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The effects of diversified technology and country knowledge on the impact of technological innovation

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Abstract This study examines diversified knowledge and how it affects the impact of technological innovation. Specifically, we examine the effect of diversified technology knowledge—measured by technologies that underlie patents, and the effect of diversified country knowledge—measured by collaboration with inventors from other countries. Using Generalized Linear Latent and Mixed Modeling, we analyze 97,118 patents in the computers and communications industry and in the drugs and biotechnology industry, which were applied for and granted in the US to inventors from 13 countries over a period of 5 years. Controlling for economic and cultural variables, we find that diversified technology knowledge and diversified country knowledge are both positively associated with the impact of technological innovation. These findings provide new insights for firm managers, industry leaders, and policy makers regarding effective actions designed to increase the impact of technological innovation.

Keywords Innovation · Technology · Diversified knowledge · Inventors · Patents · Citations

1 Introduction

Innovation is critical for industries because it can facilitate national growth and improve the position of the country and the industry in global markets. A national industry exhibiting reputable innovation can attract foreign investment, lead global markets, and consequently propel entire economies. Innovation-focused industry leaders, policy makers, and managers are largely aware of the importance of innovation, and are thus willing to

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invest considerable amounts of money in advancing the innovativeness of their firms and industries. However, it is not entirely clear in which aspects of research and development one should invest if the goal is to increase the impact of technological innovation. Consequently, much of the funding allocated for developing innovative technologies could turn out to be ineffective, rendering the investment suboptimal. For example, should industry leaders invest in inter-industry or inter-country collaborations? What type of knowledge exchange is most effective and should thus be incentivized by firm managers and industry leaders?

The current research aims at answering the following research question: How does diversified knowledge affect the impact of innovation in an industry? Specifically, we examine the effect of diversified *technology* knowledge—measured by the share of technologies adapted from other technology domains that underlie patents, and the effect of diversified *country* knowledge—measured by the share of collaboration of inventors from the focal country with inventors from other countries. We test how these two types of knowledge affect the impact of innovations of inventors from 13 countries in two important industries—the computers and communications industry and the drugs and biotechnology industry.

The effect of diversified knowledge on the innovation of an industry is important because such innovation could be critical for nations looking to sustain or improve their position in global markets. Indeed, governments invest hundreds of billions of dollars in innovation in their industries in an attempt to facilitate economic growth and to establish and sustain industry leadership. For example, in 2013 the US government spent about $396 billion on research and development, Japan spent about $141 billion, and China spent about $294 billion, constituting between 2 and 3.5 % of the GDP in these countries (OECD R&D statistics 2015). These numbers attest to the importance that governments attribute to innovation in their industries, as well as to the value of the present research that offers effective investment priorities.

The present study examines two types of industry-relevant knowledge: (1) diversified technology knowledge, and (2) diversified country knowledge. We define diversified *technology* knowledge as the extent to which an innovation adapts technologies from other technology domains. For example, to develop the innovation of the microwave oven, Raytheon adapted short-wave technology used in radars (US patent number 2495429A); technology knowledge was thus adapted from radars to cooking. To develop the innovation of CD-ROM, researchers at the Pacific Northwest National Laboratory used compact disc technology originally designed for playing music (Dew et al. 2004); technology knowledge was thus adapted from music playing to computer data storage. Given our interest in industries, we look at diversified technology knowledge of innovations aggregated to industry level.

We define diversified *country* knowledge as the extent to which an industry employs the knowledge of inventors from other countries for developing innovation. For example, to develop the innovation of the television camera, RCA recruited Vladimir Zworykin, an engineer who received his technological education in Russia, to direct the American team of inventors (Abramson 1995), thus utilizing knowledge of an inventor from another country.

The drivers that can affect innovation in national industries have long been of great interest to scholars (e.g. Lanjouw and Schankerman 2004; Shane 1992; Tellis et al. 2009). However, the role of diversified knowledge has thus far not been directly addressed. Moreover, diversified technology knowledge has previously been examined primarily at the inventor level (Hargadon 2002; Hargadon and Sutton 1997). We contribute to the literature (1) by examining the effect of diversified technology knowledge at the national industry level and deciphering a specific form of technology recombination (Fleming 2001), and (2) by testing the effect of diversified technology knowledge simultaneously with the effect of diversified country knowledge, across a large international sample.

We use patent, economic, and cultural data to test our hypotheses, which we develop to answer the research question stated above. Our data include 97,118 patents granted by the United States Patent and Trademark Office (USPTO) to inventors from 13 countries over a period of 5 years in two major industries. We find that diversified technology and country knowledge can critically affect the impact of innovation in these industries.

The remainder of the paper is organized as follows. We begin with establishing a theoretical framework, from which we develop our hypotheses. We then describe our data and measures. We go on to present our results and discuss the findings and limitations of the study, and finally we suggest future research opportunities and implications.

2 Theoretical framework and hypotheses

In this section we establish a theoretical framework that we use throughout the paper, and from which we develop our hypotheses regarding the effects of diversified technology knowledge and country knowledge on the impact of innovation. We exhibit our conceptual framework in Fig. 1.

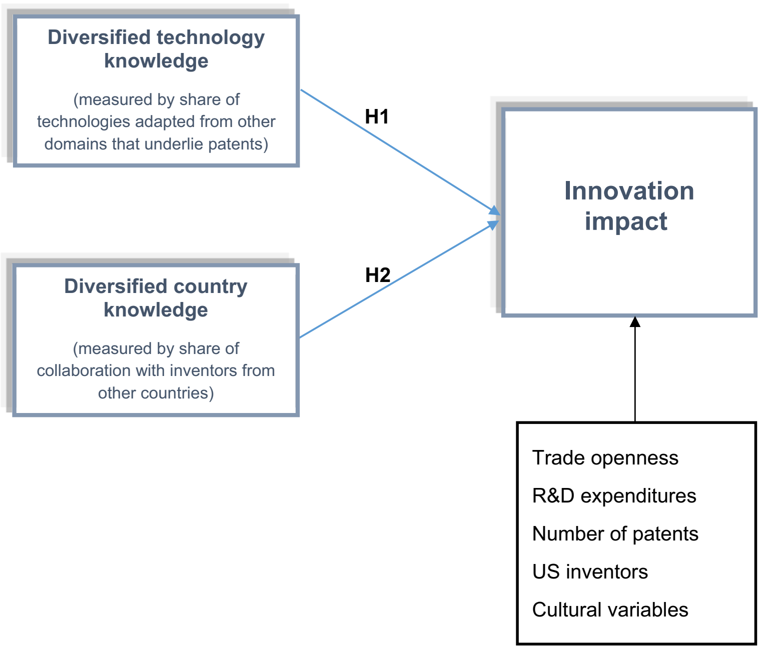

Fig. 1 Conceptual framework: diversified knowledge and the impact of innovation

2.1 Diversified knowledge and innovation

Research suggests that external knowledge inputs are vital for accelerating innovation (Saebi and Foss 2014). A frequent mean of accessing external knowledge is through R&D collaborations and innovation networks (see Bouty 2000; Dhanaraj and Parkhe 2006). Such collaborations enable firms to access knowledge that exists outside the specific firm; This type of knowledge mobility facilitates synergies that lead to enhanced innovation performance (Dhanaraj and Parkhe 2006).

