical Innovation, *Scientometrics,* 70(2), pp. 459–89.

Reitzig, M. 2003. What determines patent value?: Insights from the semiconductor industry. *Research Policy*, *32*(1), pp. 13-26.

Roach, M., and Cohen, W.M. 2013. Lens or Prism? Patent Citations as a Measure of Knowledge Flows from Public Research. *Management Science*, 59(2), pp. 504–525.

Rosenberg, N. 1994. Medical Device Innovation, *Cepr/Aaas Conference*, Stanford University.

Rosenberg, N., Gelijns, A.C., and Dawkins, H. 1995a. The Changing Nature of Medical Technology Development. *Sources of Medical Technology: Universities And Industry*, NAS.

Rosenberg, N., Gelijns, A.C., and Dawkins, H. 1995b. From the Scalpel to the Scope: Endoscopic Innovations in Gastroenterology, Gynecology and Surgery. *Sources of Medical Technology: Universities and Industry*, NAS.

Rosenberg, N., and Trajtenberg, M. 2001. A General Purpose Technology At Work: The Corliss Steam Engine in the Late 19th Century Us. *National Bureau of Economic Research,* No. W8485

Rosenkopf, L., and Nerkar, A. 2001. Beyond Local Search: Boundary-Spanning, Exploration, and Impact in the Optical Disk Industry. *Strategic Management Journal,* 22(4), pp. 287–306.

Rothwell, R. 1980. The Impact of Regulation on Innovation: Some U.S. Data. *Technological Forecasting and Social Change,* 17(January), pp. 7–34.

Scherer, F.M. 1982. Inter-Industry Technology Flows and Productivity Growth. *The review of economics and statistics*, pp. 627–634.

Schlich, T. 2002. Surgery, science and industry. *Palgrave Macmillan*.

Schmoch, U. (2008) Concept of a technology classification for country comparisons. *Final Report to the World Intellectual Property Office (WIPO*), Karslruhe: Fraunhofer ISI.

Schoenmakers, W., and Duysters, G. 2010. The Technological Origins of Radical Inventions. *Research Policy* 39(8), pp. 1051–59.

Schumpeter J. (1942), "Capitalism, Socialism, and Democracy", Harper, New York

Shane, S. 2001. Technology Regimes and New Firm Formation. *Management Science,* 47(9), pp. 1173–90.

Shin, J., and Park, Y. 2007. Building the national ICT frontier: The case of Korea. *Information Economics and Policy,* 19(2), pp. 249–277.

Singh, J. 2005. Collaborative Networks as Determinants Of Knowledge Diffusion Patterns. *Management Science,* 51(5), pp. 756–770.

Sonn, J. W., and Storper, M. 2003. The Increasing Importance of Geographical Proximity in Technological Innovation. *In Conference: What Do We Know About Innovation*.

Stewart, R. B. 1981. Regulation, Innovation, and Administrative Law : A Conceptual Framework. *California Law Review*, 69(5), pp. 1256–1377.

Strumsky, D., and Lobo, J. 2015. Identifying the Sources of Technological Novelty in the Process of Invention. *Research Policy,* 44(8), pp. 1445–61.

Stuart, T. E., and Podolny, J. M.. 1996. Local Search and the Evolution of Technological Capabilities. *Strategic Management Journal,*17, pp. 21–38.

Storper, M., and Venables, A.J. 2004. Buzz: Face-To-Face Contact and The Urban Economy. *Journal of Economic Geography,* 4(4), pp.351–370.

Swissmedic. 2014. Annual Report, *Bern*.

Tarasconi, G., and Coffano, M. 2014. Patstat Database : Sources, Contents and Access Rules. *Working Paper Series Crios,* no. February.

Tirole, J. 1988. The theory of industrial organization. *MIT press*.

Trajtenberg, M. 1990. A Penny for Your Quotes: Patent Citations and the Value of Innovations. *The RAND Journal of Economics*, 21(1), pp. 172–87.

Trajtenberg, M., Henderson, R., and Jaffe, A. 1997. University Versus Corporate Patents: A Window On The Basicness Of Invention. *Economics of Innovation and New Technology*, 5(1), pp. 19-50.

