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http://orcid.org/0000-0002-4917-5552Florenta Teodoridis

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Understanding Team Knowledge Production: The Interrelated Roles of Technology and Expertise

Florenta Teodoridis[a]

[a] Marshall School of Business, University of Southern California, Los Angeles, California 90089
Contact: florenta.teodoridis@marshall.usc.edu, http://orcid.org/0000-0002-4917-5552 (FT)

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Abstract. Teamwork is an increasingly important aspect of knowledge production. In particular, factors influencing team formation relative to the composition of expertise are crucial for both organizational performance and for informing policy. In this paper, I draw attention to technology access as a highly influential factor impacting expertise in team formation. I examine the hack of Microsoft Kinect as an exogenous event that suddenly reduced motion-sensing technology costs. I show that great reductions in technology costs substitute for ex ante optimal involvement of area specialists and facilitate involvement of outside-area specialists through collaboration with researchers with broader knowledge—generalists. In other words, technology costs influence the composition of expertise in teamwork, with sufficiently large reductions leading to knowledge creation that combines more broadly across knowledge areas. These findings have important implications for organizations and policy makers in crafting incentives for more diverse knowledge creation through strategic investments that lower technology costs and influence team formation.

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1. Introduction

Knowledge production plays a central role in economic growth. An increasingly important aspect of knowledge production is teamwork. Indeed, the lone inventor as the primary unit of knowledge production has been replaced by collaborative work (Jones 2009, Singh and Fleming 2010). Moreover, relative to singular knowledge production, collaborative work has been shown to yield more impactful and influential discoveries (Wuchty et al. 2007). A first order concern in team knowledge production is the composition of expertise that reflects directly in knowledge output. Indeed, team knowledge production leveraging diverse expertise has been found to accentuate the effect of impactful team discoveries (e.g., Weitzman 1998, Uzzi et al. 2013).

Despite evidence of the growing importance of team knowledge production, our understanding of factors influencing the composition of expertise in teamwork remains limited. Prior literature primarily focused on human capital attributes influencing collaboration decisions[1] and largely ignored other inputs in knowledge production that influence breadth of knowledge in teamwork (Stephan 2012). In particular, the relationship between human capital and technology remains underexplored despite the increasingly influential role of equipment in adding knowledge in the process of innovation (Stephan 2012, Murray et al. 2016) through the algorithms embedded in the technology (Mokyr 2002). This paper seeks to understand the interrelated roles of technology and breadth of knowledge in team production.

Conditions of access to technology carry the potential to influence team formation relative to the composition of expertise. This in turn impacts output, a primary concern for private and public organizations interested in innovation (e.g., Nelson 1982, Cockburn and Henderson 1998, Owen-Smith and Powell 2004). For example, reductions in costs of computational power gave rise to advancements in machine learning and big data–driven decision making. Various firms organized to utilize the technology, from entrepreneurial teams to large organizations. For instance, at Netflix, collaborations between economists and software engineers were consequently formed and translated into significant economic returns for the company (e.g., Smith and Telang 2016). In the sciences, access to the Large Hadron Collider attracted researchers with a variety of expertise from around the globe. The subsequent discovery of the Higgs particle was the result of a large-scale collaboration between more than 3,000 scientists from 182 institutions in 38 countries.[2]

In all such cases, it is unclear how knowledge production would have unfolded under a different technology cost regime or what economic consequences would have followed. In this paper, I focus on the influential role of technology costs for team formation relative to the composition of expertise in collaboration.

I motivate my empirical analysis with a formal model of knowledge production, acknowledging that actors vary in their breadth of expertise. This is important for two main reasons. First, the fact that division of labor, or specialization, positively impacts productivity is well accepted, dating back to Adam Smith's (1776) seminal work. Second, specialization correlates with increased coordination frictions in team production (Becker and Murphy 1992), suggesting a role for agents with broader expertise—generalists—in reducing such frictions (Jones 2010). The model demonstrates the usefulness of separating generalists, within-area specialists, and outside-area specialists, and shows that a technology cost decrease can be either democratizing—individuals, regardless of their level of focal area expertise, incorporate new knowledge by using the technology—or increase returns to within-area specialization. Stated differently, the model indicates that the magnitude of technology costs alters team formation relative to the composition of expertise.