We posit that diversified knowledge positively affects the impact of innovation for two major reasons: (1) diversified knowledge enables *entrenchment escaping and closure avoidance*; and (2) diversified knowledge drives an *increased variety of the knowledge stock available for innovation*. We discuss these reasons next.

2.1.1 Entrenchment escaping and closure avoidance

Innovation processes founded solely on currently existing knowledge, or on narrow knowledge, are likely to lead to entrenchment of the thought and development processes. Without stretching knowledge boundaries firms become entrenched and cannot achieve innovation (Leonard-Barton 1992). Knowledge that is not open to new directions leads to closure, which only allows for the further exploitation of already existing knowledge, rather than the exploration of new knowledge that may open new opportunities and expand technological possibilities. Accordingly, an important innovation-related competence is the ability to access new knowledge that does not exist within the current knowledge boundaries, and to integrate it into the innovation effort (Henderson and Cockburn 1994).

2.1.2 Increased variety of the knowledge stock available for innovation

Prior studies indicated that the diversity of the knowledge available for innovation can be critical. For example, Hargadon (2002) and Hargadon and Sutton (1997) have identified that learning about resources in multiple domains and then combining ideas, artifacts, and individuals across domains to solve problems positively affects innovation. The more varied the stock of knowledge available for innovation, the larger the recombinant opportunities it potentially has. The variety improves the selection process and decreases the likelihood of technological dead-ends (Singh and Fleming 2010). The variety of knowledge also promotes combining ideas that had not been brought together before, thus leading to increased innovation performance (Ahuja and Lampert 2001; Singh and Fleming 2010). This notion of variety is in line with the increased variance associated with exploration activities, as opposed to exploitation, and is associated with increased innovation performance (March 1991). In the following sections we develop our hypotheses regarding diversified knowledge based on the above ideas of avoiding closure and increasing variety.

2.2 Innovation and diversified technology knowledge

A number of scholars have addressed the use of diversified technology knowledge, and, more specifically, knowledge that originated in a specific technology domain and was then taken out of the original domain and adapted into a different technological domain (e.g.

Cattani 2005; Dew et al. 2004, 2008). For example, the development of the LCD television flat screen adapted a technology originally developed for car safety windshields (Cattani 2006), thus increasing the diversity of the technology used to develop the innovation. Similarly, the development of Viagra adapted a technology originally developed for treatment of heart disease (Dew et al. 2004). The diversified technology base of Viagra contributed to the impact of this innovation.

With the ever-increasing importance of utilizing technology from external sources, appropriately managing external sources of technology has become critical for innovation (Van de Vrande 2013). For example, combining knowledge across diverse technologies was found to be associated with exploration activities that supported innovation in the optical disk industry (Rosenkopf and Nerkar 2001). Accordingly, we posit that a technology adapted from a different technology domain is likely to increase the impact of innovation, because it enables avoiding closure and increasing the variety of knowledge.

First, an idea taken from its original context and adapted to a new context is perceived as creative (Goldenberg et al. 1999), and thus it breaches any entrenchment potential and facilitates *closure avoidance*. As a result, the target market perceives the technology as richer and more promising. Moreover, a technology may be evolutionary in its own domain, but once adapted into a new domain it is effectively quite different from the existing technology in that new domain, thus creating a revolutionary technological leap. For example, for the development of Pyrex home cooking-ware, the inventors adapted an extreme temperature-enduring glass technology that was used for railroad lanterns. The heat-resistant glass was evolutionary in the railroad lantern industry, but once adapted into the cooking domain Pyrex became revolutionary as a substitute for metal and clay cooking-ware (Rosenzweig et al. 2015).

Second, a combination of components and processes from more than one technology domain, i.e. *increased variety*, can potentially produce impactful innovation (Fleming and Sorenson 2004). Technological evolution in a specific market may reach a certain limit, but adapting a technology that was originally developed in a different technology domain to a new domain enables cross-fertilization, and provides new benefits to the new customers (Foster 1986). The combining of diverse technological components generates unique and thus genuine innovation (Van de Vrande 2013), enabling inventors to adapt solutions across technology domains and thereby creating innovations based on a variety of technologies (Hargadon and Sutton 1997). This wide recombination of knowledge is likely to lead to innovations with high economic value (Kaplan and Vakili 2015). The above evidence and arguments suggest that:

HP 1 Diversified technology knowledge positively affects the impact of innovation.

2.3 Innovation and diversified country knowledge

With the increase in the complexity, risks, and costs of innovation in recent decades, cooperation for the sake of innovating has become increasingly important (Hagedoorn 2002). Prior studies have found that learning from other countries is critical for R&D (e.g. Rosenberg and Steinmueller 1988), and that access to foreign R&D meaningfully affects a country's productivity (e.g. Coe and Helpman 1995). R&D cooperation with other countries can considerably affect technological advancements (Feinberg and Gupta 2004), and foreign R&D activities can have a meaningful influence on the innovation performance of firms that utilize such activities (Liu and Buck 2007).

We argue that cooperation with inventors from other countries increases the impact of innovation for two main reasons. First, cooperation with inventors from other countries enables *closure avoidance*. When inventors enter a certain field they usually spend most of their professional time with others just like them—people who share the same ideas and same assumptions. This closure impedes creativity and innovation (Kanter 1996). Networking with similar professionals implies social closure. In a state of closure, individuals in a network are connected more to each other than to outsiders, thus restricting their access to resources and information that outsiders possess (Burt 1992; Granovetter 1992). Conversely, cooperating with diverse individuals who increase the heterogeneity of one's network increases the heterogeneity of the social capital embedded in the network (Granovetter 1973; Rosenzweig et al. 2016). Thus, cooperating with inventors from other countries enables closure avoidance.