Ter Wal, A.L.J., and Boschma, R.A. 2009. Applying Social Network Analysis in Economic Geography: Framing Some Key Analytic Issues. *The Annals of Regional Science,* 43, pp.739–756

Uzzi, B. 1997. Social Structure and Competition in Interfirm Networks: The Paradox of Embeddedness. *Administrative Science Quarterly,* 42(1), pp.35–67.

Vanhaverbeke, W., Gilsing, V., Beerkens, B., and Dysters, G. 2009. The Role of Alliance Network Redundancy In The Creation Of Core And Non-Core Technologies. *Journal of Management Studies*, 46(2), pp 215-244.

Verbeek, A., Debackere, K., Luwel, M., and Zimmermann, E. 2002. Measuring progress and evolution in science and technology – I: The multiple uses of bibliometric indicators. *International Journal of management reviews*, 4(2), pp. 179–211.

Verhoeven, D., Bakker, J., and Veugelers, R. 2016. Measuring Technological Novelty with Patent-Based Indicators. *Research Policy,* 45, pp. 707–23.

Vernon, J.A. 2003. Drug research and price controls. *Regulation*, 25(4), pp. 22-25

Verspagen, B. 1997. Measuring Intersectoral Technology Spillovers : Estimates from the European and US Patent Office Databases. *Economic Systems Research,* 9(1), pp. 47–65.

Von Wartburg, I., Teichert, T., and Rost, K. 2005. Inventive progress measured by multi-stage patent citation analysis. *Research Policy,* 34(10), pp. 1591–1607.

Weitzman, M. L. 1998. Recombinant Growth. *The Quarterly Journal of Economics,* 113(2), pp. 331–60.

Youtie, J., Iacopetta, M., and Graham, S. 2008. Assessing The Nature Of Nanotechnology: Can We Uncover An Emerging General Purpose Technology? *Journal Of Technology Transfer,* 33, pp. 315–29.

Yazdandoost, K. Y., Kohno, R. 2007. Wireless communications for body implanted medical device. *In 2007 Asia-Pacific Microwave Conference* pp. 1-4. IEEE.

Winters, J. M., & Wang, Y. (2003). Wearable sensors and tele rehabilitation. *IEEE Engineering in Medicine and Biology Magazine*, 22(3), pp. 56-65.

Wooldridge, J. M. (2015). Introductory econometrics: A modern approach. *Nelson Education.*

Wuchty, S., Jones, B.F., and Uzzi, B. 2007. The Increasing Dominance of Teams in Production of Knowledge. *Science* 316, pp. 1036–1039.

Zucker, L.G., Darby, M.R., and Armstrong, J. 1998. Geographically localized knowledge: spillovers or markets? *Economic Inquiry*, 36(1), pp. 65-86.

Zuniga, P., Guellec, D., Dernis, H., Khan, M., Okazaki, T., and Webb, C. 2009. OECD patent statistics manual. *Francia: OECD Publications.*

Curriculum Vitae

MONICA COFFANO

Home: Route du Bois 8
1024 Ecublens (CH)
Email: monica.coffano@hotmail.com
Phone: (+41) 788976278

RESEARCH INTERESTS

My principal research interest lies in the understanding of the innovation dynamics. I analyze the Medical device sector in Switzerland, with the aim to grasp the forces that lead to the success of the sector. In particular I focus my attention on the economic environment, on the role played by different actors (firms, inventors) in the network and on the policy implications of these connections.

