CrossMark

To Collaborate or Not to Collaborate? A Study of the Value of Innovation from a Sectoral Perspective

Talya Ponchek[1] (ID)

Abstract The purpose of this study is to examine the link between collaboration and innovation. Recent years have witnessed hype over the need for collaborations in the innovation process. A vast literature supports the notion that collaboration leads to more innovations. Less heard claims that collaboration might hinder innovation. This study offers empirical data on the sectoral level for two reasons: scientific research is mostly corporate; the data are collected from the stem cell industry in Israel, in which the research is conducted by research organizations. No inventors work in this field alone due to high costs of research and development (R&D). The focus on this industry provides a unique opportunity to examine the entire population and not make do with just a sample. The data include patent-based indicators of the value of innovations. Regression results support the notion of collaboration as an innovation generator, but also shed light on the nature of knowledge produced by collaborations. Collaborative patents are cited more, and they also encompass more primary and groundbreaking knowledge, as opposed to knowledge embedded in non-collaborative patents. For the first time, this study provides systematic evidence of the innovative value of collaborative patents, and thus tips the scale in favor of those supporting the establishment of collaborations. From a policy perspective, a sound innovation policy should take into account that the innovation ecosystem is organized in the form of Quadruple Helix, but more impotently, that to foster cross-sectoral collaborations, an emphasis must be placed especially on motivating firms to include in their Targeted Open Innovation Strategy, the main strategy employed by firms operating in the Quadruple Helix ecosystem, the initiation of cross-sectoral collaborations. This paper shows the need for a more open innovation ecosystem and calls for further research to assess the targeted partners.

Keywords Innovation · Collaboration · Quadruple Helix framework · Targeted Open Innovation · Patent-based indicators · Forward citations · Regression analysis · Stem cells

✉ Talya Ponchek
talya.ponchek@gmail.com

[1] Haifa Center for Law & Technology (HCLT), Faculty of Law, University of Haifa, 199 Aba Khoushy Ave, Mount Carmel, Haifa 3498838, Israel

Introduction

The philosopher and scientist Michael Polanyi stated that acquiring and discovering knowledge is both a deeply collective and a deeply individual endeavor (Polanyi 1958). This notion describes the two approaches towards the process of generating innovation.

In recent years, much hype is evident in the literature on the establishment of collaborations in order to generate more innovations (e.g., Lee and Bozeman 2005; Sonnenwald 2007). This vast literature somehow obscures other opinions, namely that collaboration hinders innovation, so if more innovation is sought by a research organization it should be done in a silo structure manner (Beyerlein et al. 2006; Lane and Lubatkin 1998; de Man and Duysters 2005).

The link between collaboration and innovation might seem obvious and "off the top of one's head," but the sparse empirical literature on this link focuses on the firm level of analysis, not taking into account the bigger picture of the innovation process and has produced equivocal result (see, e.g., Katila 2000; Wuchty et al. 2007a, b; Jones et al. 2008; Singh and Fleming 2010). Moreover, this literature mainly utilizes paper bibliometrics, but neglects the method of patents bibliometrics (Perkmann and Walsh 2009). Thus, the benefits of collaboration are more often assumed than investigated.

The emphasis on the need to generate innovations stems from an understanding of their vitally important role. Innovation drives economic, employment, and income growth; quality of life improvements; and the competitiveness of nations (Teece 1992; Atkinson and Ezell 2012: 128). Economists have always recognized the central importance of technological innovation for economic growth and welfare (Teece 1992). Adam Smith, Karl Marx, and Joseph Schumpeter explicitly incorporated innovation as a central variable in economic analysis (Cassiolato et al. 2014).[1] Innovation is the engine of the economy, but how is innovation generated?

This paper draws on the notion that the technological impact of a patent can indicate the value of innovation (Trajtenberg 1990). It does so to investigate the controversy, discussed below in Part 2, regarding the place collaboration has in the innovation process, and provides empirical evidence. The data collected and analyzed are from the stem cell industry in Israel. These data are unique as they provide the opportunity to subject an entire industry to the analysis, not only a sample. This is also the first time that the data from stem cell industry in Israel have been subjected to an analysis of patent-based indicators of innovation.

This study's innovative strength lies in the examination of the link between innovation and collaboration on the sectoral level for the first time. The relation among different sectors in the Israeli stem cell industry is analyzed through the lens of Quadruple Helix (QH) theory. Previous literature mainly focused on firms and inter-firm relations.

Part 2 discusses the theoretical background and the hypotheses, more especially recent innovation theories which emphasize collaboration. It reviews the different meanings given to the term collaboration in the literature and proposes a definition of collaboration for the purpose of this study. It presents the debate over how innovation is generated: through collaborative endeavors or by the lone research organization. In Part

---

[1] There is however an on-going debate as to how innovation leads to growth, a discussion that is left outside the scope of this paper.

3, I discuss the data and method on analysis. This part begins with the question of why the data analyzed are collected on the stem cell industry in Israel. It then continues to discuss why QH is the appropriate framework. Lastly, it explains how the data were collected and the method of analysis. Part 4 discusses the results, Part 5 the study's limitations and further research, and Part 6 reviews the highlights of this study and provides concluding remarks.

Theoretical Background and Hypotheses

The Collaborative Nature of the Innovation Process

A stream of theories, starting in the 1960s and still emerging, aim at explaining the innovation process. The following discussions do not aim to present a comprehensive review of all innovation theories, but those within which this study is situated. Early signs of the emphasis collaboration have gained in innovation theories were visible in the later work of Joseph Schumpeter. The shift in his views, from what is known as Mark I to Mark II, can be understood as representing the realization of the place of teamwork and collaboration in the innovation process. Schumpeter mark, I refers to his early writings describing the innovation process as being carried out by an individual entrepreneur, from invention to innovation, and into the market (Schumpeter 1934). In later writings however Schumpeter (1942) claims that large companies are the major source of innovation. This view of Schumpeter is often understood as referring to some sort of collaboration, since the shift in his view is associated with his understanding that the market is moving toward larger industrial units. That is, research becomes corporate, but is also able to adapt to changing environments, especially the increasing intervention of the public sector in research life, i.e., a growing need to interact with the public sector (Westeren 2012).

The concept of cross-organizational collaboration was first introduced to innovation theories during the 1990s with economists' understanding that the complexity of innovation requires interactions in the organization itself (among its units), but also collaboration with other organizations. The emergence of the notion of Systems of Innovation (SI) (Edquist 1997) marked the realization that innovation did not take place in isolation but in collaboration and interdependence with other organizations. SI focused on the firm's role in the innovation process and the need of firms lacking resources to develop an in-house innovation to establish collaborations with other organizations (Marinova and Phillimore 2003: 47). These organizations may be other firms (suppliers, customers, etc.) or non-firms (universities, government ministries, etc.). The most well-known SI model is the National System of Innovation (NSI) (for a comprehensive review of this theory, see Freeman 1987; Lundvall 1992; Nelson 1993). The concept of SI is not confined to the national level. It can also be applied worldwide (Spencer 2003), to regions (Asheim and Gertle 2005: 291; Marinova and Phillimore 2003: 50–1), sectors (Pavitt 1984), and technologies (Metcalfe 1995).

Alongside, the SI model another model explaining the innovation process has emerged. The Triple Helix (TH) was introduced by Etzkowitz and Leydesdorff (Leydesdorff and Etzkowitz 1998, 2001; Etzkowitz and Leydesdorff 2000). According to this model, university plays an enhanced role in the innovation process in the knowledge-based economy. It deems innovation dependent on collaborations

between the public, private, and academic spheres to create new knowledge to drive the innovation process (Etzkowitz 2003: 295–96; Etzkowitz and Leydesdorff 2000: 111–12; Boland et al. 2012: 16). This model was the basis on which the concept of the entrepreneurial university has emerged. As a side note, TH model is viewed as a natural development of Mode 1 and Mode 2 theories (Gibbons et al. 1994). While some say that Mode 2 overlaps with the concept of entrepreneurial university (Carayannis and Campbell 2012), I view Mode 3 as closely related and very similar to the TH model, as I read TH as being flexible enough to include a wide interpretation of the term "university" as Carayannis and Campbell (2012) read into Mode 3.

I view TH as a complementary framework to SI theory, as it adds to it, or more precisely, to NSI theory by explaining or describing the dynamics between the variety of the institutional arrangements and policy models that are part of the NSI (Etzkowitz and Leydesdorff 2000: 109). In other words, I see TH theory as an elaborate explanation of the interactions between some of the organizations and institutions in NSI's "grand scheme." This view is reaffirmed by Ranga and Etzkowitz's new concept of "Triple Helix Systems" (THS) (Ranga and Etzkowitz 2013). Whether one views SI as an analytical framework different from TH, or as two complementary frameworks, one must recognize the emphasis these frameworks place on collaboration. They are a stepping-stone for innovation scholars toward understanding the place of collaboration in the innovation process.

But before the THS approach has emerged, a hot topic of debates between scholars was the introduction of additional dimensions to the TH theory, as Ivanova (2014) summarizes eloquently: "[T]he very word 'triple' invites for further generalization and implies that there also may be quadruple, quintuple and other kinds of helixes." The question though of whether the co-founders of TH theory Leydesdorff and Etzkowitz agree with the need to add more dimensions to the TH model is left outside the scope of this discussion (for a comprehensive summary of the debate between Leydesdorff and Carayannis and Cambell, see Ivanova 2014).

Quadruple Helix (QH) emerged as an answer to the understanding that TH or SI theories do not address the multilevelness of the GloCal (global/local) knowledge economy and society (Carayannis and Campbell 2012). The literature also discusses Quintuple Helix, which view the fifth pillar to be the environment or natural environments (Carayannis and Rakhmatullin 2014). However, bearing in mind the exemplary case here, QH is better suited theory to frame the analysis, as I further discuss in Section "Industry Setting" below. For this reason, I do not further develop the discussion here to include the Quintuple Helix as well.

It has been argued that TH theory does not take into account all the needed conditions for long-term growth (Colapinto and Porlezza 2012). QH seeks to include, not only top-down policies, as in TH, but also bottoms-up initiatives (Carayannis 2013) (This shift is actually already embodied into Mode 3 theory, see Carayannis and Campbell 2009). Though SI theory addresses different levels of the knowledge economy, the boundaries these levels create however do not represent accurately how innovation is produced in the GloCal knowledge economy and society (e.g., Ranga and Etzkowitz 2013). The appropriate theory would be a somewhat convergence of the two, as explained by Colapinto and Porlezza (2012: 347–49). Indeed, the co-founders of QH theory Carayannis and Campbell (2009) do refer to it as "the Quadruple Helix Innovation System theory" (Carayannis and Campbell 2014). But it is not merely the

name that signifies this convergence, as Arnkil et al. (2010: 17, 65) explain, QH is a very wide and multidimensional concept referring to numerous different activities and actors. It seems that it is more reasonable to consider QH as a continuum or even as a space rather than as a single model. Similarly, Ranga and Etzkowitz's (2013) THS model is based on boundaries between spheres, yet this model is more limited in capacity. This multidimensional attributes of QH explains the concept of the Twenty-first Century Fractal Research, Education and Innovation Ecosystem (FREIE) (Carayannis and Campbell 2009: 222–23; 2012: 10–2) where people, culture, and technology (the building blocks) "meet and interact to catalyze creativity, trigger invention, and accelerate innovation across scientific and technological disciplines, public and private sectors (government, university, industry, and nongovernmental knowledge production, utilization, and renewal entities as well as other civil society entities, institutions, and stakeholders), in a top-down, policy driven as well as bottom-up, entrepreneurship-empowered fashion" (Carayannis and Campbell 2009: 222–23; 2011: 330; 2012: 11–2).

QH is also the result of the need for additional categories of actors, then those included in the TH model. However, there are different views as to what the fourth pillar entails (Carayannis and Rakhmatullin 2014: 218). The "classic" view of the fourth pillar is the "public", more specifically defined as the "media-based and culture-based public" and "civil society" (Carayannis and Campbell 2009: 218; 2014: 14). Others have referred to the fourth pillar as: "intermediate organizations" or "innovation-enabler organizations," which act as brokers and networkers between the TH organizations (Liljemark 2004); "independent, non-profit, member-based organizations," which have the important task of translation and coordination, in the emerging fields of knowledge between the four helices (Delman and Madsen 2007); the "user" (Yawson 2009); and the "public" (Arnkil et al. 2010: 15, explaining that this interpretation is very close to Yawson's suggestion). The "user" interpretation is also supported by the "user-driven innovation" strategy as an essential factor of success for both firms and public sector organizations (Lundvall et al. 2002; Thomke and von Hippel 2002).