Second, cooperating with inventors from other countries enables the integration of their knowledge and thus the *increased variety* of the stock of knowledge, leading to increased productivity (Grossman and Helpman 1991). When cooperating with R&D personnel in other countries, inventors can learn not only from innovation activities in their own country but also from the technological advancements that their peers are achieving in other countries (Grossman and Helpman 1991). Moreover, inventors from different countries are likely to have diverse technical experience, which was found to positively affect innovation performance (Singh and Fleming 2010). Such considerable positive effects are far greater than any transaction costs of a cooperative effort (Becker and Dietz 2004). We therefore hypothesize that:

HP 2 Diversified country knowledge positively affects the impact of innovation.

3 Data and methods

3.1 Sample

We use countries' patents and economic and culture indicators to test our hypotheses. Patents are good indicators of knowledge mobility and transfer (Agrawal and Henderson 2002). Numerous management studies have used patenting indicators to measure technological outputs and innovative performance (e.g. Artz et al. 2010; Chatterji and Fabrizio 2014; Rosenzweig and Mazursky 2014; Sorescu et al. 2007; Van de Vrande 2013). Specifically, we use the National Bureau of Economic Research (NBER) patent dataset. We examine patents applied for and granted in the US in two technological categories: (1) computers and communications (including communications, computer hardware and software, computer peripherals, and information storage subcategories), and (2) drugs and biotechnology (including drugs and biotechnology subcategories). We select US patent data because the US is the global arena for high-tech and bio-tech innovations, and any firm in any country that wishes to export goods protects its intellectual property in the US. The United States Patent and Trademark Office (USPTO) is the global standard for patenting, and a patent granted in the US is likely to be protected by international law in other countries (Trajtenberg 2001). We select these two industries because they are of primary interest for researchers, as is evident in prior management studies that have examined them (e.g. Chatterji and Fabrizio 2014, 2016; Narasimhan et al. 2006; Rosenzweig 2015; Zidorn and Wagner 2013).

3.2 Measures

3.2.1 Dependent variable

Using the NBER patent dataset, we adapt Trajtenberg's (1990) measure of the average number of citations that patents received from subsequent future patents (forward citations) to measure *innovation impact*. We then aggregate the patents to the industry level:

$$Innovation\_impact_{jt} = \frac{\sum_{i=1}^{n_{jt}} (1 + Forward\_citations_i) - n_{jt}}{n_{jt}} \quad (1)$$

where i is a patent, j is an industry, t is time (year), and n is the number of patents applied for in industry j in year t. The logic behind this measure is that patents that are cited more often by subsequent patents are more impactful (Narasimhan et al. 2006). Economic and managerial research have used citation counts as innovation performance indicators (e.g. Audia and Goncalo 2007; Benner and Tushman 2002; Lanjouw and Schankerman 2004; Rosenzweig and Mazursky 2014; Sorescu et al. 2007). To be approved by patent examiners, inventors must cite all prior patents on which they relied but have no incentive to over-cite prior patents; thus, patent citations are not biased or tainted by unnecessary citations of friends or famous inventors (Chandy et al. 2006; Gomes-Casseres et al. 2006). We use citations received until 2006 by patents applied for and granted between 1995 and 1999. This enables us a sufficient historic and future time windows to measure future impact avoiding truncation bias (Chatterji and Fabrizio 2014). We follow prior studies that have used a similarly far-back time window; for example, Lanjouw and Schankerman (2004) examined patents applied for until 1993, and Singh and Fleming (2010) examined patents applied for until 1995. We exclude self-citations, i.e., citations made by firms of their own prior patents. Because a patent granted in 1995 has had more time to be cited than a patent granted in 1999, we use citation counts corrected for this truncation (Hall et al. 2001). We examine patents applied to by inventors from 13 countries.[1] The convention of the US patent office is to determine the nationality of the patent according to the address of the first inventor, and we follow this convention (Trajtenberg 2001; see also Hall et al. 2001). The total number of patents included in our analysis is 97,118, aggregated to the industry level within a country and year (see Table 1). Accordingly, our level of analysis is an industry within a country. Because the counts are averaged and aggregated, their distribution is close to normal, with no zero inflation.

3.2.2 Independent variables

We measure *diversified technology knowledge* using a patent's citations of prior patents (backward citations), indicating the technologies the patent relies on. We count the number of prior patents that a given patent cites that are from technology domains different from the technology domain of the focal patent:

$$Diversified\_technology_i = 1 - \sum_{j}^{m_i} D_{ij}^2, \quad (2)$$

[1] We select all the countries examined by Trajtenberg (2001), but exclude Hong Kong, Singapore, and Taiwan because we were unable to obtain reliable country-level data for some of the examined years.

Table 1 Countries and number of patents included in the analyses

Country	Total number of patents	Number of patents in computers and communications	Number of patents in drugs and biotechnology
US	59,215	41,418	17,797
Japan	22,318	19,653	2665
Germany	3389	1749	1640
UK	2706	1398	1308
France	2674	1300	1374
Korea	2542	2386	156
Canada	2005	1229	776
Italy	751	344	407
Israel	697	483	214
Finland	571	471	100
Spain	132	43	89
New Zealand	64	29	35
Ireland	54	39	15
Total	97,118	70,542	26,576

Data were classified by the author

where D_{ij}^2 is the percentage of citations cited by patent i that belongs to industry j out of m_i industries. If a patent cites very few patents from other technology domains then this measure is close to zero, indicating it is not diversified because it relies primarily on technology from the same domain. However, if it cites many patents from other technology domains then the measure is close to one, indicating it is highly diversified because it relies heavily on technology domains other than its own (Hall et al. 2001).

We measure *diversified country knowledge* using the share of patents of a country that were co-invented with inventors from other countries:

$$Diversified\_country\_knowledge_{ct-1} = \frac{Patents\,with\,inventors\,from\,other\,countries_{ct-1}}{Total\,patents_{ct-1}}, \quad (3)$$

where $Patents\,with\,inventors\,from\,other\,countries_{ct-1}$ is the number of patents of country c in year $t-1$ in which inventors from the focal country c co-invented patents with inventors from other countries, and $Total\,patents_{ct-1}$ is the total number of patents applied for by inventors from the focal country c in year $t-1$. This measure is frequently used—for example, by the Organization for Economic Co-operation and Development (OECD)—to estimate the extent of collaboration between inventors across countries. Accordingly, this measure was not derived from our patent data but rather from the OECD 'international co-operation in patents' database.[2] Given that this measure relates to cooperation with inventors from other countries in all industries of a country in a given year, the measure is not industry-specific but rather country-specific, and thus is in line with our theory. We use this measure with a 1-year lag to ensure causal ordering.