In observational data, it is difficult to isolate the role of cost conditions from a team composition selection effect, since the knowledge creation process endogenously affects the cost of technology. For example, in the sciences, funding is selectively provided to high-quality research technologies that are expected to significantly and positively impact innovation (Stephan 2012). Similarly, in firms, senior managers devote significant effort to selecting and allocating funds to the most promising projects (e.g., Astebro and Elhedhli 2006, Hallen 2008). As such, observed team formation decisions might be endogenous to anticipated or allocated funding, making the study of team formation particularly challenging. To address such concerns, I leverage as a natural experiment an exogenous event correlated with reductions in the cost of motion-sensing research technology, but not with the ex ante rate and direction of inventive activity. The unanticipated hack of Microsoft Kinect provides the event.

On November 4, 2010, Microsoft launched Kinect for Xbox 360, a motion-sensing video gaming device. Unexpectedly, and within days of Kinect's launch, the open-source community released a driver that made it possible to use Kinect as a motion-sensing research technology. Given Kinect's technological sophistication relative to its low price ($150 at launch and lower thereafter), the consequence has been an unforeseen cost reduction for motion-sensing technology in research. Its release marked the start of what Microsoft eventually coined the "Kinect Effect."[3] In personal interviews, researchers confirmed Kinect's unexpected use in academia and its role in lowering the cost of motion-sensing research technology. For example, one researcher noted that his use of Kinect "is not the designated one from Microsoft . . . not a gaming one . . . the depth measurement done by this camera is so affordable it is a breakthrough for computer vision," while another said that "the Kinect sensor is the first camera that provides the depth images with sufficient resolution for typical computer vision tasks at an affordable price to most [researchers]."

In my empirical analysis, I focus on how collaboration varies with researchers' breadth of expertise as observed in researchers' breadth of involvement with research topics. I separate specialists (individuals with narrow, well-defined research topics) from generalists (researchers with diverse research topics). Specifically, I examine changes in the collaboration rate between generalists, outside-area specialists, and within-area specialists, as well as changes in the composition of authorship on academic papers referencing motion-sensing keywords, before and after the launch of Kinect. I find evidence of an increase in the total number of publications referencing motion-sensing keywords after the launch of Kinect, driven by an increase in collaboration between generalists and non-motion-sensing specialists on such publications, and a decrease in collaboration between generalists and motion-sensing specialists.

I use the theoretical model to sharpen the inferences drawn from these empirical findings. Specifically, when the reduction in cost is democratizing, the optimal collaboration composition is altered to reduce ex ante optimal involvement of within-area specialists and to facilitate involvement of outside-area specialists through collaboration with generalists. Stated differently, with great cost reductions, the research technology substitutes for the need to include within-area specialists in coauthorship teams.[4] In turn, this frees up coauthorship capacity, which is otherwise limited by collaboration frictions (Bikard et al. 2015), to include specialists from other research areas and drive an increase in publications referencing motion-sensing keywords. Generalists appear to act as intermediaries in the process. The empirical results indicate the effect occurs for 1 in 10 papers. Intuitively, this mechanism suggests a shift to knowledge creation occurring more broadly across knowledge areas as a consequence of a reduced cost of research technology.