Alongside the theories of SI and TH, and their derivatives, a new paradigm has emerged during the early years of the twenty-first century. Open Innovation is understood as the antithesis of the traditional vertical integration model, also known as the "closed model of innovation" (Chesbrough 2006; Vanhaverbeke 2006). While these theories are operated by policymakers, Open Innovation is operated by the firm itself. It is a strategic decision of a firm to incorporate into its business model access to external sources of innovations (West 2006) through establishing ties with other organizations (Vanhaverbeke 2006). The rational according to Chesbrough (2006) is that research and development (R&D) is viewed as a more open system. Valuable ideas can come from inside and outside the firm and can enter the market from inside or outside the firm as well (Chesbrough 2006). Open innovation strategies are implemented by the firm as it operates in a QH ecosystem (Arnkil et al. 2010: 15). Today, we witness a shift from Open Innovation, in the sense of innovation from any source, and away from the blind belief in "the wisdom of the crowd" as it is unclear if this practice has an actual added value, towards Targeted Open Innovation (TOI) aligned with strategy driven by community and by a desire to build relationships and loyalty (Eagar et al. 2011: 24).

In the 10 years that passed since the emergence of Open Innovation, a new paradigm has emerged—Open Innovation 2.0 (OI2). OI2 is a new paradigm based on principles

of integrated collaboration, co-created shared value, cultivated innovation ecosystems, unleashed exponential technologies, and extraordinarily rapid adoption (Curley and Salmelin 2013: 2). You can say that OI2 strategy embodies the QH as this model place more emphasis on collaboration in innovation (Carayannis and Rakhmatullin 2014: 218). In today's complex scientific environment, R&D simply cannot be conducted in isolation. Collaborative research accelerates the innovative process and improves the quality of its outcomes (Curley and Salmelin 2013: 2). The key concept of QI2 is the involvement of all stakeholders into a collaborative, co-creative culture (Salmelin 2013: 9, discussing the H2020 program as an example of QI2 paradigm). The relevance of the discussion of QI2 to this study is an example of an approach implementing the QH model where government, firms, universities, and civil participants work together to co-create the future and drive structural changes far beyond the scope of what any one organization or person could do alone (Curley and Salmelin 2013: 5). Having said that, Carayannis (2013) holds the opinion that current ecosystem has not yet completed the transition into OI2, and the dominant paradigm is still TOI.

Making Sense of "Collaboration"

Collaboration is an intricate term, with many definitions and similar terms that are used interchangeably by diverse scholars in different disciplines and in a variety of contexts.

In the literature, collaboration is often referred to as "alliance," "cooperation," "coalition," "coordination," "network," "joint venture," "clusters," "consortium," and "public-private partnership (PPP)."[2] As if the long list of these coincident terms is not enough, collaboration also entails a vast range of activities. The activities it refers to differ according to the term used to describe the relationship. That said, there are those who view collaboration as the final and most complex process on a continuum made up of the above synonyms (Himmelman 1996: 22).

Collaboration may take place at each and every stage of the production chain, from research and development, through manufacturing and ending with marketing (Dodgson 1993: 10), and it has many forms: infrastructural, formal (or contractual), and informal (Dodgson 1993: 11). Infrastructural collaborations are forms embedded in national technology and innovation systems, and are created especially to support that system, for example, public policy support for the creation of PPP or public-private consortia. Formal and informal forms of collaborations are relationships in the industry (also known as the private sector). They differ in the existence, or lack, of an agreement or contract that governs the relationship. The existence of a contract is typical to forms of collaboration whereas equity is shared, such as a joint venture, but also of collaborations based on continued commitment to shared objectives without equity sharing, commonly known as strategic alliance. Informal forms of collaborations are very important to the innovation process in that they are between peers. This form of collaboration describes the informal knowhow trading between peers (Von Hippel 1988), which involves routine and informal trading of proprietary information (Von Hippel 1988: 6). This knowledge belongs to individuals in research organizations and

---

[2] Though this long list of terms is brought here as of one piece, you can roughly divide them to two main groups: normative vs. descriptive (for a comprehensive discussion of this and further explanation of the differences, see Ponchek, forthcoming 2016).

cannot be easily transferred across because the organizational boundaries serve as "knowledge envelopes" (Kim and Song 2007: 462).

The full range and scope of collaboration are too broad for comprehensive consideration in this paper. The definition I use for the present purposes is *any activity that leads to joint R&D that ends with at least a patent application*. It may be performed by two or more partners contributing resources and knowhow. This definition is wide enough to include privately created and publicly promoted interactions. These include outputs of (1) collaborative research programs or consortia; (2) joint ventures and strategic alliances; (3) shared R&D production contracts. However, it does not cover licensing agreements and one-way knowledge transfers, such as technology acquisition.

The Equivocal Nature of Innovation: Collaboration vs. Silo Structure

The reasons for entering into and the benefits from collaboration are well described and discussed in the literature. There are however several main reasons worth mentioning even if only in a nutshell. There are situations in which working alone is not sufficient to achieve the desired ends (Cropper 1996; Galison 1992). These situations include scientific research in fields in which the research is more complex and requires more specialized knowledge—more than any single individual or research organization may be expected to possess (Lee and Bozeman 2005; Hara et al. 2003). In the last few decades, it has become increasingly recognized that no one scientist or research organization can themselves do most of the scientific R&D, given the increasing scientific and technological complexities (Weinberg 1961; Galison 1992; Bubela et al. 2010: 26). This situation is part of what the literature terms as "value gained" motivation to enter collaboration (Huxham 1996b: 3). Under this motivation, we also find joint funding. The value gained here is of course financial. But it also entails value gained by granting access to additional or hitherto unavailable expertise, prior knowledge, scarce biological materials, expensive research tools, and other capabilities needed to compete in changing markets, etc. (Katz and Martin 1997; Sonnenwald 2007; Munos 2009). An individual scientist can seldom provide all the expertise and resources necessary to address complex research problems (Hara et al. 2003: 952; Katz and Martin 1997: 9). Certain fields of research, traditionally considered independent, are now becoming more collaborative because of these circumstances (for example, Munos (2009) indicates that even pharmaceutical companies that traditionally held inter-based R&D activities now recognize that new drugs will only be developed through innovative partnership with public research institutions and biotechnology companies). This is in a sense the other side of the coin, that is, of the complexity of scientific research, which dictates the need for highly specialized expertise. Multidisciplinary collaborations provide the knowledge, skills, and abilities required for the advancement of science (Hara et al. 2003: 953). In summary, the more science-based and complex the research is, the more collaboration is required (Hagedoorn 2002). Another important motivation is cost-cutting or efficiency (Huxham 1996b: 3). Through collaboration, duplication of efforts can be avoided, but also it leads to better utilization of resources. Collaboration prevents scientists from investing resources only to find out that the technology they have been working on vigorously already exists, developed by another research group (Sørensen 2006).

From a sociological perspective, collaboration to some degree inheres in the scientific process. Scientific research is shaped by social norms of practice. One central element of these norms is openness and data sharing (Rai 1999; Winickoff et al. 2009: 55). Traditionally, science is perceived as the outcome of collaboration and data sharing between researchers (Kuhn 1961; joint publications and scientific conferences for example are forms of traditional data sharing, see Winickoff et al. 2009: 61), which are considered the hallmark of modern scientific practice (Birnholtz and Bietz 2003: 339–40, albeit stating that despite its importance data sharing is not easy). Some will go even farther, saying that collaboration is a tool of science (Hara et al. 2003: 953).

Collaboration is also consistent with the cumulative nature of science (Rai 1999: 90). Openness and data sharing through collaborations lead to transparency. Transparency enables scientists to advance science (Bok 1982: 32). Science is built layer upon layer, hence transparency grants scientists access to previous knowledge, on which the new layer is built.

Most studies of collaboration assume that it leads to more innovations (Lee and Bozeman 2005: 673). As discussed above, there is good reason to think that collaboration may enhance innovation through the exchange of knowledge, biological materials, expertise, research tools, and other capabilities (Sonnenwald 2007). Despite the ubiquitous nature of collaboration, its benefits are more often assumed than investigated. However, there is limited empirical evidence to support this standpoint. Its focus is mainly on teamwork within an organization (Wuchty et al. 2007a, b; Jones et al. 2008; Singh and Fleming 2010).

Empirical literature on the need for collaboration in the innovation process is limited. To date, no attempt has been made to examine the connection among collaboration, type of collaboration, and innovation on the industry level. In short, the literature includes the following studies: Singh and Fleming (2010) examine if the lone inventor is less likely to invent breakthroughs and more likely to invent failures. Today most of the work is conducted in research teams affiliated to a certain research organization (Salzberger 2011). In order to promote social benefit and scientific progress, collaboration and data sharing between research organizations from the same sector and/or from different sectors must be strived. Providing evidence that the lone inventor is less likely to reach breakthroughs is in a way stating the obvious. If one research organization can no longer perform R&D by itself, what is then the surprise that the lone inventor, without any institutional affiliation or support is the most disadvantaged in terms of innovation? Wuchty et al. (2007a, b) and Jones et al. (2008) analyzed vast number of research articles and patent records to construct what they refer to as the relative team impact (RTI). Their analysis led them to the conclusion, with regard to both articles and patents, that there is a broad tendency for teams to produce more highly cited work than individual authors. Again, the focus is on the inventor/researcher level. Katila (2000) analyzes forward citations to determine whether collaborations between firms lead to radical (breakthrough) innovations as oppose to incremental. Her paper is limited only to the examination of firms' innovative practices and lacks the "big picture view" that is suggested by QH.

> *Hypothesis 1a: Inter-sector collaborations signify innovations of higher value than intra-sector collaboration because each sector brings to the collaboration different skills, resources, and knowledge, in contrast to same-sector research organizations.*

Though most of the literature on collaboration holds that it leads to more innovations, other opinions are apparent. Different systems of knowledge production, different organizational culture, high administrative cost, or different aims may cause friction between partners and hinder the innovation process (Lane and Lubatkin 1998; Beyerlein et al. 2006; de Man and Duysters 2005). Even where the aims are joint, the tension between autonomy and accountability and lack of authority structure may rise and slow down the joint activity (Huxham 1996b). These factors often lead to a situation that Huxham (1996a) calls "collaborative inertia." This term describes the situation where the apparent rate of work output from collaboration is considerably slowed down in comparison with what the casual observer might expect it to be able to achieve (Huxham and Vangen 1994; Huxham 1996a). Other reasons may be that the partners in the collaboration are often competitors. Fear of helping a competitor to develop a new technology may cause a slowdown of the joint work (de Man and Duysters 2005). Empirical evidence to support this notion almost does not exist. Katila's research is an example of such a "white unicorn" (Katila 2000).

Some collaborative activities do not just slow down but come to a complete halt (de Man and Duysters 2005). Mishkin (1995) lists problems arising from the dissolution of collaborative teamwork while the work is still ongoing. Some escalate to the point of litigation. Though the discussion is about team work, it gives a taste of the magnitude of the problems caused by the dissolution of collaborative R&D conducted by several organizations.

Indicators of the Value of Innovations

A patent provides its owner an exclusive right to exploit the protected invention (i.e., to use, manufacture, sell, import, and export) and prohibits others from doing the same. An invention, be it a product or a process in any field of technology, which is new and useful, has industrial application and involves an inventive step, is a patentable invention (while this is the latter of the Israeli Patents Law, 5727–1967, similar provision is included in patents laws across the world). A patent is also a document containing immense information on the technology behind the invention, the inventor, the owner (if different from the inventor), references to previous knowledge (also known as "prior art"), the inventive step, and so on. The patent document then provides us with information on the scientific advancement and economic value of the invention (Nagaoka et al. 2010). Another advantage of patent data is that they are easily accessible at a relatively low cost (OECD 2009: 13; Czarnitzki et al. 2011: 5).

When filing a patent application, the applicant must include all relevant prior art as references (Lanjouw and Schankerman 2004: 446). Patent references are citations to previous relevant technology protected by or described in other patents, filed anywhere in the world, at any time, in any language (OECD 2009: 107). Prior art can be both patent references and non-patent references (NPRs). NPRs include a variety of documents, such as journal articles, conference papers, technical papers, text books, technical bulletins, technical manuals, abstracting services, database guides, standards descriptions, etc. (Guan and Heb 2007: 407; OECD 2009: 107). The legal purpose of patent references is to indicate which parts of the described knowledge are claimed in the patent, and which should be excluded from the scope of protection because they have been claimed by preceding patents (Criscuolo et al. 2005: 422). Granting a patent

is a legal statement that the idea embodied in the patent makes a novel and useful contribution over and above the previous state of knowledge, as represented by the citations. So, in principle, a citation of Patent X by Patent Y means that X represents a piece of previously existing knowledge upon which Y is built (Jaffe et al. 1993). The citations link, or pair, one patent to another, thereby providing a track of knowledge stream, linking the production of one innovation to the earlier one (Huang and Murray 2009). This linkage bears information about the innovative value of each of the patents (Czarnitzki et al. 2011: 11).

Patent indicators have drawbacks as well, which is why they must be used and interpreted with caution. First, not all inventions are patented. This may be due to firm's preference to protect the knowledge as a trade secret (for example, to gain market dominance, a practice that may differ among industries) or because subject matter is not patentable. Secondly, the value distribution of patents is skewed, as a few have very high technical and economic value whereas many are ultimately never used (OECD 2009: 13–14). Thirdly, patent data are complex due to various factors: the patent offices are diverse and their requirements vary. For example, the requirement to include a full list of prior art known or believed to be relevant leads to differences in citation intensities. This raises concerns as to the true impact for which citations are used as a proxy (OECD 2009: 107–108, 110). Lastly, the number of citations received by any given patent is truncated because only the citations received to date are known. Patents of different age are subject to differing degrees of truncation. There has been less time to cite more recent patents (OECD 2009: 112).