[2] The data are available at http://stats.oecd.org/# under 'international co-operation in patents' (percent of patents with foreign co-inventors)/patents statistics/science, technology and patents section of the OECD statistics. To construct the OECD measure, the number of patent applications to the Patent Cooperation Treaty (an international patent law contract that provides a uniform procedure for filing patent applications) of each country in a given year was counted, and the share of these patents in which inventors from the focal country collaborated with inventors from other countries from this number was calculated.

3.2.3 Control variables

Our analysis controls for additional variables that are potentially relevant to the industries' impact of innovation. Because the extent to which a country is open for international imports and exports has been found to affect a country's innovation (see Furman et al. 2002; Liu and Buck 2007; Rosenzweig and Mazursky 2014), we control for the *trade openness* of the countries in our sample. We use the sum of imports and exports as a share of the GDP, with a 1-year lag to ensure causal ordering. Following prior research, we also control for the *R&D expenditure* of the focal country (e.g. Furman et al. 2002; Gallié and Legros 2012; Liu et al. 2008), and for the *number of patents* per industry granted by the US patent office, because it measures the ability of a national industry to convert knowledge into innovation and potential economic value (e.g. Andrew 2009; Liu et al. 2008; Rosenzweig and Mazursky 2014). These data were obtained from the OECD databases. Following prior research controlling for national cultural aspects, we control for the following cultural variables (Hofstede 2001): *individualism* (vs. collectivism), *masculinity*, *uncertainty avoidance*, *long-term orientation*, and *power distance index*. Power distance is a cultural dimension that reflects the extent to which individuals accept the fact that the distribution of power in their culture is unequal. Individuals in societies high in power distance expect their society to behave hierarchically. Consequently, individuals in such societies (high power distance index) accept the authority of individuals who are considered socially superior to them. In societies low in power distance, individuals do not expect hierarchical behavior and tend to treat individuals who are considered to be socially superior to them as equals (Hofstede 2001; Hofstede et al. 2010; Roozmand et al. 2011). Specifically, we used the power distance index, and all other cultural variables, provided by Hofstede (2001). Hofstede's cultural measures are frequently used in innovation studies (e.g. Efrat 2014; Engelen et al. 2012, 2014).

To control for *time effects*, we use year of patent application dummy variables. Whereas we include patents granted until 1999, the time indicator in our analysis refer to the year the patent was applied for, because this point in time is close to the time the innovation was actually developed. To control for *industry effects* we use a dummy variable denoting 1 for computers and communications, and 0 for drugs and biotechnology. Finally, because we examine citations of patents granted by the US patent office, we also include a dummy variable to control for patents of *American* inventors, because they are likely to be over-represented compared with non-American inventors.

4 Analysis and results

4.1 Descriptive findings

Table 2 provides the correlations of the study's variables. Figure 2 exhibits the average impact of innovation by countries and industries. We find that the highest impact for innovation in the computers and communications industry in the examined years is of New Zealand (31.73), followed by Ireland (29.19) and Canada (29.05). The highest impact for innovation in drugs and biotechnology is of the US (9.83), followed by Israel (8.79) and Ireland (8.10). Figure 3 exhibits the average share of diversified technology knowledge by country and industry. The highest level of diversified technology is of the US (an average of 38.6 % of the technology is adapted from other technological domains for both

Table 2 Correlation matrix of the study's variables

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Innovation impact	1										
2. Diversified technology knowledge	.593***	1									
3. Diversified country knowledge	−.005	−.062	1								
4. Trade openness	−.191*	−.116	−.052	1							
5. R&D expenditure	−.238*	−.139	−.012*	.975***	1						
6. Individualism	.240**	.193*	.097	−.762***	.809***	1					
7. Masculinity	−.002	−.123	.000	−.271**	−.120	.208*	1				
8. Uncertainty avoidance	−.350***	−.268**	−.127	.345***	.417***	−.723***	−.064	1			
9. Long−term orientation	−.432***	−.354***	−.142	.605***	.687***	−.676***	.198*	.662***	1		
10. Power distance index	.428***	.310***	.183	−.391	−.434***	.373***	.019	−.587***	−.592***	1	
11. Number of patents	.234*	.257**	−.069	−.074	−.040	.222*	.220*	−.116	−.143	−.047	1

+ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

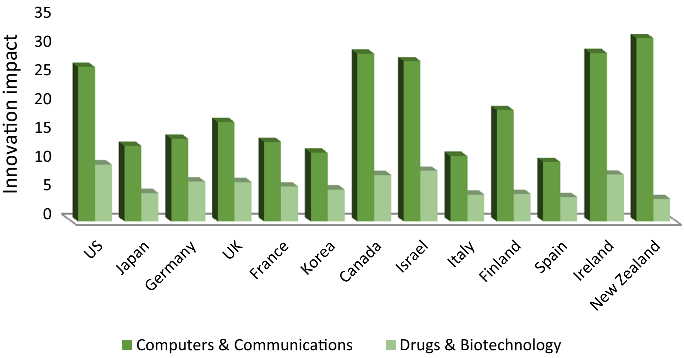

Fig. 2 Average impact of innovation by country and industry

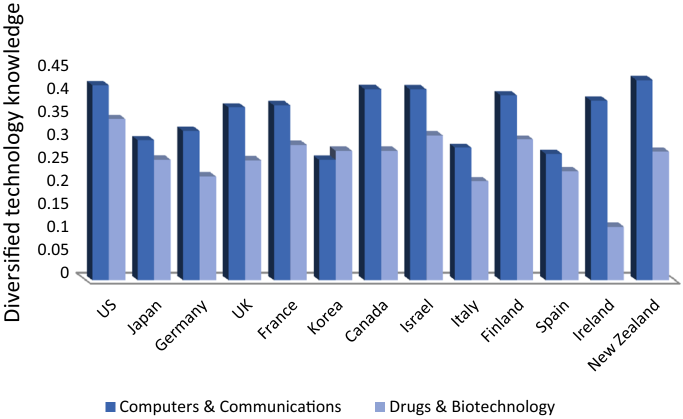

Fig. 3 Diversified technology knowledge (average share of technology from other domains underlying patents)

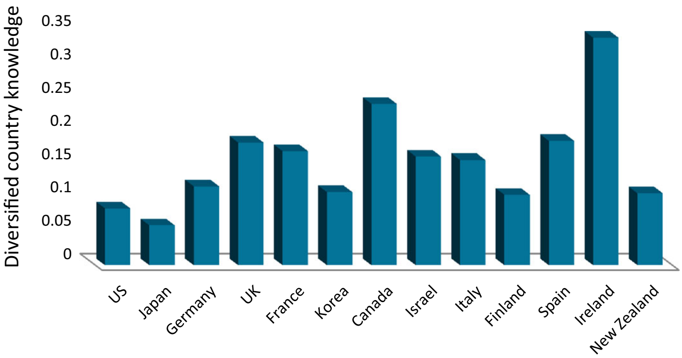

Fig. 4 Diversified country knowledge (share of cooperation with inventors from other countries)

examined industries), followed by Israel (36.4 %) and Finland (35.3 %). Figure 4 exhibits the share of cooperation with inventors from other countries. The highest tendency for diversified country knowledge is of Ireland (34.1 %), followed by Canada (24.2 %) and Spain (18.6 %).