This study makes two main contributions to our understanding of the knowledge creation process. First, the results contribute to the literature on productivity in knowledge creation by drawing attention to the interrelated roles of technology and individual-level expertise. Technology substitutes for expertise in knowledge production, thus altering collaboration costs and influencing optimal team formation. This finding suggests implications for domains where collaboration decisions are discretionary, such as scientific research and entrepreneurship, as well as settings where managers coordinate team formation. For example, policy makers interested in influencing innovation output (e.g., Solow 1956, Romer 1990, Aghion et al. 2008, Acemoglu 2012) could strategically evaluate funding decisions for technologies with a goal of increasing diversity in team knowledge production. Similarly, managers and executives could consider technology acquisitions as levers for influencing research and development (R&D) outcomes.

Second, this study contributes to the literature on team formation by unlocking a particular avenue through which diversity functions in knowledge production. Specifically, I find that researchers with broader exposure to knowledge play an important role in team formation in environments with democratizing technology cost reductions. These results suggest fundamental changes in the organization of knowledge creation relative to individuals' breadth of knowledge and their differential roles in knowledge production. In the sciences, the role of generalists in the organization of knowledge creation might grow in significance, as knowledge accumulation leads to specialization in progressively narrower niches (Jones 2009). This suggests a reevaluation of academic incentives that encourage a narrow research focus through reputational benefits or in response to monetary awards (e.g., Franzoni et al. 2011, Stephan 2012). Similarly, the finding provides direction for firms interested in evaluating their R&D staffing requirements or in crowdsourcing aspects of their knowledge creation needs (e.g., Nielsen 2011, Franzoni and Sauermann 2014).

2. Theory and Hypotheses

2.1. Specialization, Research Technology, and Knowledge Production

Breadth of knowledge characterizes the composition of expertise in knowledge production. Technology contributes through the knowledge contained in embedded algorithms (Stephan 2012), which reduce frictions of incorporating existing knowledge in the production of new knowledge (Mokyr 2002).

It is unclear ex ante how reductions in technology costs might influence team formation. On the one hand, cost reductions might be democratizing: agents, regardless of their level of focal area expertise, can incorporate the focal type of knowledge or algorithms in their projects by simply using the technology. For example, reductions in cost of computational capabilities facilitate engagement with complex statistical analysis software notwithstanding specialized knowledge in mathematics. On the other hand, cost reductions might increase returns to within-area specialization. For example, computer-aided design and drafting software increases returns for architects and structural engineers.

It follows that a starting point in understanding the interrelated roles of technology and breadth of knowledge in team production is to consider the well-established role of division of labor. The approach facilitates an understanding of team dynamics relative to agents' expertise and thus provides a foundation to consider the role of technology in potentially altering those dynamics.

The fact that division of labor, or specialization, positively impacts productivity and hence economic growth is well accepted, dating back to Adam Smith's (1776) seminal work. Furthermore, evidence indicates a trend toward specialization in increasingly narrower niches, explained by the growth in knowledge stock and the knowledge frontier's continuous forward movement (Jones 2009, 2010, 2011).

Specifically, Jones (2009) puts forth a "knowledge burden" hypothesis, in which successive generations of innovators face an increasing education burden due to the advancing knowledge frontier. As a consequence, time spent in education lengthens, and the domain of individual-level expertise narrows. In turn, this leads to an increased need for collaborative work to move knowledge forward by combining the increasingly narrower niches of specialization (Jones 2009, Agrawal et al. 2016). This suggests that coordination of inventive activity across knowledge areas grows in complexity as specialization increases. First, it is increasingly costly to search for ideas that span knowledge areas. This is important because impactful innovations draw from diverse knowledge and include unusual combinations (e.g., Weitzman 1998, Uzzi et al. 2013). Second, it is getting progressively more difficult to coordinate efficient teams of specialists (Becker and Murphy 1992) who work on topics bridging knowledge areas (Jones 2010). This search problem is indicative of a potential demand for individuals who have enough exposure to broad knowledge (generalists) to lower coordination costs between collaborating specialists on projects that require bridging across knowledge areas (within-area and outside-area specialists; (Jones 2010)).[5]