With regard to forward citations (the number of citations a patent application receives in subsequent patent applications), two main arguments to support their validity as indicators of the value of innovation have been presented by the OECD (2009). First, they indicate the existence of downstream research efforts, suggesting that money is being invested in the development of the technology; hence, there is a potential market (commercialization of the invention). Secondly, the fact that a given patent has been cited by subsequent patent applications suggests that it has been used by patent examiners to limit the scope of the monopoly claimed by a subsequent patentee, to the benefit of society. In this sense, forward citations were found to be strongly associated with the economic (Harhoff et al. 1999) and the social (Trajtenberg 1990) value of the patented invention. In short, forward citations are related most directly to the measurement of the value of innovation (Trajtenberg 1990; Archibugi and Planta 1996; Lanjouw and Schankerman 2004; Guan and Heb 2007). For this reason, forward citations are deemed the most prominent and frequently used value indicator (OECD 2009: 138).

> *Hypothesis 1b: Collaborative patented inventions receive on average more forward citations than non-collaborative patented inventions. Higher number of forward citations denotes higher value of innovations.*

Citations received soon after the filing of the patent application suggest rapid recognition of the importance of the invention as well as the presence of others working in a similar area, which is a valuable technological field (Lanjouw and Schankerman 2004: 448).

> *Hypothesis 2: Collaborative patented inventions enter the "market of citations" sooner than non-collaborative patented inventions, meaning that on average their*

citation lag, the time elapsed between the first publication of the application and the first citation, is shorter.

Patent citations are consistent with the view of innovation as a cumulative process (Trajtenberg 1990: 173; Goto and Motohashi 2007: 1441). Forward citations over a long period of time indicate an innovation that has contributed to future research (Lanjouw and Schankerman 2004: 448).

Hypothesis 3: Collaborative patented inventions are cited more during their life span than non-collaborative patented inventions.

The use of patent forward citations as a proxy for the value of innovation raises questions as to the identity of the citing party. Some scientists choose to cite certain patents because of a personal relationship or previous acquaintanceship, not because of their significance. The concern is that these citations might distort the results (Jaffe et al. 1993: 583). Unlike citations in academic papers, patent citation has a meaning that exceeds all the niceties the applicant might feel obligated to. Prior art defines the scope of protection sought. Prior art defines what is new in the invention, and protection is thus given to that part alone. For this reason, it seems unlikely that a citations inflation of that sort may occur.

Hypothesis 4: The innovation levels of patents are not influenced by the inclusion of self- and co-citations in the total number of forward citations. The coefficients are expected to be similar in size and direction.

Apart from forward citations, other indicators of the value of innovation are discussed in the literature. This list of indicators is by no mean exhaustive. I only discuss indicators that are relevant to data at hand. The family size innovation indicator was proposed by Putnam (1997). Generally speaking, a patent family is a group of patents which, like the members of a family, are all related to each other by way of the priority of a particular patent document (Nomaler and Verspagen 2008). Applying for protection in each country is costly. For this reason, some see a family's size as a proxy of innovativeness (Lanjouw and Schankerman 2004: 448). Backward citations are patent references included in the application as prior art. The smaller the number of backward citations, the more innovative the patent is since it relays less on prior art (Nomaler and Verspagen 2008). Large numbers of citations to others (backward) also suggests that the particular innovation is likely to be more derivative in nature (Lanjouw and Schankerman 2001: 134).

Hypothesis 5: Backward citations and family size serve as indicators of the value of innovation. The analysis results in similar coefficients, direction- and size-wise.

Data and Method

Industry Setting

The stem cell industry in Israel served as the setting for testing the hypotheses. This is an appropriate setting for several reasons. First, it is a relatively small industry, which

allowed us to examine the entire population and not subject ourselves to conclusions based on a sample (here the population is patents, as they serve as the evaluation tool). Secondly, despite the understanding that to advance innovations, there is a need to bring together scientists from different research organizations and to forge cross-disciplinary and cross-sector collaborations (Katz and Martin 1997), no real attempt has been made so far to examine the link between collaboration and innovation on the sectoral level. This industry's small size allowed us to analyze it through the lens of QH using patent indicators for the first time. Stem cell research in Israel is conducted by several sectors: universities, firms, medical centers, and public research institutes (here defined as research institutes supported by the government, but are neither a medical center nor a university per se; for example, a veterinarian teaching hospital supported at least partly by the government). The bottom line is that research is corporate. Unlike other research fields or industries where a sole inventor can conduct research on her own, here the high costs of research, be they for the biological materials or the advanced equipment, make it necessary to conduct research in under the "umbrella" of a research organization. This fact dictates that the analysis unit is the sector. An important trait of the Israeli stem cell research is that no products are currently being marketed to customers, and there is still some uncertainty regarding the viability of research outputs. I do not take into account all sorts of cosmetics products which are at best their efficiency has not yet been determined, and in any event are not part of the scope of this paper. The most advanced studies in this field are only at the clinical trial stage. In this case, patents constitute a good indicator since the innovation process does not end with the diffusion of a product into the market (Lundvall 2007) but with the generation of inventions. In addition, as also emerges from the previous point, since intellectual property protection plays a relevant role in the stem cell industry in Israel (Elkin Koren et al. 2013), patents function as appropriate proxies to capture the value of innovations. For example, scientists from public research institutes in the stem cell industry in Israel are cited stating that firms do not establish collaboration with the perspective partner without being certain that its knowledge is well protected. Patents provide just that, even though they are not the only mechanism available, though the use of trade secret to protect invention in the stem cell field is scarce (Elkin Koren et al. 2013).

I suggest that the framework for the analysis of the stem cell industry in Israel is QH. The government pillar (the third pillar) is represented by the legal regime, the Patents Law, and the Report of the Bioethics Committee of the National Israeli Science Academy (2001). These make stem cell research possible in Israel and are largely responsible for the leading position the country has attained in the global arena of stem cell research. It is also represented by several governmental initiatives to foster cross-sectoral collaboration which were initiated over the years. The Office of the Chief Scientist of the Ministry of Industry, Trade and Labour has initiated MAGNET Program in 1994 which sponsors innovative generic industry-oriented technologies to strengthen Israel's technological expertise and enhance competitiveness through academia-industry collaborations. Several programs operate under MAGNET; the main program is the clusters. Clusters program aims to initiate collaborations between firms and academic and public research institutions on the basis of a shared vision, identification of technologies that could provide a competitive advantage and their application, and the division of labour among the partners. In the stem cell, field operated the "Genesis" cluster during the years 2003–2009.

However, since the ending of the latest initiative in 2009, the government has made no further real effort to promote collaboration. The fourth pillar here is the organizations, other than firms and universities, involved in the research. The fourth pillar however can also refer to the its most classic attribute—the entrepreneur. As I explain in Section "Data Collection," the identity of the inventors (the entrepreneurs) was also taken into account while conducting the analysis. Notwithstanding, since science in this industry is corporate, the analysis here is from a sectoral point of view. This still in accordance with the QH analysis as the main actors are organizations. From a broader perspective of the forth pillar as civil society, it can be argued (as do Arnkil et al. 2010: 14) that as stem cell research is a scientific field, scientific paradigms are granted their legitimacy through the scrutiny of the relevant scientific community (Kuhn 1961; Winickoff et al. 2009: 55; considering the accuracy, quality, and meaning of the results, Deb. Beaver 2001: 370)—a wide interpretation of civil society.

Furthermore, since QH model is a multilevel system which includes SSI framework (as well as RSI, but not NSI as it does not sit with the GloCal notion), I provide here a short explanation as to how stem cell industry in Israel also sits with the SSI framework. According to Malerba (2005), SSI focuses on three main dimensions (also Malerba 2004): *(a) Knowledge and technological domain*. Stem cell research is characterized by a specific knowledge base that dictates the way the analysis is conducted; (b) *Actors and networks*. Stem cell research is categorized by its heterogeneous actors. The research is corporate. There are no lone inventors working in this field due to the high costs of research and the need for biological materials. In a sectoral system framework, innovation is considered to be a process that involves broad collaborative activities (Malerba 2005: 385). The definition of collaboration in this study therefore meets this requirement; (c) *Institutions*. As discussed before stem cell industry in Israel is shaped by the Patents Law and the Report of the Bioethics Committee of the National Israeli Science Academy (2001) alongside several governmental initiatives. We see that even from this sense, QH is the suitable framework for this study.

Data Collection

The data are 1016 "Israeli" patent families. The focus of this study was the Israeli industry and its unique traits so the search was limited to inventors and/or assignees with an address in Israel. A patent family is a group of patents which, like the members of a family, are all related by way of the priority of a particular patent document, i.e., first patent application (Nomaler and Verspagen 2008: 345). The families include both registered patents and patent applications, as the database used cannot separate the two. The construction of the data in families overcomes the problem of equivalents. Citations for a patent can vary. A given invention can be covered by a number of documents issued by different offices (e.g., OECD 2009: 109). A group of patent equivalents make up a patent family. This may lead to underestimation of citation counts because each equivalent is cited by different patent, that is, the citations of a given invention are spread across the different versions of a patent family, which may result in these different citations not being taken into account in the analysis (OECD 2009: 109–111).

The data were collected by first mapping the actors in this industry in Israel. A list of all Israeli research organizations and scientists was created. A search was then conducted using PatBase. The list was uploaded to PatBase as assignees. The quest was

circumscribed by the search for the key words "stem cell(s)" in the title, abstract, and claims of the patents in the database. Sometimes, Israeli research organizations emerged that were missing from our initial mapping. If such an organization was indeed active in stem cell research in Israel, it was added to the list and further search for its stem cell-related patents was conducted. Secondly, key-words search was repeated, now limited to the relevant classes. When the search discovered research organizations missing from the initial mapping, they were further investigated and a patent search was conducted.

The search produced data of 1047 patent families. A rigorous and manual clean-up of the data were needed. Because this study is focused on sectors, over 3000 institutional assignees had to be identified. However, on account of this paper's definition of collaboration, almost 4000 inventors and their institutional affiliation had to be identified too (for a discussion of similar methodologies see Nagaoka et al. 2010: 1099; Lechevalier et al. 2011: 310–311). Each of the (affiliated) inventors, institutional assignees, and private assignees (a small number of the assignees are inventors who appear in the patent/application documentation also as the assignees, an honor usually saved for "star scientists") were ascribed to one of the four sectors operating in the Israeli stem cell industry. The identification process was far from perfect due to the need to identify foreign assignees as well (For more on the general difficulties of the clean-up process see OECD 2009: 97–98). Identification was accomplished by means of Lexis Nexis Academic, which enables retrieval of information on firms, and by an Internet search for information not available via Lexis. This search was not free of errors. Another problem besetting identification of the assignees was incomplete information or numerous spelling mistakes in the patent document. For this reason, inventors' and assignees' names had to be normalized, namely during the identification process their names were manually corrected to ensure that a patent was assigned to its rightful owner and inventors. To ensure that the analysis adhered to the definition of collaboration proposed in this study, patents owned by an international institution, but whose inventors belonged to an Israeli university, were carefully scrutinized. In my quest for further information on the relationship, if I found that a patent represented an acquisition of the technology or licensed technology it was removed from the data. Furthermore, when additional research revealed that with regard to two firms-patentees of a patents, if at some time one firm has acquired or merged with the other the other, a patent that had both registered firms as patentees, but the decisive date was earlier than the transaction date, was deemed solely owned. This process of course was not error-free, but great effort was invested in ensuring that collaborative patents in the data concurred with the definition of collaboration. At the end of the clean-up process, the data contained 1016 patent families.

For convenience, and unless otherwise mentioned, I use the term "patents" as an overall name for both registered patents and patent applications, and instead of the term patent families. For every patent family in the data, information was also collected on its "age," the "birth date" being determined as the date it was first published (known as earliest publication date). The patent families were first published between January 1977 and March 2013. Further information was gathered on the number of the cited patents of each of the families. The information gathered is updated for the period up to June 2013.

The data are classified into three categories: non-collaborative patents, patents representing intra-sector collaborations (e.g., university-university), and inter-sector collaborations (e.g., university-firm). Hereinafter, I refer to these categorize as the *patent type*. Table 1 shows the number of patents assigned to each group and their percentage in the data.

Table 1 Summary of number and percentage of patents by patent type

Total number of patents	No collaborations	Intra-sector collaborations	Inter-sector collaborations
1016	713	70	233
100 %	70 %	7 %	23 %

Out of 1016 patents, 70 % or 713 are non-collaborative. They are owned by one research organization; 233 patents represent inter-sector collaboration; they are 23 % of the data. A small number of patents, 70, which are only 7 % of the data, represent intra-sector collaborations.

Measures

Independent Variables

no_collab	Patents resulting from R&D conducted by one research organization.
intra_collab	Patents resulting from joint R&D activity between research institutions from the same sector.
inter_collab	Patents resulting from joint R&D activity between research organizations from the different sectors.