4.2 Hypotheses testing

To test our hypotheses we use a generalized linear latent and mixed model (gllamm) regression procedure (Rabe-Hesketh et al. 2002). This multilevel regression model is superior to other models in analyzing our data in that it accounts for multilevel variables. Our data have multilevel variables of observations nested in different industries, which are nested within countries. The gllamm model includes both fixed and random effects in the linear predictor, and is especially fitted for observations that are grouped in clusters and thus are mutually dependent (Rabe-Hesketh et al. 2002). In other words, our data have three levels: level-1 units are the measurement of innovation impact. These level-1 units are nested in level-2 units, which are the two industries (1) computation and communications; and (2) drugs and biotechnology. These level-2 units are nested in level-3 units, which are the 13 countries that we examine. Our gllamm procedure ascribes random effects at the industry and country levels, but the variation is constant for the two industries that belong to the same country.[3] We use this model because the innovation impact of two industries within a single country is affected by similar macro-economic and cultural variables. Note that the objective of this model is to assess diversified knowledge effects on industries, and the countries we examine are *integrated* into the analysis rather than compared to one another.

We execute the gllamm procedure using Stata, specifying a three-level model. Following the recommendation of Rabe-Hesketh et al. (2004), we use the following model specifications: the family for the continuous response is Gaussian; we use 10 quadrature points; and we use the adaptive quadrature option that provides better parameter estimates than the ordinary quadrature, as it better accounts for potential large clusters, large number of events and instances of intra-class correlations (Rabe-Hesketh et al. 2002). We fit a model where the dependent variable is the innovation impact, diversified technology knowledge and diversified country knowledge are predictors, and the covariates are as listed in Table 3, with 26 level-2 units (two industries in each of the 13 countries) and with 13 level-3 units (13 countries).

Column 1 in Table 3 reports the results of our main model. We find that diversified technology knowledge, in terms of technologies underlying patents, is positively and significantly associated with the impact of innovation ($\beta = 16.92$, $p = .024$), in support of Hypothesis 1. Similarly, we find that diversified country knowledge, in terms of cooperating with inventors from other countries, is positively and significantly associated with the impact of innovation ($\beta = 47.19$, $p = .001$), in support of Hypothesis 2. We also find that the computers and communications industry is positively associated with the impact of innovation compared with the drugs and biotechnology industry, and that power distance is negatively and significantly associated with the impact of innovation.

[3] A frequent example is pupils in classes, where there are random effects at the class level but variation is constant for pupils in the same class (Rabe-Hesketh et al. 2004).

Table 3 The effect of diversified knowledge on innovation impact—coefficients (SE)

DV: innovation impact	Generalized linear latent and mixed models					
	(1) Main model		(2)		(3)	
Diversified technology knowledge	**16.92**	(**7.508**)*	−62.25	(16.826)***	−48.93	(27.470)$^{+}$
Diversified country knowledge	**47.19**	(**14.843**)**	−97.62	(31.192)**	−97.06	(34.670)**
Diversified technology knowledge × diversified country knowledge			**456.57**	(**88.889**)***	**457.94**	(**96.254**)***
Trade openness	−.000	(.000)	.000	(.000)$^{+}$	.000	(.000)
R&D expenditure	1.29	(1.149)	1.91	(1.040)$^{+}$	3.36	(2.519)
Number of patents	.000	(.000)	.000	(.000)**	.001	(.000)**
Individualism/collectivism	.07	(.108)	.17	(.099)$^{+}$	.18	(.099)$^{+}$
Masculinity	−.03	(.066)	−.12	(.061)*	−.13	(.063)*
Uncertainty avoidance	.05	(.071)	.09	(.065)	.09	(.065)
Long-term orientation	−.001	(.061)	−.02	(.055)	.03	(.059)
Power distance index	−.24	(.073)**	−.29	(.066)***	−.18	(.172)
Diversified technology knowledge × trade openness					.000	(.000)
Diversified technology knowledge × R&D expenditure					−5.06	(8.052)
Diversified technology knowledge × power distance index					−.344	(.485)
Computers and communication	6.05	(1.104)***	6.08	(.992)***	6.24	(1.021)***
American inventors	6.43	(3.763)$^{+}$	5.96	(3.383)$^{+}$	5.81	(3.443)$^{+}$
1995						
1996	.10	(1.527)	−.03	(1.372)	−.17	(1.368)
1997	−1.22	(1.568)	−1.27	(1.409)	−1.45	(1.410)
1998	−.76	(1.664)	−.373	(1.497)	−.60	(1.501)

Table 3 continued

DV: innovation impact	Generalized linear latent and mixed models					
	(1) Main model		(2)		(3)	
1999	−3.24	(2.292)	−3.87	(2.064)$^{+}$	−4.09	(2.092)$^{+}$
Intercept	2.41	(10.229)	23.24	(10.049)*	18.35	(12.808)
Log likelihood	−339.610		−327.775		−327.052	

Bold values indicate the coefficients of the independent variables (hypothesized effects)

$^{+}$ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

4.3 Additional analyses and robustness checks

It would be valuable to understand the potential effect of a combination of diversified knowledge, that is, whether the effect of an interaction between diversified technology knowledge and diversified country knowledge also positively affect innovation impact. For this purpose, we have added an interaction of these two types of diversified knowledge to our main model (Table 3 column 2). We find that the coefficient of the interaction is positive and significant ($\beta = 456.57$, $p < .001$), indicating that highly diversified technology and country knowledge significantly increase innovation impact. Moreover, it could be argued that it is not the cooperation with inventors from other countries that matters, as much as the country being open to goods and ideas from other countries, or the country being culturally open to ideas of different social groups or sectors within the country that increases the positive effect of diversified technology. We therefore add an interaction of diversified technology knowledge with both trade openness, and power distance index respectively. Similarly, one could argue that diversified technology could flourish if the country invests considerable funds in research and development. We thus added an interaction of diversified technology and R&D expenditure. The results, presented in Table 3 column 3, suggest that whereas the interaction of diversified technology and country knowledge remains positive and significant, these additional interactions are insignificant. These findings further strengthen the importance of diversified knowledge to the impact of innovation.