Technology can potentially reduce the burden of knowledge and hence collaboration frictions by contributing the knowledge contained in embedded algorithms (Mokyr 2002, Stephan 2012). The level of influence seems to depend on the total cost advantage captured through technology usage and its consequent impact on collaboration frictions and hence team formation relative to the composition of expertise. For example, rapid developments in DNA sequencing over the past decades reduced the costs of DNA sequencing technology.[6] The fields of genomics and molecular biology consequently propelled forward. However, the reductions in cost of DNA sequencing technology also benefited researchers and organizations in other medical fields, such as in epidemiology, immunology, evolutionary biology, and forensics. It is unclear ex ante how the cost reduction influenced the process of knowledge creation relative to agents' expertise: who benefited most from the reduction and how.

To shed light on this process, I developed a simple formal model that explicitly considers the impact of a technology cost reduction on agents' collaboration choices in acting on knowledge creation opportunities. I use the model not only to inform my empirical approach, but also to sharpen the inferences that might be drawn from my findings. Overall, the model shows that the beneficiaries of the technology shock depend on the incidence of the cost reduction. While at some level the results of the model are intuitive, the model provides a useful framework for understanding the impact of a reduction in technology cost on knowledge production, particularly with respect to the behavior of generalists and specialists in team formation.

2.2. Formal Model

Consider a set $\{V_{1,\ldots,n}\}$ of opportunities for knowledge creation that involve the algorithms contained in a technology, where V represents the value of one such opportunity. Also, consider a cost c of including these algorithms in the focal project. The technology lowers these costs since, absent an aiding device, agents interested in projects involving such algorithms would have to, for example, manually design and run the algorithms.

With these notations in mind, consider a set of agents $i(V^i, C, c_i)$ engaging with such projects, where V^i is the value of the project accruing to agent i, C is the cost of collaboration on the project, and c_i is the cost of engagement with the algorithms contained in the technology. Opportunities for knowledge creation involving the algorithms contained in the technology can arise for any agent i.[7] I consider three types of agents i: generalists (*GEN*), outside-area specialists (*OAS*), and within-area specialists (*WAS*).

Assumptions. I make several assumptions regarding V^i, C, and c_i. First, agent i has the option to pass on the opportunity or engage with it. If the agent chooses to pass, the value accruing from his or her outside option is V_O^i. If the agent chooses to pursue the opportunity, he or she has the option to collaborate[8] with a generalist and capture value V_{GEN}^i, with a within-area specialist and capture value V_{WAS}^i, or with an outside-area specialist and capture value V_{OAS}^i. For simplicity, I denote all values V_{GEN}^i resulting from collaboration with generalists by V_{GEN} and all values V_{OAS}^i resulting from collaboration with outside-area specialists by V_{OAS} (note that under this notation, V_{GEN}^{OAS} and V_{OAS}^{GEN} are equivalent to $\max(V_{OAS}, V_{GEN})$). I assume $V^i < V_{GEN}$ and $V^i < V_{OAS}$, while I remain agnostic on the relationship between V_{GEN} and V_{OAS}. The approach acknowledges the fact that generalists and/or outside-area specialists are more likely to produce more innovative work, since they combine more broadly across knowledge areas (Weitzman 1998, Uzzi et al. 2013).[9] This observation also motivates assumptions on agents' outside options. Specifically, I remain agnostic on the relationship between V_O^{WAS} and the value accruing to within-area specialists from engaging with the opportunity since both occur within area and assume V_O^{GEN} and V_O^{OAS} are lower than the values accruing to these types from engaging with the opportunity.