In the model, the patent type is represented by three dummy variables. However, due to the "dummy variable trap" the constant (_cons) represents the non-collaborative patents (which is also the intercept β_0). In regression analysis, we should always include one less dummy variable in the model, otherwise we introduce multicollinearity into the model. The dummy variable trap transpires in the case of perfect multicollinearity. If we include all dummy variables, they exhaust the set of possible categories, so the sum of these dummy variables is always 1 for each observation in the regression data set. The presence of a constant which receives the value of 1, no matter which dummy variable is spotted in the observation, leads to multicollinearity between the constant and dummy variables for each observation. To solve this, we drop one of the dummy variables. Then the sum of variables will no longer equal one for every observation in the data. In our case, Stata omitted the *no_collab* variable. It does not matter which one you drop. Stata does so automatically. However, changing the "default" category does change the coefficients, since, as discussed below, all dummy variables are measured relative to this "default" reference category. The rest of the dummy variables effects are measured relative to the missing dummy variable, which effectively is now picked up by the constant term. The coefficients of variables should be read in comparison with the constant coefficient, as it serves as a "base line."

Dependent Variables

NUMFCT	Number of forward citation each of the patent family received.
new_NUMFCT	Number of forward citations minus number of citations by patents owned by one of the partners (either the owner of cited patent and/or its partner).

| NUMBCT | Number of backwards citations, meaning those cited as prior art by the patent family. |
| fam_size | Size of patent family, namely the number of countries wherein protection is sought. |

Controls

| age_year | The age of the patent family in years, calculated from first publication. |
| citation_lag | The time in years elapsed since first publication of the patent family until first cited (by citing patent's first publication date). |

Robustness Check

| collab | Represents collaborative patents in general. Includes both inter-sector and intra-sector types of patents. |
| NUMFCT5 | To make sure truncation effect does not create bias in the results, the number of forward citations is limited to 5 years after publication of the cited patent. |

Findings and Discussion

To examine the hypotheses, I employed the Ordinary Least Squares (OLS) method, with fixed robustness standard deviation (Appendix A), using the data analysis and statistical software Stata 12.1.

Table 2 summarizes the descriptive statistics of the variables. Note the wide variation of the data.

The method of OLS assumes the following linear relationship between the variables:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \ldots + \beta_k x_{ki} + u_i \qquad (1)$$

y_i represents the estimated values of forward citations. The other side of the equation shows the explanatory variables. Tables 3 and 4 present the results of the hypotheses testing.

In specification (1) intra-sector collaborations generate an expected mean of 11 forward citations more than non-collaborative patents. Similarly, inter-sector collaborations generate an expected mean of nine forward citations more than non-collaborative patents. These results are statistically significant. However, due to the "truncation effect," these results are far too simplistic.

Older patents are cited more frequently than recent patents because the pool of potentially (future) citing patents is smaller (Bacchiocchi and Montobbio 2009: 171). This phenomenon is known as "right-truncation." This means that for patents first published in 2013, on the date the data were constructed, we only have information on their prior art, which is cited in the application, but we do not know into which future patents they will be incorporated (as prior art) (Nomaler and Verspagen 2008: 343).

Table 2 Descriptive statistics of variables

Variable	obs	Mean	Std. Dev.	Min	Max
no_collab	1016	0.7027559	0.45727	0	1
intra_collab	1016	0.0708661	0.2567275	0	1
inter_collab	1016	0.226378	0.4186926	0	1
NUMFCT	1016	13.84154	33.68743	0	453
age_years	1016	10.62992	6.735455	0	36
citation_lag	765	2.88366	2.174533	0	15
collab	1016	0.2972441	0.45727	0	1
new_NUMFCT	1016	11.88386	31.7685	0	425
NUMBCT	1016	15.63287	32.73843	0	403
fam_size	1016	29.80217	23.4284	1	72

Table 5 below shows a strong positive correlation between age and number of forward citations. Figure 1 provides more information by showing that the relationship between these two variables is linear, thus asserting the existence of truncation effect. For this reason, I added age into the model as a control variable.

The results from specification (2) show similar trends as specification (1) in that collaborative patents are expected to be cited more on average. Specification (2) however adds more information. First, the age variable adds to the model an expected mean of two forward citations, i.e., for every year of the patent's age it receives two forward citations. This adds another dimension to the correlation matrix in Table 5, by showing the effect of age on the expected mean of forward citations: two additional forward citations each year. Secondly, the coefficient of the *intra_collab* variable is not statistically significant, meaning that the estimate is not precise so we cannot rule out that the coefficient equals zero ($H_0 : \beta_1 = 0$). Thus, hypothesis 1a is rejected, while hypothesis 1b is supported. Inter-sector collaborations received more citations in comparison with non-collaborative patents. Specifications (1)–(2) show that in the stem cell industry in Israel, patents representing inter-sector collaboration are cited more than non-collaborative patents. This supports the conclusion that collaborations between research organizations of different sectors signify more valuable innovations than those generated by the independent R&D of a sole research organization.

If we place the coefficients in the following model (Eq. 2), we can estimate the expected mean of forward citations for each patents type and for every year of the patent's life. We do so by placing the age we are interested in and the value of zero or 1 to represent the type of patents on which we are focusing.

$$\hat{y}_i = -9 + 9\,intra\_collab + 7\,inter\_collab + 2\,age\_years \qquad (2)$$

A closer look at Eq. 2 shows that a positive value of expected mean of forward citation (a negative value has no meaning) depends in fact on the age we insert into the model. This is due to the relatively large negative coefficient

Table 3 OLS results (with robust standard errors) for NUMFCT as dependent variable

	(1) NUMFCT	(2) NUMFCT	(3) NUMFCT	(4) NUMFCT	(5) NUMFCT	(6) NUMFCT	(7) NUMFCT	(8) NUMFCT
intra_collab	10.75* (1.76)	9.324 (1.55)	12.98 (1.34)	9.520 (1.58)	10.07 (1.05)			
inter_collab	8.810*** (2.77)	7.072** (2.46)	7.055** (2.46)	−9.205 (−1.47)	−9.168 (−1.46)	−12.96* (1.66)	−6.801 (−1.26)	−10.91* (−1.94)
age_years		1.931*** (8.67)	1.951*** (8.29)	1.666*** (7.72)	1.670*** (7.26)	1.982*** (7.47)	1.973*** (7.37)	2.674*** (6.67)
intra_span [= intra_collab×age_years]			−0.330 (−0.66)		−0.0493 (−0.10)			
inter_span [= inter_collab×age_years]				1.465* (1.90)	1.461*(1.88)	1.625* (1.89)	1.718* (1.91)	1.923** (2.09)
citation_lag						−4.484*** (−7.49)	−3.813*** (−7.49)	0.295 (0.25)
inter_cites_market [= inter_collab×citation_lag]							−2.505 (−1.43)	−1.875 (−1.13)
Lag_age								−0.286*** (−3.45)
_cons	11.09*** (11.64)	−8.948*** (−4.86)	−9.151*** (−4.67)	−6.198*** (−3.96)	−6.235*** (−3.67)	5.872** (2.04)	4.063 (1.52)	−6.126 (−1.33)
N	1016	1016	1016	1016	1016	765	765	765
R-sq	0.016	0.165	0.165	0.177	0.177	0.228	0.223	0.245

t statistic in *parentheses*

*p<0.1; **p<0.05; ***p<0.01

Table 4 OLS results (with robust standard errors) for various dependent variables

	(9) new_NUMFCT	(10) new_NUMFCT	(11) fam_size	(12) fam_size	(13) NUMBCT	(14) NUMBCT	(15) NUMFCT	(16) NUMFCT
intra_collab	9.625 (1.06)		4.426 (0.99)		17.42*(1.77)			
inter_collab	−8.964 (−1.48)	−10.83** (−2.00)	−2.345 (−1.25)	−3.321 (−1.20)	−4.191 (−1.10)	−7.421 (−1.09)	−9.289* (−1.72)	−7.994 (−1.64)
age_years	1.562*** (7.03)	2.555*** (6.53)	0.540*** (6.70)	0.626*** (4.48)	−0.359*** (−3.54)	−0.702*** (−3.37)	2.827*** (7.19)	2.204*** (4.93)
intra_span [= intra_collab×age_years]	−0.175 (−0.38)		0.399 (1.29)		−0.380 (−0.65)			
inter_span [= inter_collab×age_years]	1.321* (1.77)	1.777** (2.00)	0.426** (2.08)	0.466** (2.04)	0.637** (2.05)	0.629 (1.58)	1.786** (1.99)	1.530* (1.92)
citation_lag		0.660 (0.59)		−0.814* (−1.86)		−3.541*** (−3.47)	1.066 (0.97)	1.074 (1.03)
inter_cites_market [= inter_collab×citation_lag]		−1.722 (−1.08)		−0.414 (−0.76)		0.473 (0.37)	−1.978 (−1.21)	−1.564 (−1.06)
Lag_age		−0.281*** (−3.47)		−0.0315 (−1.12)		0.0805 (1.61)	−0.303*** (−3.67)	−0.264*** (−3.28)
NUMBCT							0.218*** (3.39)	0.0375 (1.05)
fam_size								0.793*** (3.24)
_cons	−6.609*** (−4.03)	−8.214* (−1.84)	5.613*** (8.37)	10.57*** (6.00)	17.83*** (10.46)	33.14*** (7.39)	−13.34*** (−3.37)	−15.75*** (−4.10)
N	1016	765	1016	765	1016	765	765	765
R-sq	0.168	0.235	0.118	0.099	0.016	0.027	0.228	0.365

t statistic in *parentheses*

*$p<0.1$; **$p<0.05$; ***$p<0.01$

Table 5 Correlation matrix between age (in years) and the number of forward citations (average)

	age_years	avg_NUMFCT
age_years	1.0000	
avg_NUMFCT	0.7380	1.0000

(obs=1016)

of the constant. For patents representing inter-sector collaborations, the age of the patent should be at least 2 years to obtain a positive value of forward citations (Eq. 3).

$$\hat{y}_{inter\_collab} = -9 + 0 + 7*1 + 2*2 = 2 \tag{3}$$

For the non-collaborative patents, however, inserting the estimators into Eq. 2 shows that to obtain a positive value of forward citations, the patent's age has to be at least 5 years (Eq. 4).

$$\hat{y}_{no\_collab} = -9 + 0 + 0 + 2*5 = 1 \tag{4}$$

In summary, when age is introduced as a control variable into specification (2), patents representing non-collaborative R&D activity take longer to be cited by future patents than collaborative patents. The citation lag of non-collaborative patents is longer than that of collaborative patents. This somewhat supports hypothesis 2, but further analysis is still required.

The regressions conducted so far embody simple models which assume that no other factors influence collaboration, and that collaboration does not depend on other factors.
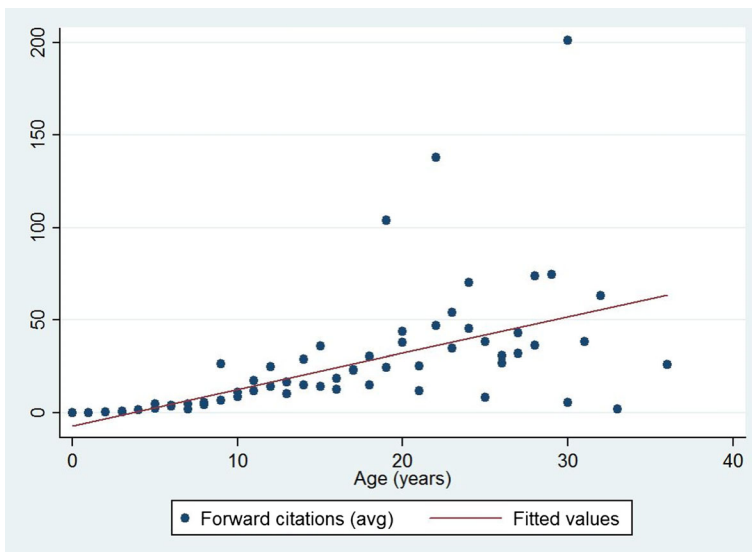
Fig. 1 The linear connection between forward citations (average) and age (in years)

However, for better understanding of the connection between collaboration and innovation, a more in-depth analysis is in order.

I constructed two interaction variables which stand for the interaction between collaboration, or more accurately type of collaboration, and age. However, this interaction actually denotes a new attribute to be examined, namely the life span of the collaborative patent. I mark them as *inter_span* [*inter_collab × age_years*] and *intra_span* [*intra_collab × age_years*]. The purpose is to see if the collaboration's life span affects the number of citations. I did not construct an interaction variable for non-collaborative patents as the aim here is to probe more closely for what can influence collaboration, and in this regression non-collaborative patents serve as the base line.

Specification (4) show that each year of the life span of inter-sector collaborations results in 1.5 additional forward citations. This remains the case in specification (5). However, with regard to intra-sector collaborations, as was first seen from specification (2), and now with more magnitude, the coefficients of both the variable and the interaction, in both specifications (3) and (5) are not statistically significant. The value of R-squared in specification (3) is lower than in specification (4), while it remains the same in specification (5) which addresses both inter- and intra-sector collaborations. This actually shows the robustness of the model represented by specification (5). Lastly, the coefficient of *inter_collab* is the same in specifications (4) and (5), higher than its value in specification (3), because in specification (5) it "absorbs" in a sense the effects of *intra_collab* and the new variable associated with it. Despite the lack of statistical significance of *intra_collab* and *intra_span* [*intra_collab × age_years*] in specification (5), the coefficients in specification (4) and (5) are similar. The change in the coefficients' signs is only visible when specification (3) is compared with specifications (4) and (5).