For robustness checks, we conducted similar gllamm analyses based on our main model, clustering years and industries in countries (as opposed to only clustering industries in countries in our main model). We report these analyses in columns 1–2 of Table 4. As an additional robustness check, we used a cross-sectional time series regression analysis. We report the results in column 3 of Table 4. In all of these analyses, we replicate the findings from our main model.

4.4 Addressing potential selection bias

Compared with patents by US inventors, the number of patents by non-US inventors in our sample is small (see Table 1). This difference could indicate a selection bias: foreign inventors select only their very best patents to invest in and to patent by the US patent office. If this is the case, then the average impact of these selected foreign patents is likely to be higher than that of US patents, whose inventors apply to the US patent office for all their patents, regardless of their quality or importance. However, such possible selection bias does not limit our findings for the following reasons. First, we do not make any assumptions regarding differences between countries. Second, for the computers and communications industry, four countries exhibit similarly high impact rates to the impact rates of American innovation, and all other countries exhibit lower impact rates. In the drugs and biotechnology industry, the average impact of American patents is considerably higher than that of other countries (see Fig. 2). These findings suggest that American innovation in our sample is no less impactful than the innovation of inventors from other countries, indicating the absence of selection bias against American inventors. Third, our regression analyses control for such a potential bias by integrating a dummy variable for patents of American inventors.

Table 4 The effect of diversified knowledge on innovation impact—robustness checks—coefficients (SE)

DV: innovation impact	Generalized linear latent and mixed models (industries and years clustered in countries)				(3) Cross-sectional time series model	
	(1)		(2)			
Diversified technology knowledge	**17.19**	(**7.443**)*	**23.14**	(**6.251**)***	**22.85**	(**6.648**)**
Diversified country knowledge	**47.48**	(**14.711**)**	**45.95**	(**14.901**)**	**45.18**	(**15.981**)**
Trade openness	.000	(.000)	.000	(.000)	−.000	(.000)
R&D expenditure	1.33	(1.139)	1.02	(1.153)	.97	(1.243)
Number of patents	.000	(.000)	.000	(.000)	.000	(.000)*
Individualism/collectivism	.07	(.107)	.04	(.107)	.04	(.117)
Masculinity	−.04	(.065)	−.02	(.066)	−.025	(.071)
Uncertainty avoidance	.05	(.071)	.05	(.071)	.04	(.078)
Long-term orientation	−.000	(.061)	−.006	(.061)	−.009	(.067)
Power distance index	−.25	(.072)**	−.23	(.072)**	−.22	(.078)**
Computers and communication	6.02	(1.093)***	5.64	(1.078)***	5.67	(1.177)***
American inventors	6.40	(.085)$^{+}$	4.87	(3.676)	4.74	(3.965)
1995						
1996	.11	(1.510)				
1997	−1.20	(1.551)				
1998	−.73	(1.646)				
1999	−3.18	(2.269)				
Intercept	2.20	(10.139)	1.36	(10.296)	1.78	(11.214)
Log likelihood	−339.630		−341.048		Wald $\chi^2_{12} = 153.53$***	

Bold values indicate the coefficients of the independent variables (hypothesized effects)

$^{+}$ $p < .1$; * $p < .05$; ** $p < .01$; *** $p < .001$

5 Discussion

5.1 Contribution and main findings

The present study suggests that the impact of innovation in both the computers and communications industry and the drugs and biotechnology industry is meaningfully affected by diversified knowledge. We contribute to the literature by examining two types of diversified knowledge—technology and country—at the national industry level across a large international sample. The key findings of this study regarding the said industries are: (1) Diversified technology knowledge, as measured by the share of technologies adapted from other technology domains that underlie patents, is positively associated with innovation impact; and (2) Diversified country knowledge, as measured by the share of collaboration with inventors from other countries, is positively associated with innovation impact. We posit that the positive effect on the impact of innovation stems from closure avoidance and the increased variety of the knowledge stock available for innovation.

5.2 Limitations and future research opportunities

Patent data have become very popular in recent years, and have been used in studies to measure innovation impact, quality, and usefulness (e.g. Artz et al. 2010; Chatterji and Fabrizio 2014, 2016; Kaplan and Vakili 2015; Rosenzweig and Mazursky 2014; Van de Vrande 2013). This popularity stems from the fact that patents are historical records that provide a systematic measure of inventors, networks, usefulness, technology spillover, and the economic value of innovations (see Kaplan and Vakili 2015; Singh and Fleming 2010; Trajtenberg 1990). That being said, patent data do have some limitations. First, not all innovations are patented, because inventors may choose to either protect their innovation by secrecy or not to protect it at all (Hall et al. 2001; Moser 2005). If innovations are not patented, then the diversified technology knowledge (if any) in these innovations is not recorded.

Second, prior studies suggest that patent citations are tainted by citations made by patent examiners rather than by the inventors themselves, suggesting that inventors may have been entirely unaware of the patents that their innovation ultimately cited (Alcacer et al. 2009; Criscuolo and Verspagen 2008; Gomes-Casseres et al. 2006). Whereas we acknowledge this limitation, it is unlikely that it biased our results because (a) in the US patenting system, as opposed to the European one, the applicants and not the examiners are responsible for complete disclosure of prior technology (Branstetter 2006; Criscuolo and Verspagen 2008); and (b) based on the seminal work of Trajtenberg (1990), it is the combined number of citations of both the inventors and the examiners that indicate the actual impact of the cited patent.

Third, our measure of diversified technology, which is based on backward patent citations, relates to whether the focal patent and the patents it relies on are from the same technology domain. It does not, however, account for the technological distance between these patents. Future research can account for any technological distance and examine whether drawing on close or distant technology domains impedes or facilitates the impact of innovation (Kaplan and Vakili 2015). For example, it could be the case that adapting a technology from a close domain positively affects the impact of innovation, but adapting a technology from a distant domain negatively affects the impact of innovation. There is also room for examining the effect of the variables we focus on at the firm level. Whereas diversified knowledge related to inventors at the firm level was examined in prior studies (e.g. Chatterji and Fabrizio 2016; Singh and Fleming 2010), we know very little about diversified technology knowledge at the firm level. In the same vein, we know very little about the effect of other diverse sources of knowledge within an organizational— rather than a national—culture context.