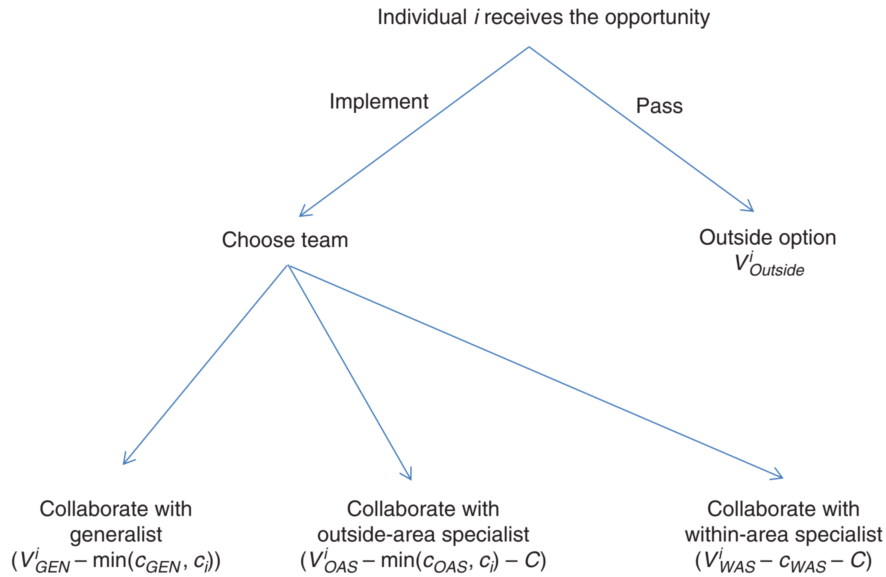
Second, if agent i engages in collaboration, the team will incur a collaboration cost C, which varies with the type of collaborator. If the collaboration occurs only between specialists, the cost will be higher than in situations in which the collaboration includes a generalist. Generalists have a lower collaboration cost compared to specialists, because of their wider breadth of exposure to knowledge that is directly reflected in the collaboration cost (Bikard et al. 2015). Thus, for simplicity, I denote the collaboration cost incurred by teams of specialists by C and normalize the collaboration cost incurred by teams that include a generalist to 0.[10]

Third, the cost of engagement with the algorithms contained in the technology c_i varies with agent's i level of expertise relative to that knowledge. Specifically, I assume $c_{WAS} < c_{GEN} < c_{OAS}$. This assumption is motivated by the fact that agents' heterogeneity in knowledge relative to the algorithms contained in the technology should reflect in their ability to incorporate these algorithms in their projects. For example, absent a motion-sensing research technology, the ability of researchers without motion-sensing skills (outside-area specialists) to incorporate motion-sensing in their research would be limited relative to that of motion-sensing specialists (within-area specialists). Since generalists, by definition, have a wider exposure to knowledge than outside-area specialists, I assume their cost of engagement with motion sensing is lower than that of outside-area specialists who lack the broad exposure to knowledge, but higher than that of within-area specialists.

Agents' Optimal Choices. I review the optimal choice of each agent i who seeks to maximize his or her payoff given the assumed costs and values. I do so to identify the conditions under which each type will and will not collaborate with another type. I assume a collaboration occurs only if the action is value maximizing for each party. I display agent's i options and payoffs in Figure 1.

OAS. Consider that the opportunity comes to an outside-area specialist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{OAS}. Otherwise, if the agent chooses to collaborate with

Figure 1. (Color online) Decision Tree for Individual i



a within-area specialist, the net value will be $V^{OAS}_{WAS} - (c_{WAS} + C)$; if the agent collaborates with a generalist, the net value will be $V^{OAS}_{GEN} - c_{GEN}$; and if the agent collaborates with another outside-area specialist, the net value will be $V^{OAS}_{OAS} - (c_{OAS} + C)$. It follows that it is optimal for outside-area specialists to collaborate with generalists if $\max(V_{GEN}, V_{OAS}) - V_{OAS} > c_{GEN} - (c_{WAS} + C)$, and to otherwise collaborate with within-area specialists. In other words, it is optimal for outside-area specialists to collaborate with within-area specialists as long as within-area specialists provide a large enough cost advantage to offset the premium value otherwise captured from collaborating with generalists. Outside-area specialists find it optimal to pursue their outside options if the average net value from collaborating with generalists or within-area specialists is lower than V^{OAS}_{O}.