There are two possible explanations for the lack of statistical significance of *intra_collab* and the interaction variable in specification (3). The fact that the coefficients seem to change their positive/negative sign when adding or subtracting the interaction variables might be the result of multicollinearity between the explanatory variables. Furthermore, the multicollinearity test I applied seemed to show that the multicollinearity that does appear is of low-level (Appendix B). Since multicollinearity is not the reason for these results, we are left with a second, more likely, explanation of the results. Recall Table 1 that summarized the number and percentage of patents by type. Of the 1016 patents in the data only 72 represented intra-sector collaborations (amounting to only 7 % of the data). The small number of patents explains why the coefficients are not statistically significant and *inter_collab* "absorptive" behavior. For this reason, I continue the analysis focusing only on inter-sector collaborations.

As discussed before, specification (2) raised the need to examine what the citation lag is. For this, the variable *citation_lag* is constructed. It represents for each patent the time elapsed since its earliest/first publication and its first citation by a future patent. However, I did not stop there but examined the interaction between the citation lag and type of collaboration, resulting in a new variable: *inter_cites_market* [*inter_collab × citation_lag*]. The interaction denotes how fast the inter-sector collaborative patent enters into "market of citations." Accordingly, the interaction variable *lag_age* [*citation_lag × age_years*] was constructed. I however did not include the results of the triple interaction, due to high levels of multicollinearity.

Specification (8) includes the variables for the complete model. This model is robust. Although the interaction variable *inter_cites_market* [*inter_collab ×*

citation_lag] is not statistically significant, *F* test shows that the variables *inter_collab*, *inter_span* [*inter_collab* × *age_years*], and *inter_cites_market* [*inter_collab* × *citation_lag*] together are statistically significant (Appendix C). More importantly R-squared in specification (8) is almost 50 % higher than in specification (5), meaning the model of specification (8) alone explains 24.5 % of the data on citations.

So far, I have tested the hypothesis by finding the estimators and testing their significance level. Finding the estimators allows us to insert one value at a time and estimate the mean. I now continue by calculating the confidence interval, which marks the range within which the population value lies (see Appendix D for covariance interval calculations of coefficients of specification (8)). The confidence level chosen is 90 percent.

Figure 2 below shows graph of predictive margins for the delta of citations, added by inter-actor collaboration to the total sum of citations, for both 1 and 6 years lag, for percentile 10 (lower limit) and percentile 90 (upper limit) of *citation_lag* distribution. The two intervals are presented one on top of the other. Each interval represents a range of values for which we are 90 % confident that the citation delta mean falls within (Hinton 2004: 69–72). As the patents representing inter-sector collaborations mature (life span), the delta of citations increases. For lag 1, the margins which fall containing zero are narrower than the margins for lag 6. Also, for lag 1, the margins containing values larger than zero are larger than the margins of lag 6. This means that as the lag increases there are fewer population values for which we cannot reject the null hypothesis (H_0). Put simply, lag 1 includes larger population of delta of forward citations that has a positive (over zero) value, than lag 6, which shows that as the lag decreases the delta of forward citation increases. I discuss some specific examples next.
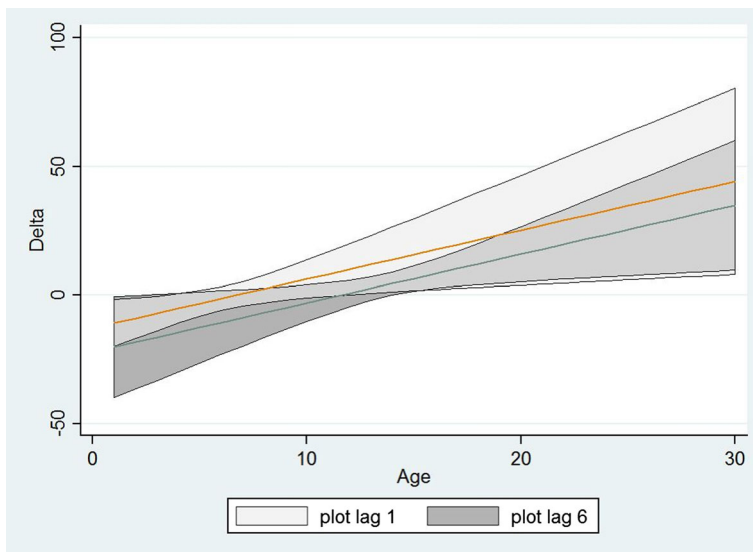

Fig. 2 Predictive margins for *inter_collab* delta of citations for percentile 10 (1 year) and percentile 90 (6 years) of *citation_lag* distribution

Equation 5 below shows the delta of forward citations added by inter-sector collaborations to the total sum of forward citations on the basis of specification (8).

$$\Delta inter\_collab = \frac{\beta_1\,inter\_collab + \beta_2\,inter\_span + \beta_3\,inter\_cite\_market}{inter\_collab}$$

$$= \frac{\beta_1\,inter\_collab + \beta_2\,inter\_collab \times age\_years + \beta_3\,inter\_collab \times citation\_lag}{inter\_collab} \quad (5)$$

$$= \quad \Delta inter\_collab \quad = \quad \beta_1 + \quad \beta_2\,age\_years \ + \beta_3\,citation\_lag$$

$$= \quad \Delta inter\_collab \quad = \ -11 + 2 \ * age\_years \ -2 \ * citation\_lag$$

We can use this model to demonstrate the result of the confidence interval. Table 6 below summarizes the effect of inter-sector collaborations on the total expected mean of a patent's forward citations, by examining the influence of the change of the patent's age (from 10 to 15 years) and the change in citation lag (from 2 to 1 year).

The results set out in Table 6 show that the number of citations added by the collaboration increases as the collaborative research output matures over time and that it increases as the time it takes the collaborative research output to be cited shortens. These results support hypotheses 2 and 3.

In accordance with the literature (Lanjouw and Schankerman 2004; Nomaler and Verspagen 2008), the models in specifications (5) and (8) were also conducted, with backward citations and family size as the dependent variables. The results of these regressions (specifications (11)–(14)) show that, at least with regard to the stem cell industry in Israel, the number of backward citations and the family size cannot be used as innovation indicators. Thus, hypothesis 5 is rejected.

Despite not being good indicators of value of innovation, they might still influence number of forward citations as an indicator of the innovation's value when introduced into the model (specifications (15)–(16)). The value of R-squared increases dramatically while the coefficient direction remains the same. The difference in value stems from the fact that the influence on number of forward citations is distributed among more factors.

On account of the criticism in the literature regarding possible inflation of forward citations by the assignee and/or the partner (Jaffe et al. 1993), a new variable was constructed. *New_NUMFCT* stands for the number of forward citations minus the number of self- and co-citations (specifications (9)–(10)). The significance, size, and direction of the coefficients are similar, thus confirming the strength of the models

Table 6 Example of the effect of inter-actor collaboration (delta) on the total expected mean of forward citations

age=10 citation lag=2	$\Delta inter\_collab = -11 + 2 * 10 - 2 * 2 = 5$
age=15 citation lag=2	$\Delta inter\_collab = -11 + 2 * 15 - 2 * 2 = 15$
lag=15 citation lag=1	$\Delta inter\_collab = -11 + 2 * 15 - 2 * 1 = 17$

discussed here, and more importantly, restressing that self- and co-citations do not create bias. Hypothesis 4 is affirmed.

Robustness Checks

To test the reliability of our findings, we conducted several robustness checks. First, the above discussion of self- and co-citations served also as robustness check (specifications (9)–(10)). Secondly, due to the small number of intra-sector collaborations, the data were divided into two groups: collaborative patents and non-collaborative patents. I ran the same regressions, but the results added no further information. I suspect it is because the new variable representing collaborative patents (*collab*) was influenced by the small number of intra-actor collaborations (specifications (17)–(21) in Table 7 below).

Finally, I constructed a new variable NUMFCT5, which is in accordance with the literature (OECD 2009: 138). Due to truncation effects, it is important to ensure the timeliness of indicators. One remedy for this problem is counting citations received by patent applications within a given time window—generally 5 years after publication of the cited patent (OECD 2009: 136–139). The results of specifications (22)–(23) show a similar trend to the results of the analysis with dependent variable *NUMFCT*, thus strengthening the model's robustness.

Limitations and Further Research

As in any empirical analysis, there are some limitations to the analysis presented in this paper. One has to do with the patents examiner. She is responsible for insuring that all appropriate patents, and other prior art, have been cited (Lanjouw and Schankerman 2004: 446). In some cases, some of the citations are the product of an extensive search of the state of the art conducted by examiners in order to assess the degree of novelty and inventive steps of inventions, which is necessary to justify their patentability (OECD 2009: 107). This procedure by the patent office is used at times to criticize the use of patent citations as indicators as the value of innovations. The patent examiner can add new references or remove ones provided by the applicant (Narin and Olivastro 1998; Van Looy et al. 2006). The argument is that patent citations added by the examiner cannot be counted as part of the citations analysis. I disagree with this statement. The patent examiner is considered a knowledgeable person in the relevant field. The fact that she adds citations does not lessen their impact—if anything, the opposite is the case. Their addition signifies that these citations constitute the appropriate string of knowledge related to the cited patents. In any event, the database I worked with cannot separate citations added by the patentee from those added by the examiner, but this would make an interesting topic for future research.

Some limitations stem directly from the construction of the dataset. To determine the age of the patents, both the cited and citing, I first had to decide on the decisive date from which the aging process begins. For the reasons I mentioned above, I chose the earliest publication date as the decisive date. This is the date from which the application or patent can be cited. But, there are other possible dates to consider. Choosing a different date could have influenced the analysis: it might have changed the actual age

Table 7 OLS results (with robust standard errors) of robustness variables

	(17) NUMFCT	(18) NUMFCT	(19) NUMFCT	(20) NUMFCT	(21) NUMFCT	(22) NUMFCT	(23) NUMFCT
collab	7.610*** (2.85)	−4.378 (−0.82)	−4.454 (−0.63)	2.088 (0.33)	−0.708 (−0.10)		
age_years	1.931*** (8.66)	1.670*** (7.26)	2.030*** (7.14)	2.015*** (6.99)	2.665*** (6.29)	0.178*** (7.00)	0.133*** (3.00)
collab_span [= collab×age_years]		1.087*	1.026 (1.77)	1.099 (1.46)	1.216* (1.52)	1.65	
citation_lag			−4.405*** (−7.68)	−3.538*** (−7.53)	0.202 (0.18)		−1.000*** (−5.08)
collab_cites_market [= collab×citation_lag]				−2.589* (−1.77)	−2.051 (−1.41)		
Lag_age [= citation_lag×age_years]					−0.262*** (−3.01)		−0.000522 (−0.05)
intra_collab						3.282* (1.69)	
inter_collab						−0.375 (−0.51)	−0.106 (−0.09)
intra_span [= intra_collab×age_years]						−0.120 (−1.26)	
inter_span [= inter_collab×age_years]						0.157* (1.90)	0.224*** (2.58)
inter_cites_market [= inter_collab×citation_lag]							−0.514** (−2.07)
_cons	−8.943*** (−4.85)	−6.235*** (−3.68)	4.154* (1.74)	1.805 (0.97)	−7.549* (−1.90)	1.009*** (4.35)	5.480*** (7.06)
N	1016	1016	765	765	765	1016	765
R-sq	0.164	0.173	0.226	0.231	0.242	0.080	0.202

t statistic in parentheses

*p<0.1; **p<0.05; ***p<0.01

of the patent. There are several possible "candidates" for serving as the decisive date: the application date, which marks the day an application was filed; the grant date, which is the day the patent registrar issues the patent; and the priority date, which marks the beginning of the 20 years' monopoly. The relative importance of these different age processes is an empirical question, the answer to which exceeds the scope of my research but may be the subject of further research. That said, choosing the earliest publication date as the decisive date has its advantages. In most countries, patent applications are published 18 months after the application date (rather than waiting until grant). Until 2000, this led to the situation in which US patents that applied for foreign protection were published in a foreign country but not in the USA. Since then, patents that have applied for foreign protection are published 18 months after application in both the foreign country and the USA (Mehta et al. 2008). As mentioned, publication drives the citation process. Until 2000, the family's earliest publication date represented the real date from which the patent could be cited, thus overcoming the timing problem.

The method I chose for the analysis also raises questions. In regression modeling, the underlying theory indicates the direction of causality between y and x, which in the context of single-equation models is from x to y (Gujarati 2002:87). Stated simply, the concern is not that collaboration leads to more innovations, but that the high level of innovation leads potential collaborators to seek entry into collaboration. From the theory perspective, I do not believe this is the case. I define collaborations as joint R&D activity which manifests itself in the output of the research—the patent. Innovations that lead to collaborations can only be examined after the fact. However, in this case, even though patents are "after the fact" in a sense, here collaborations are represented by the product of joint R&D so in that sense they are very much in the fact.