5.3 Implications

The findings of this study have implications for policy makers, industry leaders, firm managers, and researchers. First, policy makers and industry leaders should be aware of the variables that affect the impact of innovation in their industries. For example, policy makers and industry leaders should publicize the positive effects of diversified knowledge from a variety of technology domains on the impact of innovation, and incentivize such adaptation through industry and academic seminars and conferences, as well as through designated funding. It is also valuable for policy makers to be aware of the notion that inter-country collaborations at the country level may spill over and positively affect the impact of innovation, at least in the computers and communications industry and in the drugs and biotechnology industry. These two forms of knowledge diversification—technology and country—may prove to be valuable in improving innovation impact in the said industries, not only as a main effect but also through their interaction.

Second, this study examines the level of the industry. However, because the industry is a collection of the firms active in it, the findings imply that one can take measures to increase the impact of innovations not only at the industry level, but also act to increase the impact of innovation in a single firm. Consequently, managers may want to consider implementing routines of inter-country collaboration. They can also actively search for technologies in domains other than the ones in which their firm is active, and adapt and integrate them in their new products and technologies. Such an active position is likely not only to increase the impact of innovative technologies, but also to be less costly than developing entirely new technologies (Rosenzweig et al. 2015).

Third, the idea of diversified technology knowledge is discussed in the innovation literature primarily in the context of recombination. For example, Fleming (2001) relates to recombination as joining components that exist either in a similar context or a different one. Hargadon (2002) and Hargadon and Sutton (1997) address inventors as brokers of knowledge, who combine in new ways technologies with which they are already familiar. Specifically, Hargadon (2002) provides the example of Ford's innovation of mass production as the combination of four technologies that were already used in car manufacturing—interchangeable parts, an electric motor, flow production, and an assembly line, and their conflation into a single system. The present study examines a specific and different kind of recombination—a technology taken *out of its original context* and adapted to an entirely different technological context. A theoretical implication of this study, therefore, is the disentangling of recombination and empirically testing the contribution of this specific kind of recombination—diversified technology knowledge—in a single framework with other sources of diversified knowledge. Exemplifying the advantages of this specific type of a recombination is a theoretical step forward in deciphering an array of technological recombination.

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References

Abramson, A. (1995). *Zworykin, pioneer of television*. Champaign, IL: University of Illinois Press.

Agrawal, A., & Henderson, R. (2002). Putting patents in context: Exploring knowledge transfer from MIT. *Management Science, 48*(1), 44–60.

Ahuja, G., & Lampert, C. M. (2001). Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventions. *Strategic Management Journal, 22*(6–7), 521–543.

Alcacer, J., Gittelman, M., & Sampat, B. (2009). Applicant and examiner citations in US patents: An overview and analysis. *Research Policy, 38*(2), 415–427.

Andrew, J. N. (2009). Measuring knowledge spillovers: What patents, licenses and publications reveal about innovation diffusion. *Research Policy, 38*(6), 994–1005.

Artz, K. W., Norman, P. M., Hatfield, D. E., & Cardinal, L. B. (2010). A longitudinal study of the impact of R&D, patents, and product innovation on firm performance. *Journal of Product Innovation Management, 27*(5), 725–740.

Audia, P. G., & Goncalo, J. A. (2007). Past success and creativity over time: A study of inventors in the hard disk drive industry. *Management Science, 53*(1), 1–15.

Becker, W., & Dietz, J. (2004). R&D cooperation and innovation activities of firms—Evidence for the German manufacturing industry. *Research Policy, 33*(2), 209–223.

Benner, M. J., & Tushman, M. (2002). Process management and technological innovation: A longitudinal study of the photography and paint industries. *Administrative Science Quarterly, 47*(4), 676–707.

Bouty, I. (2000). Interpersonal and interaction influences on informal resource exchanges between R&D researchers across organizational voundaries. *Academy of Management Journal, 43*(1), 50–65.

Branstetter, L. (2006). Is foreign direct investment a channel of knowledge spillovers? Evidence from Japan's FDI in the United States. *Journal of International Economics, 68*(2), 325–344.

Burt, R. (1992). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Cattani, G. (2005). Preadaptation, firm heterogeneity, and technological performance: A study on the evolution of fiber optics, 1970–1995. *Organization Science, 16*(6), 563–580.

Cattani, G. (2006). Technological pre-adaptation, speciation, and emergence of new technologies: How corning invented and developed fiber optics. *Industrial and Corporate Change, 15*(2), 285–318.

Chandy, R. K., Hopstaken, B., Narasimhan, O., & Prabhu, J. (2006). From invention to innovation: Conversion ability in product development. *Journal of Marketing Research, 43*(3), 494–508.

Chatterji, A. K., & Fabrizio, K. R. (2014). Using users: When does external knowledge enhance corporate product innovation? *Strategic Management Journal, 35*(10), 1427–1445.

Chatterji, A. K., & Fabrizio, K. R. (2016). Does the market for ideas influence the rate and direction of innovative activity? Evidence from the medical device industry. *Strategic Management Journal*, *37*(3), 447–465.

Coe, D. T., & Helpman, E. (1995). International R&D spillovers. *European Economic Review, 39*(5), 859–887.

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

Dew, N., Read, S., Sarasvathy, S. D., & Wiltbank, R. (2008). Outlines of a behavioral theory of the entrepreneurial firm. *Journal of Economic Behavior and Organization, 66*(1), 37–59.

Dew, N., Sarasvathy, S. D., & Venkataraman, S. (2004). The economic implications of exaptation. *Journal of Evolutionary Economics, 14*(1), 69–84.

Dhanaraj, C., & Parkhe, A. (2006). Orchestrating innovation networks. *Academy of Management Review, 31*(3), 659–669.

Efrat, K. (2014). The direct and indirect impact of culture on innovation. *Technovation, 34*(1), 12–20.

Engelen, A., Brettel, M., & Wiest, G. (2012). Cross-functional integration and new product performance—The impact of national and corporate culture. *Journal of International Management, 18*(1), 52–65.

Engelen, A., Schmidt, S., Strenger, L., & Brettel, M. (2014). Top management's transformational leader behaviors and innovation orientation: A cross-cultural perspective in eight countries. *Journal of International Management, 20*(2), 124–136.

Feinberg, S. E., & Gupta, A. K. (2004). Knowledge spillovers and the assignment of R&D responsibilities to foreign subsidiaries. *Strategic Management Journal, 25*(8–9), 823–845.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science, 47*(1), 117–132.