EDUCATION

09.2011 - now	**PhD** in "Economics and Management of Innovation" at Swiss Federal Institute of Technology in Lausanne (EPFL), Lausanne (Switzerland) • Chair of Economics and Management of Innovation (CEMI) • Supervisor: Prof. Dominique Foray
2013	Gerzensee Study center, Gerzensee, Switzerland Swiss Bank Program for Beginning Doctoral Students in Economics
09.2002-01.2009	B.Sc. and M.Sc. in Industrial and Business Engineering at Brescia University Thesis title: "Optimization of time and costs in the organization of shifts of University staff" (Creation of an algorithm based on heuristics techniques)

WORK and RESEARCH EXPERIENCE

2016- now	**Seminar series Organizer** Swiss Federal Institute of Technology in Lausanne (EPFL), Lausanne (Switzerland)
2015 - now	**Start-up funder** 'Authorscout'
2011- now	**Research assistant** Swiss Federal Institute of Technology in Lausanne (EPFL), Lausanne (Switzerland)
09.2014 - 11.2014	**Internship** World Intellectual Property Organization (WIPO), Genève (Switzerland)
01.2010-09.2011	**Research assistant** and **Database manager** for the project "Academic Patenting in Europe", funded by the European Science Foundation at Bocconi University, Milan (Italy)

PUBLICATIONS AND PAPERS

PUBLICATIONS

- Lissoni, F., Coffano, M., Maurino, A., Pezzoni, M., & Tarasconi, G. (2010) 'Ape Inv's "NameGame" Algorithm Challenge: A Guideline For Benchmark Data Analysis & Reporting', http://www.esf-ape-inv.eu/
- Coffano, M., & Tarasconi, G. (2014). "Patstat Kites patent database: history, sources and uses" Kites working paper www.researchgate.net/profile/Gianluca_Tarasconi/publication/261296661_CriosPatstat_Database_Sources_Contents_and_Access_Rules/links/0c960533d2b666c96b000000.pdf
- Coffano, M., & Foray, D. (2014). "The Centrality of Entrepreneurial Discovery in Building and Implementing a Smart Specialisation Strategy", Smart Specialisation and the new EU cohesion policy reform, Regional Science, Vol.13 N°1/2014, Franco Angeli

WORKING PAPERS

- Coffano, M., Foray D., Pezzoni M. (2016) "Does the centrality of specialized inventors foster regional innovation? The case of the Swiss Medical Device Sector" (under review for Regional Studies)
- Coffano, M., Visentin F. (2016) "The effect of Regulation Changes on Innovation: The case of the European Medical Device sector" (under review for Research Policy)
- Coffano M., Foray D. (2016) "How did traditional medical technologies integrate ICT: a new methodological approach" (working paper)

TECHNICAL SKILLS:

- Software: MySql, , Stata, SAS, SAP, R, VBA, Matlab, MPL, Office

COURSES AND CONFERENCES:

Courses attended

- Technology Foresight, EPFL
- Swiss Program for Beginning Doctoral Students in Economics led by the Suisse Central bank (Econometrics) – Gerzensee
- Qualitative research methods, EPFL
- Survey and psychometrics, EPFL
- Microeconomics, EPFL
- Technology & Innovation Management, Eindhoven
- Readings in Organization Economics, EPFL
- Publishing in Management, Technology and Innovation June EPFL

Conferences and schools attended

- June 2016 – Internal Seminar Economics and Statistics department WIPO, Geneve
- January 2016 – DRUID Conference, Bordeaux (France)
- May 2015 – Internal Seminar Economics and Statistics department WIPO, Geneve
- July 2015 – Governance of a Complex World, Nice (France)
- November 2014 – Asia Pacific innovation Conference, Sydney (Australia)
- June 2014 – Governance of a complex world, Turin (Italy)
- September 2013- EPIP conference, Leuven (Belgium)

- June 2013 – I.S.E.O. Summer School, Iseo (Italy)
- December 2012 - Network analysis School-Imperial college London

TEACHING EXPERIENCE

2012 - now	• Teaching assistant for "Economics of Innovation" Prof. Vernet (EPFL) • Teaching assistant for "Entrepreneurship & New Venture Strategy" Prof. Gruber (EPFL) • Teaching assistant for "Information strategy and Economics" Prof. Weber (EPFL)
2009 - 2011	• Conference organizer for the project "Academic Patenting in Europe", funded by the European Science Foundation - Bocconi University • Teaching assistant for "Industrial Economics" (Brescia University)

LANGUAGES:

- Italian: Mother tongue
- English: C2
- French: C1
- German: A2