Conclusions and Ramifications

The study reported here sets out to provide empirical data to resolve the controversy in the literature regarding the need for collaboration in the innovation process. It began with a review of the collaborative nature of recent leading innovation theories. These place collaboration as a central element in the innovation process, and they coincide with most literature today supporting this notion, stating that collaboration leads to more innovation, as opposed to the situation of a silo structure, meaning one research organization working alone. However, it is not a clear cut as one may think. Another opinion expressed in the literature—less noticeable but backed by some empirical evidence, is that collaboration does not necessarily lead to more innovations, and at times a research organization working on its own benefits more from an innovation point of view.

This study uses forward citations as a proxy for the value of innovation to investigate the link between innovation and collaboration. Its contribution lies in its examining this debate through the lens of QH, so that the analysis level is the sector. Furthermore, it uses data on the stem cell industry in Israel. These data are unique in that they encompass all the patents of Israeli actors, hence are not based on a sample but in fact represent the entire industry.

The results of the analysis support those who hold that collaboration generates more innovation than research conducted by a silo structure. Patented collaborative R&D activity is cited more than patented output of non-collaborative R&D. It has been shown that patents

representing both intra-sector and inter-sector collaborations have a larger expected mean of forward citations than that of non-collaborative patents. These results tip the scales in favor of initiating R&D collaborations. However, the paper does not end there.

Further analysis, focused on inter-sector collaborative patents (due to small number of patents representing intra-sector collaborations, which leads to statistically insignificant coefficients), revealed that inter-sector collaborations produce more groundbreaking knowledge. The analysis shows that inter-sector collaborative patents are cited more as they mature, meaning that through their life span the knowledge they encompass is used more in the establishment of a new layer of knowledge (in contrast to non-collaborative patents). Also, and in a sense the other side of the same coin, inter-sector collaborative patents enter the market of citations quicker than non-collaborative patents. This is shown by the influence citation lag has on these patents. The shorter the citation lag is, the more they are cited. These results strengthen the initial conclusion regarding the innovative strength of collaboration. Based on current literature (Katila 2000; Lanjouw and Schankerman 2004), the conclusion of the regression analysis is not just that inter-sector collaborations lead to groundbreaking knowledge, but also that these patents portray radical innovations.

The results of the analysis of are summarized in the following conceptual model (Fig. 3 below).

The paper presents the use of the methodological tool of the analysis of patent-based indicators. This paper implements the methodology on the stem cell industry in Israel. Despite limitations of the use of this methodology, patent-based indicators are still good indicators, and this methodology is also applicable to other emerging technologies/industries where information on patents is the only available data. But not only the regression model offered here is flexible enough to include alongside patent-based indicators other innovation indicators as well, data on these indicators is usually readily available in more mature industries.

From a policy perspective, this study reaffirms the transition discussed in the literature from TH model to QH model of innovation. This study shows that R&D activity is not
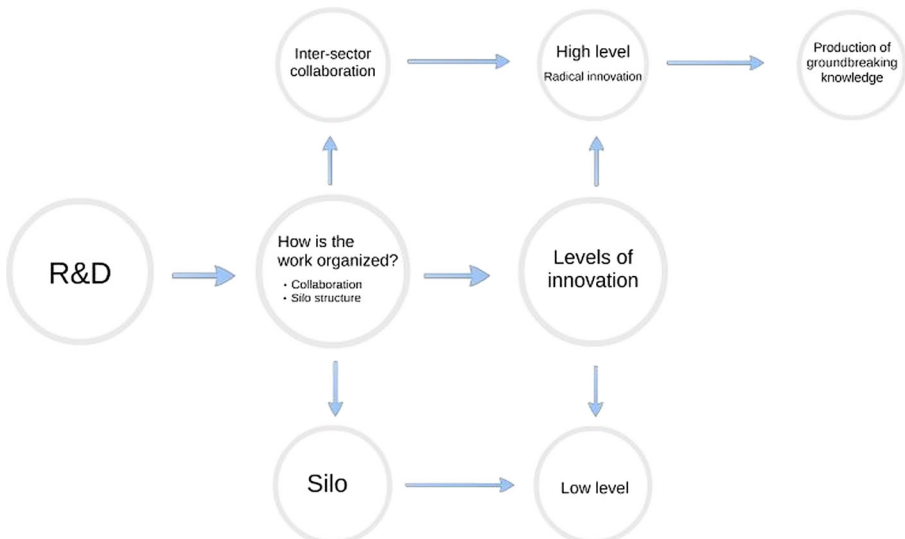

Fig. 3 Conceptual model of the link between collaboration and innovation

conducted only by the three helixes of TH. Cross-sectoral collaborations, which take into account the fourth helix as well, produce groundbreaking and radical innovations, thus progressing economic growth. For policymakers innovation is not only an end, it is also a mean to an end–economic growth. Thus, a sound policy should take into account that in the innovation ecosystem production of innovations is organized in a QH manner, in which collaboration is needed to the advancement of innovation, it is a tool policymakers should employ. A sound innovation policy should not only take into account the QH framework, but also the strategy employed by firms operating in the QH ecosystem, mainly TOI. For this reason, a sound innovation policy should aspire to foster cross-sectoral collaborations, placing emphasis especially on motivating firms to include in their TOI strategy the initiation of cross-sectoral collaborations.

This study will greatly benefit from further analysis into the identity of the targeted collaborator, i.e., the collaborator with whom the collaborative R&D activity generates the highest levels of innovation, since, as current literature postulates, focused, and targeted open innovation efforts leads to optimal innovation.

On a final note, it should be said that the analysis here is based mainly on one innovation indicator. It would be interesting to do this analysis 10 years from now, using innovation indicators associated with products in the market, and to revisit this paper's results and conclusions. It would also be interesting to apply this analysis to other fields of research and see if the difference in scientific field has any bearing on the results.

Appendix A: Testing Homoscedasticity

One of the OLS assumptions is that the error term is constant. This is the homoscedasticity assumption. If the error terms do not have constant variance, they are said to be heteroscedastic. In this case, OLS estimates are no longer BLUE. That is, among all the unbiased estimators, OLS does not provide the estimate with the smallest variance. However, the standard errors are biased when heteroskedasticity is present, which leads to incorrect statistical tests and confidence intervals (Salvatore and Reagle 2011: 207).

Figure 4 presents a visual inspection of residuals plotted against fitted values. If the data were homoscedastic, we would have expected the residuals to be roughly the same size for all values of X, an "envelope" graph (or, with a small sample, slightly larger near the mean of X). In Fig. 4, the plot of residuals shows some uneven envelope of residuals, so that the width of the envelope is considerably larger for some values of X than for others. In this case, a more formal test for heteroscedasticity should be conducted.
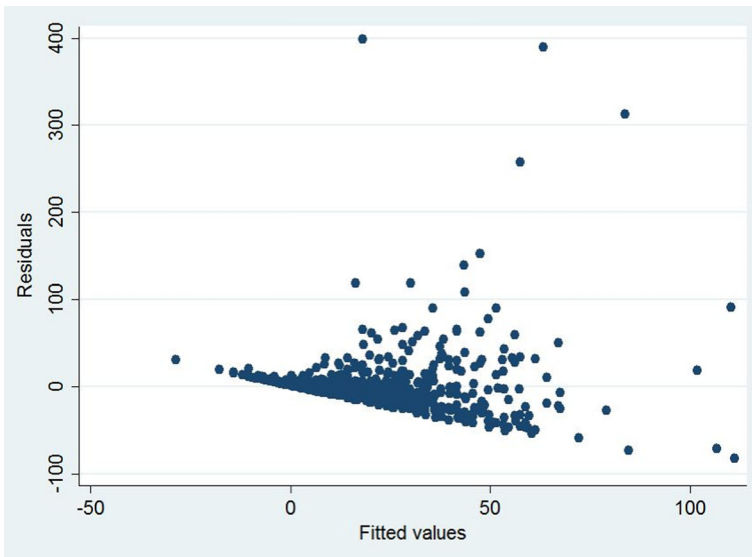
Fig. 4 Residuals versus fitted values

Breusch-Pagan/Cook-Weisberg tests the null hypothesis (H_0) that the error variances are all equal versus the alternative that the error variances are a multiplicative function of one or more variables. The alternative hypothesis (H_1) states that the error variances increase (or decrease) as the predicted values of Y increase, e.g., the bigger the predicted value of Y, the bigger the error variance is. Thus, if the p value is very small, we would have to reject the hypothesis and accept the alternative hypothesis that the variance is not homogenous. In Fig. 5, p value is zero which indicates that heteroscedasticity is present (http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm).

```
Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
        Ho: Constant variance
        Variables: fitted values of sum_NUMFCT

        chi2(1)      =      962.96
        Prob > chi2  =      0.0000
```
Fig. 5 Breusch-Pagan/Cook-Weisberg test

The combination of the Breusch-Pagan/Cook-Weisberg test results with diagnostic plot teaches us that a correction is needed for heteroscedasticity. In order to correct it, I recompute the results using Stata's robust parameter. The robust parameter relaxes the assumption that the errors are identically distributed.

Appendix B: Testing Multicollinearity between the Main Variables

The VIF test shows us how much the variance of the coefficient estimate is being inflated by multicollinearity (Williams 2015). As a rule of thumb, a variable whose VIF

values are greater than 10 may merit further investigation. Tolerance, defined as 1/VIF, is used by many researchers to check on the degree of multicollinearity. A tolerance value lower than 0.1 is comparable to a VIF of 10. It means that the variable could be considered as a linear combination of other independent variables (http://www.ats.ucla.edu/stat/stata/webbooks/reg/chapter2/statareg2.htm).

The data are divided into three groups of patents, as explained above. The distribution was done manually according to the identification of assignees and inventors. However, this division is prone to mistakes and somewhat artificial. The two groups of collaborative patents are connected to each other and this connection is demonstrated in Tables 8 and 9.

Table 8 Regression of specification (2) results

sum_NUMFCT	Coef.	Robust Std. Err.	t	p>|t|	(95 % confidence interval)	
intra_collab	9.32437	6.012176	1.55	0.121	−2.473388	21.12213
inter_collab	7.072303	2.873573	2.46	0.014	1.43346	12.71115
age_years	1.931095	0.2228088	8.67	0.000	1.493875	2.368315
_cons	−8.947646	1.840936	−4.86	0.000	−12.56013	−5.335157

Linear regression: Number of obs = 1016; F(3, 1012) = 28.43; Prob > F = 0.0000; R-squared = 0.1646; Root MSE = 30.836

Table 9 Multicollinearity test (VIF) of the variables of specification (2)

variable	VIF	1/VIF
inter_collab	1.03	0.974689
intra_collab	1.02	0.976925
age_years	1.00	0.996550
Mean VIF	1.02	

Appendix C: *F* Test

We can use an *F* test to examine whether a group of variables have no effect on the dependent variable. More precisely, the null hypothesis is that a set of variables has no effect on *y*, once another set of variables has been controlled (Wooldridge 2002: 139).

The *F* test of the variables *inter_collab*, *inter_span*, and *inter_cite_market* is statistically significant as seen on Table 10 and Fig. 6 below, meaning that even though specifications (6) and (7) include more variables which are statistically significant, they are not a better model than the one described in specification (8), because the results of the *F* test are statistically significant thus null hypothesis is rejected.

Table 10 Regression of specification (6) results

sum_NUMFCT	Coef.	Robust Std. Err.	t	p>|t|	(95 % confidence interval)	
inter_collab	−10.9052	5.627641	−1.94	0.053	−21.95282	0.1424126
age_years	2.674314	0.4007751	6.67	0.000	1.887553	3.461075
inter_span	1.923058	0.9209436	2.09	0.037	0.1151552	3.730961
citation_lag	0.2954934	1.160966	0.25	0.799	−1.983597	2.574584
inter_cites_Market	−1.87483	1.653171	−1.13	0.257	−5.120168	1.370509
lag_age	−0.2859625	0.0828626	−3.45	0.001	−0.4486299	−0.1232951
_cons	−6.12562	4.598752	−1.33	0.183	−15.15342	2.902183

Linear regression: Number of obs = 765; F(6, 758) = 18.90; Prob > F = 0.0000; R-squared = 0.2453; Root MSE = 32.912

```
. test inter_cite_market citation_lag lag_age

 ( 1)  inter_cite_market = 0
 ( 2)  citation_lag = 0
 ( 3)  lag_age = 0

       F(  3,   758) =   23.85
            Prob > F =    0.0000
```

Fig. 6 *F* test of variables *inter_cite_market*, *citation_lag* and *lag_age*

Appendix D: Covariance Integral Calculations

To calculate the confidence interval for delta of inter-sector collaboration type of patents for lag 1 and lag 6, we begin first with the following equation for delta:

$$= \Delta inter\_collab = -10.9 + 1.9age - 1.87lag \tag{6}$$

Equations 7 and 8 present the delta for lag 1 and lag 6, respectively:

$$= \Delta inter\_collab_{lag\,1} = -10.9 + 1.9 \times age - 1.87 \times 1 \tag{7}$$

$$= \Delta inter\_collab_{lag\,6} = -10.9 + 1.9 \times age - 1.87 \times 6 \tag{8}$$

Stata computes the upper and bottom limits of the confidence interval for both lag 1 and lag 6. However, to do so, we need to enter the formula for the confidence interval. Eq. 9 below presents *t*-based confidence interval for the mean. We use *t* distribution confidence interval as the population standard deviation σ is unknown (*S* is its estimate). *t* is a critical value determined from the t_{n-k-1} distribution in such a way that there is area 1 − α between *t* and −*t*. 1 − α represents the desired coverage level, here set on 90 % probability. t_{n-k-1} represents the value of *t* distribution table within $n - k - 1$ degrees of freedom (http://www.statisticsmentor.com/tables/table_t.htm), whereas *n* stands for number of observations and *k* stands for number of variables in the model. The square of standard deviation equals to the square root of variance (*v*) which allows us to calculate the limits of the interval for delta of forward citations of *inter_collab*.

$$CI: \quad \overline{x} \pm S_{\hat{x}} \times \quad t_{n-3} = \overline{x} \pm \sqrt{v\left(\hat{x}\right)} \times \quad t_{n-3} \tag{9}$$

We now turn to calculate the variance, for the model in Specification (8) presented in Eq. 9 below:

$$\Delta inter\_collab = \beta_1 + \beta_3\,age + \beta_5\,lag \tag{10}$$

To do so, we need to know for each estimator the relevant standard error as the standard error of an estimate may also be defined as the square root of the estimated error variance $\hat{\sigma}^2$ of the quantity $s_e = \sqrt{\hat{\sigma}^2}$ (Table 11) and use the following covariance matrix of coefficients of Specification (8) as was computed using Stata (Table 12).