Fleming, L., & Sorenson, O. (2004). Science as a map in technological search. *Strategic Management Journal, 25*(8–9), 909–928.

Foster, R. N. (1986). *Innovation: The attacker's advantage*. New York, NY: Summit.

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. *Research Policy, 31*(6), 899–933.

Gallié, E. P., & Legros, D. (2012). Firms' human capital, R&D and innovation: A study on French firms. *Empirical Economics, 43*(2), 581–596.

Goldenberg, J., Mazursky, D., & Solomon, S. (1999). Templates of original innovation: Projecting original incremental innovations from intrinsic information. *Technological Forecasting and Social Change, 61*(1), 1–12.

Gomes-Casseres, B., Hagedoorn, J., & Jaffe, A. B. (2006). Do alliances promote knowledge flows? *Journal of Financial Economics, 80*(1), 5–33.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology, 78*(May), 1360–1380.

Granovetter, M. (1992). Problems of explanation in economic sociology. In N. Nohria & R. G. Eccles (Eds.), *Networks and organizations: Structure, form, and action*. Boston, MA: Harvard Business School Press.

Grossman, G. M., & Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European Economic Review, 35*(3), 517–526.

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

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). *The NBER patent citation data file: Lessons, insights and methodological tools. NBER working paper no. 8498*. National Bureau of Economic Research.

Hargadon, A. B. (2002). Brokering knowledge: Linking learning and innovation. *Research in Organizational Behavior, 24*, 41–85.

Hargadon, A., & Sutton, R. I. (1997). Technology brokering and innovation in a product development firm. *Administrative Science Quarterly, 42*, 716–749.

Henderson, R., & Cockburn, I. (1994). Measuring competence? Exploring firm effects in pharmaceutical research. *Strategic Management Journal, 15*, 63–84.

Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions and organizations across nations*. Thousand Oaks, CA: Sage.

Hofstede, G., Hofstede, G. J., & Minkov, M. (2010). *Cultures and organizations: Software of the mind* (3rd ed.). New York, NY: McGraw-Hill.

Kanter, R. M. (1996). When a thousand flowers bloom: Structural, collective, and social conditions for innovation in organizations. In P. S. Myers (Ed.), *Knowledge management and organizational design*. Newton, MA: Butterworth-Heinemann.

Kaplan, S., & Vakili, K. (2015). The double-edged sword of recombination in breakthrough innovation. *Strategic Management Journal*, *36*(10), 1435–1457.

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

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal, 13*(S1), 111–125.

Liu, K., Arthurs, J., Cullen, J., & Alexander, R. (2008). Internal sequential innovations: How does interrelatedness affect patent renewal? *Research Policy, 37*(5), 946–953.

Liu, X., & Buck, T. (2007). Innovation performance and channels for international technology spillovers: Evidence from Chinese high-tech industries. *Research Policy, 36*(3), 355–366.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization Science, 2*(1), 71–87.

Moser, P. (2005). How do patent laws influence innovation? Evidence from nineteenth-century world's fairs. *The American Economic Review, 95*(4), 1214–1236.

Narasimhan, O., Rajiv, S., & Dutta, S. (2006). Absorptive capacity in high-technology markets: The competitive advantage of the haves. *Marketing Science, 25*(5), 510–524.

OECD Research and Development Statistics. (2015). http://www.oecd.org/innovation/inno/researchanddevelopmentstatisticsrds.htm, http://www.oecd.org/sti/msti.htm.

Rabe-Hesketh, S., Skrondal, A., & Pickles, A. (2002). Reliable estimation of generalized linear mixed models using adaptive quadrature. *The Stata Journal, 2*(1), 1–21.

Rabe-Hesketh, S., Skrondal, A., & Pickles, A. (2004). GLLAMM manual. U.C. Berkeley Division of Biostatistics working paper series no. 160.

Roozmand, O., Ghasem-Aghaee, N., Hofstede, G. J., Nematbakhsh, M. A., Baraani, A., & Verwaart, T. (2011). Agent-based modeling of consumer decision making process based on power distance and personality. *Knowledge-Based Systems, 24*(7), 1075–1095.

Rosenberg, N., & Steinmueller, W. E. (1988). Why are Americans such poor imitators? *The American Economic Review, 78*(2), 229–234.

Rosenkopf, L., & Nerkar, A. (2001). Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal, 22*(4), 287–306.

Rosenzweig, S. (2015). Innovation in retrospect: An exploratory study of trends in the levels of innovation. *International Journal of Business and Management*, *10*, 63–73.

Rosenzweig, S., Grinstein, A., & Ofek, E. (2016). Social network utilization and the impact of academic research in marketing. *International Journal of Research in Marketing*. doi:10.1016/j.ijresmar.2016.02.002

Rosenzweig, S., & Mazursky, D. (2014). Constraints of internally and externally derived knowledge and the innovativeness of technological output: The case of the United States. *Journal of Product Innovation Management, 31*(2), 231–246.

Rosenzweig, S., Tellis, G. J., & Mazursky, D. (2015). *Where does innovation start: With customers, users, or inventors? Marketing science institute working paper series report no. 15–108* (pp. 1–52). http://www.msi.org/reports/where-does-innovation-start-with-customers-users-or-inventors/.

Saebi, T., & Foss, N. J. (2014). Business models for open innovation: Matching heterogeneous open innovation strategies with business model dimensions. *European Management Journal, 33*(3), 201–213.

Shane, S. A. (1992). Why do some societies invent more than others? *Journal of Business Venturing, 7*(1), 29–46.

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

Sorescu, A. B., Chandy, R. K., & Prabhu, J. C. (2007). Why some acquisitions do better than others: Product capital as a driver of long-term stock returns. *Journal of Marketing Research, 44*(1), 57–72.

Tellis, G. J., Prabhu, J. C., & Chandy, R. K. (2009). Radical innovation across nations: The preeminence of corporate culture. *Journal of Marketing, 73*(1), 3–23.

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

Trajtenberg, M. (2001). Innovation in Israel 1968–1997: A comparative analysis using patent data. *Research Policy, 30*(3), 363–389.

Van de Vrande, V. (2013). Balancing your technology-sourcing portfolio: How sourcing mode diversity enhances innovative performance. *Strategic Management Journal, 34*(5), 610–621.

Zidorn, W., & Wagner, M. (2013). The effect of alliances on innovation patterns: An analysis of the biotechnology industry. *Industrial and Corporate Change, 22*(6), 1497–1524.