Table 11 Robust standard errors of Specification (8)

sum_NUMFCT	Coef.	Robust Std. Err.	t	$p>|t|$	[95 % Conf. Interval]	
inter_collab	−10.9052	5.627641	−1.94	0.053	−21.95282	0.1424126
age_years	2.674314	0.4007751	6.67	0.000	1.887553	3.461075
inter_span	1.923058	0.9209436	2.09	0.037	0.1151552	3.730961
citation_lag	0.2954934	1.160966	0.25	0.799	−1.983597	2.574584
inter_citation_market	−1.87483	1.653171	−1.13	0.257	−5.120168	1.370509
lag_age	−.2859625	0.0828626	−3.45	0.001	−0.4486299	−0.1232951
_cons	−6.12562	4.598752	−1.33	0.183	15.15342	2.902183

Linear regression: Number of obs=765; F (6, 758)=18.90; Prob>F=0.0000; R-squared=0.2453; Root MSE= 32.912

Table 12 Covariance matrix of coefficients of specification (8)

e (v)	inter_collab	age_years	inter_span	citation_lag	inter_citation_market	lag_age	_cons
inter_collab	31.670347						
age_years	−0.00777199	0.16062071					
inter_span	−3.908135	0.0181239	0.84813703				
citation_lag	−1.1435559	0.29204192	0.5268357	1.3478418			
inter_cite_market	2.9162503	−0.05142575	−1.2859284	−1.1283807	2.7329757		
lag_age	0.11996531	−0.02714054	−0.03240067	−0.08711983	0.05855106	0.00686621	
_cons	−1.6724996	−1.5872412	−0.77441643	−4.6068427	2.33397	0.320389	21.148521

Once we get an equation for the variance, we can place it in the above interval margins formula. The following calculation is based on Eq. 9 above.

$$v \ (\Delta inter\_collab) \ = \ v \ \left(\hat{\beta}_1 + \hat{\beta}_3\, age + \hat{\beta}_5\, lag\right)$$

$$= v\left(\hat{\beta}_1\right) + age^2 \ \times v\left(\hat{\beta}_3\right) + lag^2 \times \ v\left(\hat{\beta}_5\right) + 2 \times age \ \times \ cov(\beta_1,\beta_3) \ + \ 2 \ \times \ lag \\ \times \ c\,o\,v\,(\beta_1,\beta_5) \ + \ 2 \ \times \ age \ \times \ lag \ \times \ c\,o\,v\,(\beta_3,\beta_5)$$

$$= 31.67 + age^2 \ \times 0.85 + lag^2 \ \times \ 2.74 \ + \ 2 \ \times \ age \ \times \ (-3.9) \ + 2 \ \times \ lag \ \times (2.91) \ + \ 2 \\ \times \quad lag \quad \times \quad age \quad \times \quad (-1.28)$$

$$= 31.67 + age^2 \ \times 0.85 + lag^2 \ \times \ 2.74 \ + \ age \ \times \ (-7.8) \ + lag \ \times \ 5.82 \ + \ lag \ \times \ age \\ \times \quad (-2.56)$$

(11)

Now, we place the values of lag 1 and lag 6 in the above equation and receive the following equations:

$$v(\Delta inter\_collab)_{lag \ 1}$$
$$= \ 31.67 \ + \ age^2 \ \times \ 0.85 \ + \ 1 \ \times 2.74 \ + \ age \ \times (-7.8) \ + \ 1 \ \times \ 5.82 \ + 1 \\ \times \quad age \quad \times \quad (-2.56) \quad = \quad 40.23 \quad + \quad 0.85 \ age^2 \ - \quad 10.36 \ age$$

(12)

$$v(\Delta inter\_collab)_{lag \ 6}$$
$$= \ 31.67 \ + \ age^2 \ \times \ 0.85 \ + \ 36 \ \times 2.74 \ + \ age \ \times (-7.8) \ + \ 6 \ \times \ 5.82 \ + 6 \\ \times \quad age \quad \times \quad (-2.56) \quad = \quad 165.23 \quad + \quad 0.85 \ age^2 \ - \quad 23.16 \ age$$

(13)

Each of Eqs. 11 and 13 are introduced into the confidence interval limits formula. We receive the following equations for the limits of the confidence interval for lag 1 and lag 6:

$$CI_{lag \ 1} \ : \ -12.77 + 1.9\,age \ \pm \ 1.645 \ \times \ \sqrt{40.23 \ + \ 0.85\,age^2 - \ 10.36\,age} \qquad (14)$$

$$CI_{lag \ 6} \ : \ -22.12 + 1.9\,age \ \pm \ 1.645 \ \times \ \sqrt{165.23 \ + \ 0.85\,age^2 - \ 23.16\,age} \qquad (15)$$

The results of computing these formals with Stata are presented in Fig. 2.

References

Archibugi, D., & Planta, M. (1996). Measuring technological change through patents and innovation surveys. *Technovation, 16*(9), 451–468.

Arnkil, R., Järvensivu, A., Koski, P., & Piirainen, T. (2010). *Exploring Quadruple Helix: Outlining User-Oriented Innovation Models (85/2010Working Paper, Final Report on Quadruple Helix Research for the*

CLIQ project). Retrieved from: https://tampub.uta.fi/bitstream/handle/10024/65758/978-951-44-8209-0.pdf?sequence=1.

Asheim, B. T., & Gertle, M. S. (2005). The geography of innovation: Regional innovation systems. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), *The oxford handbook of innovation* (pp. 291–317). Oxford: Oxford University Press.

Atkinson, R. D., & Ezell, S. J. (2012). *Innovation Economics*, Kindle Edition. New Haven: Yale University Press.

Bacchiocchi, E., & Montobbio, F. (2009). Knowledge diffusion from university and public research: a comparison between us, japan and europe using patent citations. *The Journal of Technology Transfer, 34*(2), 169–181.

Beyerlein, M. M., Beyerlein, S. T., & Kennedy, F. A. (2006). Introduction. In M. M. Beyerlein, S. T. Beyerlein, & F. A. Kennedy (Eds.), *Innovation through collaboration* (Vol. 12, pp. xiii–xviii). Oxford: Elsevier.

Bioethics Committee of the National Israeli Science Academy (2001). *Report on The Use of Embryonic Stem Cells for Therapeutic Research*. Retrieved from the Bioethics Committee website: http://bioethics.academy.ac.il/english/report1/Report1-e.html [Hebrew].

Birnholtz, J. P., & Bietz, M. J. (2003). Data at Work: Supporting Sharing in Science and Engineering. *Proceedings of the 2003 international ACM SIGGROUP conference on supporting group work.* Sanibel Island, Florida, USA, November 9–12, 2003, pp. 339–348. Retrieved from: https://www.interaction-design.org/references/conferences/proceedings_of_the_international_acm_siggroup_conference_on_supporting_group_work_2003.html.

Bok, S. (1982). Secrecy and openness in science: Ethical considerations. *Science, Technology & Human Values, 7*(38), 32–41.

Boland, W. P., Phillips, P. W. B., Ryan, C. D., & McPhee-Knowles, S. (2012). Collaboration and the generation of new knowledge in networked innovation system: a bibliometric analysis. *Procedia - Social and Behavioral Sciences, 52*, 15–24.

Bubela, T., Strotmann, A., Adams, R., & Morrison, S. (2010). Commercialization and collaboration: Competing policies in publicly funded stem cell research? *Cell Stem Cell, 7*(1), 25–30.

Carayannis, E. G. (2013). *Proceedings from Open Innovation 2.0 Conference: Innovation 2.0.* Dublin, Ireland. Retrieved from YouTube: http://www.youtube.com/watch?v=hwIqwwUM5pI.

Carayannis, E. G., & Campbell, D. F. (2009). "Mode 3" and "Quadruple Helix": Toward a 21st Century Fractal Innovation Ecosystem. *International Journal of Technology Management, 46*(3/4), 201–234.

Carayannis, E. G., & Campbell, D. F. (2011). Open Innovation Diplomacy and a 21st Century Fractal Research, Education and Innovation (FREIE) Ecosystem: Building on the Quadruple and Quintuple Helix Innovation Concepts and the "Mode 3" Knowledge Production System. *Journal of the Knowledge Economy, 2*(3), 327–372.

Carayannis, E. G., & Campbell, D. F. (2012). Mode 3 Knowledge Production in Quadruple Helix Innovation Systems Twenty-first-Century Democracy, Innovation, and Entrepreneurship for Development. In *Quadruple Helix Innovation Systems, Springer Briefs in Business* (vol. 7, pp. 1–63). New York: Springer.

Carayannis, E. G., & Campbell, D. F. (2014). Developed democracies versus emerging autocracies: Arts, democracy, and innovation in quadruple helix innovation systems. *Journal of Innovation and Entrepreneurship, 3*, 12–34.

Carayannis, E. G., & Rakhmatullin, R. (2014). The quadruple/quintuple innovation helixes and smart specialisation strategies for sustainable and inclusive growth in Europe and beyond. *Journal of the Knowledge Economy, 5*(3), 212–239.

Cassiolato, J. E., de Matos, M. P., & Lastres, H. (2014). Innovation Systems and Development. In B. Currie-Alder, R. Kanbur, D. M. Malone, & R. Medhora (Eds.), *International Development: Ideas, Experience, and Prospects*. Retrieved from: http://www.globelicsacademy.org/2013_pdf/Readings/Cassiolato%20at%20all%20_2.pdf.

Chesbrough, H. (2006). Open Innovation: a new paradigm for understanding industrial innovation. In H. Chesbrough, W. Vanhaverbeke, & J. West (Eds.), *Open Innovation: Researching a new paradigm* (pp. 1–14). Oxford: Oxford University Press.

Colapinto, C., & Porlezza, C. (2012). Innovation in creative industries: From the quadruple helix model to the systems theory. *Journal of the Knowledge Economy, 3*(4), 343–353.

Criscuolo, P., Narula, R., & Verspagen, B. (2005). Role of home and host country innovation systems in r&d internationalisation: a patent citation analysis. *Economics of Innovation and New Technology, 14*(5), 417–433.

Cropper, S. (1996). Collaborative working and the issue of sustainability. In C. Huxham (Ed.), *Creating collaborative advantage* (pp. 80–100). London: Sage.

Curley, M., & Salmelin, B. (2013). *Proceedings from Open Innovation 2.0 Conference: Open Innovation 2.0: A New Paradigm*. Dublin, Ireland. Retrieved from: http://ec.europa.eu/information_society/newsroom/cf/dae/document.cfm?doc_id=2182.

Czarnitzki, D., Hussinger, K., & Leten, B. (2011). *The Market Value of Blocking Patent Citations (Discussion Paper No. 11–021, Centre for European Economic Research (ZEW))*. Retrieved from SSRN: http://ssrn.com/abstract=1803315.

de Man, A., & Duysters, G. (2005). Collaboration and Innovation: a review of the effects of mergers, acquisitions and alliances on innovation. *Technovation, 25*, 1377–1387.

Deb. Beaver, D. (2001). Reflections on scientific collaboration (and its study): Past, present and future. *Scientometrics, 52*, 365–377.

Delman, J., & Madsen, S. T. (2007). *Nordic Triple Helix Collaboration in Knowledge, Innovation, and Business in China and India: A Preliminary Study*. Bangalore: NIAS press.

Dodgson, M. (1993). *Technological Collaboration in Industry*. London: Routledge.

Eagar, R., van Oene, F., Boulton, C., Roos, D., & Dekeyser, C. (2011). The future of innovation management: the next 10 years. *Prism, 1*, 21–37.

Edquist, C. (Ed.). (1997). *Systems of innovation: technologies, institutions, and organizations*. Abingdon: Routlage.

Elkin Koren, N., Getz, D., Bergman-Eschet, Y., Bar-Ziv, S., & Ponchek, T. (2013). *Facilitating Collaboration in Stem Cell Research through Intellectual Property: Report submitted to Ministry of Science and Technology as part of the 2009 Programme for the Development of Scientific and Technological Infrastructures*. Retrieved from: http://weblaw.haifa.ac.il/he/Research/ResearchCenters/techlaw/StemCells/publications/Documents/ip_stem_cells_full_report.pdf [Hebrew].

Etzkowitz, H. (2003). Innovation in innovation: the triple helix of university-industry-government relations. *Social Science Information, 42*(3), 293–337.

Etzkowitz, H., & Leydesdorff, L. (2000). The dynamics of innovation: from national systems and "mode 2" to a triple helix of university–industry–government relation. *Research Policy, 29*(2), 109–123.

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

Galison, P. (1992). Introduction: the many faces of big science. In P. Galison & B. Hevly (Eds.), *Big science: the growth of large-scale research* (pp. 1–17). Stanford: Stanford University Press.

Gibbons, M., Limoges, C., Nowotny, H., Schwartzman, S., Scott, P., & Trow, M. (1994). *The new production of knowledge, the dynamics of science and research in contemporary societies*. London: Sage.

Goto, A., & Motohashi, K. (2007). Construction of a Japanese patent database and a first look at Japanese patenting activities. *Research Policy, 36*(9), 1431–1442.

Guan, J., & Heb, Y. (2007). Patent-bibliometric analysis on the Chinese science: Technology linkages. *Scientometrics, 72*(3), 403–425.

Gujarati, D. (2002). *Basic Econometrics* (4th ed.). New York: McGraw Hill.

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

Hara, N., Solomon, P., Kim, S., & Sonnenwald, D. H. (2003). An emerging view of scientific collaboration: Scientists' perspectives on collaboration and factors that impact collaboration. *Journal of the Association for Information Science and Technology, 54*(10), 952–965.

Harhoff, D., Narin, F., Scherer, F. M., & Vopel, K. (1999). Citation frequency and the value of patented inventions. *The Review of Economics and Statistics, 81*(3), 511–515.

Himmelman, A. T. (1996). On the theory and practice of transformational collaboration: From social service to social justice. In C. Huxham (Ed.), *Creating collaborative advantage* (pp. 19–43). London: Sage.

Hinton, P. R. (2004). *Statistics explained* (2nd ed.). New York: Routledge.

Huang, K. G., & Murray, F. E. (2009). Does patent strategy shape the long-run supply of public knowledge? Evidence from human genetics. *Academy of Management Journal, 52*(6), 1193–1221.

Huxham, C. (1996a). Advantage or Inerita? Making collaboration work. In R. Paton, G. Clark, G. Jones, J. Lewis, & P. Quintas (Eds.), *The new management reader*. London: Routledge.

Huxham, C. (1996b). Collaboration and collaborative advantage. In C. Huxham (Ed.), *Creating collaborative advantage* (pp. 1–18). London: Sage.

Huxham, C., & Vangen, S. (1994). *Naivety and Maturity, Inertia and Fatigue: Are Working Relationships Between Public Organizations Doomed to Fail?* (Working Paper 94/17, Department of Management Science, University of Strathclyde).

Ivanova, I. (2014). Quadruple helix systems and symmetry: a step towards helix innovation system classification. *Journal of the Knowledge Economy, 5*(2), 357–369.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *The Quarterly Journal of Economics, 108*(3), 577–598.

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

Katila, R. (2000). Measuring innovation performance. *International Journal of Business Performance Measurement, 2*, 180–193.

Katz, J., & Martin, B. R. (1997). What is research collaboration? *Research Policy, 26*, 1–19.

Kim, C., & Song, J. (2007). Creating new technology through alliances: an empirical investigation of joint patents. *Technovation, 27*(8), 461–470.

Kuhn, T. (1961). *The Structure of Scientific Revolutions*. Chicago: University of Chicago Press.

Lane, P. J., & Lubatkin, M. (1998). Relative absorptive capacity and interorganizational learning. *Strategic Management Journal, 19*(5), 461–477.

Lanjouw, J. O., & Schankerman, M. (2001). Characteristics of patent litigation: a window on competition. *RAND Journal of Economics, 13*, 129–151.

Lanjouw, J. O., & Schankerman, M. (2004). Patent quality and research productivity: measuring innovation with multiple indicators. *The Economic Journal, 114*(495), 441–465.

Lechevalier, S., Ikeda, Y., & Nishimura, J. (2011). Investigating collaborative r&d using patent data: the case study of robot technology in japan: a case study of robot technology in Japan. *Managerial and Decision Economics, 32*, 305–323.

Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social Studies of Science, 35*(5), 673–702.

Leydesdorff, L., & Etzkowitz, H. (1998). The triple helix as a model for innovation studies. *Science and Public Policy, 25*(3), 195–203.

Leydesdorff, L., & Etzkowitz, H. (2001). The transformation of university-industry-government relations. *Electronic Journal of Sociology, 5*(4), 195–203.

Liljemark, T. (2004). *Innovation Policy in Canada (Working Paper no. A2004:024, Swedish Institute for Growth Policy Studies)*. Retrieved from: http://www.growthanalysis.se/download/18.56ef093c139bf3ef8902731/1349863392488/innovation-policy-in-canada-04.pdf.

Lundvall, B.-Å. (Ed.) (1992). *National Systems of Innovation: Towards a Theory of Innovation and Interactive Learning*. London, UK: Anthem Press.

Lundvall, B.-Å. (2007). *Introduction to Central Concepts in Innovation Management and Innovation Research*. Retrieved from http://www.globelicsacademy.net/2011_pdf/Lundvall%20-%20Introduction%20on%20Innovation.pdf.

Lundvall, B.-Å., Johnson, B., Andersen, E. S., & Dalum, B. (2002). National systems of production, innovation and competence building. *Research Policy, 31*(2), 213–231.

Malerba, F. (Ed.). (2004). *Sectoral systems of innovation: concepts, issues and analyses of six major sectors in Europe*. Cambridge: Cambridge University Press.

Malerba, F. (2005). Sectoral Systems: How and Why Innovation differs across Sectors. In J. Fagerberg, D. C. Mowery, & R. R. Nelson (Eds.), *The Oxford Handbook of Innovation* (pp. 380–406). Oxford: Oxford University Press.

Marinova, D., & Phillimore, J. (2003). Models of Innovation. In L. V. Shavinina (Ed.), *The International Handbook on Innovation* (pp. 44–53). Oxford: Elsevier.

Mehta, A., Rysman, M., & Simcoe, T. (2008). Identifying the age profile of patent citations: New estimates of knowledge diffusion. *Journal of Applied Econometrics, 25*(7), 1179–1204.

Metcalfe, J. S. (1995). Technology systems and technology policy in an evolutionary framework. *Cambridge Journal of Economics, 19*(1), 25–46.

Mishkin, B. (1995). Urgently needed: Policies on access to data by erstwhile collaborators. *Science, 270*(5238), 927–928.

Munos, B. (2009). Lessons from 60 years of pharmaceutical innovation. *Nature Reviews Drug Discovery, 8*, 959–968.

Nagaoka, S., Mothohashi, K., & Goto, A. (2010). Patent Statistics as an Innovation Indicator. In A. Kenneth & M. Intriligator (Eds.), *Handbooks in Economics* (vol. 2, pp. 108–1127). Oxford: Elsevier.

Narin, F., & Olivastro, D. (1998). Linkage between patents and papers: an interim epo/us comparison. *Scientometrics, 41*(1–2), 51–59.

Nelson, R. R. (Ed.). (1993). *National innovation System: A Comparative Analysis*. Oxford: Oxford University Press.

Nomaler, ., & Verspagen, B. (2008). Knowledge flows, patent citations and the impact of science on technology. *Economic Systems Research, 20*(4), 339–366.

Organization for Economic Co-Operation and Development (OECD). (2009). *Patent statistics manual*. Paris: OECD.

Pavitt, K. (1984). Sectoral patterns of technical change: Towards a taxonomy and a theory. *Research Policy, 13*, 343–373.

Perkmann, M., & Walsh, K. (2009). The two faces of collaboration: impacts of university-industry relations on public research. *Industrial and Corporate Change, 18*(6), 1033–1065.

Polanyi, M. (1958). *Personal knowledge.* Chicago: The University of Chicago Press.

Ponchek, T. (2016). *Collaboration is Scientific R&D: Patent-Based Indicators Analysis, Evidence from Stem Cell Research in Israel* (Unpublished doctoral dissertation). Haifa, Israel.

Putnam, J. D. (1997). *The Value of International Patent Rights.* Retrieved from http://www.competitiondynamics.com/wp-content/uploads/International-Patent-Rights.pdf.

Rai, A. K. (1999). Regulating scientific research: Intellectual property rights and the norms of science. *Northwestern University Law Review, 95*(2), 77–152.

Ranga, M., & Etzkowitz, H. (2013). Triple helix systems: an analytical framework for innovation policy and practice in the knowledge society. *Industry and Higher Education, 27*(3), 237–262.

Salmelin, B. (2013). Policy letter: the horizon 2020 framework and open innovation ecosystems. *Journal of Innovation Management, 1*(2), 4–9.

Salvatore, D., & Reagle, D. (2011). *Statistics and Econometrics* (2nd ed.). New York: McGraw Hill.

Salzberger, E. M. (2011). The Law and Economics Analysis of Intellectual Property: Paradigmatic Shift from Incentives to Traditional Property. *Review of Law & Economics, 7*(2), 435–480.

Schumpeter, J. (1934). *Theory of economic development.* Cambridge: Harvard University.

Schumpeter, J. (1942). *Capitalism, Socialism and Democracy.* New York: Harper & Brothers.

Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality? *Management Science, 56*(1), 41–56.

Sonnenwald, D. H. (2007). Scientific collaboration. *Annual Review of Information Science and Technology, 41*(1), 643–681.

Sørensen, A. (2006). R&D subsidies and the surplus appropriability problem. *The B.E. Journal of Macroeconomics, 6*(2), 1–29.

Spencer, J. W. (2003). Firms' knowledge-sharing strategies in the global innovation system: Empirical evidence from the flat panel display industry. *Strategic Management Journal, 24*(3), 217–233.

Teece, D. J. (1992). Competition, cooperation, and innovation organizational arrangements for regimes of rapid technological progress. *Journal of Economic Behavior and Organization, 18*(1), 1–25.

Thomke, S., & von Hippel, E. (2002). Customers as Innovators: A New Way to Create Value. *Harvard Business Review, 80*(4), 74–81.

Trajtenberg, M. (1990). A penny for your quotes: Patent citations and the value of innovations. *The RAND Journal of Economics, 21*(1), 172–187.

Van Looy, B., Debackere, K., Callaert, J., Tijssen, R., & van Leeuwen, T. (2006). Scientific capabilities and technological performance of national innovation systems: an exploration of emerging industrial relevant. *Scientometrics, 66*(2), 295–310.

Vanhaverbeke, W. (2006). The Inter-Organizational Context of Open Innovation. In H. Chesbrough, W. Vanhaverbeke, & J. West (Eds.), *Open Innovation: Researching a New Paradigm* (pp. 205–219). Oxford: Oxford University Press.

von Hippel, E. (1988). *The Sources of Innovation.* Oxford: Oxford University Press.

Weinberg, A. M. (1961). Impact of large-scale science on the United States. *Science, 134*(3473), 161–164.

West, J. (2006). Does Appropriability Enable or Retard Open Innovation? In H. Chesbrough, W. Vanhaverbeke, & J. West (Eds.), *Open Innovation: Researching a New Paradigm* (pp. 109–133). Oxford: Oxford University Press.

Westeren, K. I. (2012). Innovation: From Schumpeter to the Knowledge Economy. In K. I. Westeren (Ed.), *Foundations of the Knowledge Economy: Innovation, Learning and Clusters* (pp. 57–74). Northampton: Edward Elgar.

Williams, R. (2015). *Multicollinearity.* Retrieved from: https://www3.nd.edu/~rwilliam/stats2/l11.pdf.

Winickoff, D. E., Saha, K., & Graff, G. D. (2009). Opening stem cell research and development: a policy proposal for the management of data, intellectual property, and ethics. *Yale Journal of Health Policy, Law, and Ethics, 9*, 52–127.

Wooldridge, J. W. (2002). *Introductory Econometrics: A Modern Approach* (2nd ed.). South-Western.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007a). The increasing dominance of teams in production of knowledge. *Science, 316*(5827), 1036–1039.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007b). Response: Why Do Team-Authored Papers Get Cited More? *Science, 317*(5844), 1496–1498.

Yawson, R. M. (2009). Proceedings from the Future of Innovation Proceedings of the XXIV ISPIM 2009 Conference: *The Ecological System of Innovation: A New Architectural Framework for a Functional Evidence-Based Platform for Science and Innovation Policy.* Vienna, Austria. Retrieved from: http://ssrn.com/abstract=1417676.