GEN. Consider that the opportunity comes to a generalist. If the agent chooses to pass on the opportunity, the net value accruing will be V^{GEN}_{O}. Otherwise, if the agent chooses to collaborate with an outside-area specialist, the net value will be $V^{GEN}_{OAS} - c_{GEN}$; if the agent collaborates with a within-area specialist, the net value will be $V^{GEN}_{WAS} - c_{WAS}$; and if the agent collaborates with another generalist, the net value will be $V^{GEN}_{GEN} - c_{GEN}$. It follows that it is optimal for generalists to collaborate with outside-area specialists if $\max(V_{GEN}, V_{OAS}) - V_{GEN} > c_{GEN} - c_{WAS}$, and to otherwise collaborate with within-area specialists. In other words, it is optimal for generalists to collaborate with within-area specialists as long as within-area specialists provide a large enough cost advantage to offset the premium value otherwise captured from collaborating with outside-area specialists. Generalists find it optimal to pursue their outside options if the average net value of collaborating with outside-area specialists or within-area specialists is lower than V^{GEN}_{O}.

WAS. Consider the opportunity comes to a within-area specialist. If the agent chooses to pass on the opportunity, the net value accruing will be V^{WAS}_{O}. Otherwise, if the agent chooses to collaborate with an outside-area specialist, the net value will be $V^{WAS}_{OAS} - (c_{WAS} + C)$; if the agent collaborates with a generalist, the net value will be $V^{WAS}_{GEN} - c_{WAS}$; and if the agent collaborates with another within-area specialist, the net value will be $V^{WAS}_{WAS} - (c_{WAS} + C)$. It follows that it is optimal for within-area specialists to collaborate with generalists if $(V_{OAS} - V_{GEN}) < C$, and to otherwise collaborate with outside-area specialists. Within-area specialists find it optimal to pursue their outside option if its value is higher than both $V_{OAS} - C$ and V_{GEN}.

Proposition 1. *The equilibrium outcome depends on the difference between costs c_i such that* (a) *if the difference is sufficiently large, then, in equilibrium, within-area specialists and either generalists or outside-area specialists collaborate on the opportunity, with the realization determined by the difference between $(V_{OAS} - V_{GEN})$ and C;* (b) *if the difference is sufficiently small, approaching* 0*, then, in equilibrium, generalists and outside-area specialists collaborate on the opportunity, while within-area specialists are left to pursue their outside options.*

Proof. Consider the optimal choice of each agent i who seeks to maximize his or her payoff. It follows that when the difference between c_{WAS} and c_{GEN} is sufficiently large ($c_{WAS} \gg c_{GEN}$), within-area specialists match with either generalists or outside-area specialists. Within-area specialists with outside options valued higher than $V_{OAS} - C$ and V_{GEN}, and generalists and outside-area specialists with outside options valued higher than the average net value of collaborating with within-area specialists, pursue their outside options. Absent the cost advantage of within-area specialists (i.e., the difference between costs c_{WAS} and c_{GEN} is sufficiently small, approaching 0), in equilibrium, generalists and outside-area specialists match, while within-area specialists are left to pursue their outside options. Note that in this case, as a consequence, total within-area output increases since both generalists and outside-area specialists always prefer to collaborate on the opportunity over pursuing their outside options. □

This proposition captures the key argument of this paper: the equilibrium collaboration behavior depends on the difference between costs c_i, and it is unclear how the change in technology cost might affect this difference. The change can either increase returns to within-area specialization, accentuating the cost advantage of within-areas specialists, or be democratizing, reducing the difference between costs c_{WAS}, c_{OAS}, and c_{GEN} toward 0.

In the first case, the technology cost reduction disproportionally benefits within-area specialists. For example, the reduction in cost of motion-sensing research technology facilitates access to a tool that executes complex motion-sensing algorithms necessary for capturing and analyzing 3D data. It follows that the cost reduction might disproportionately benefit motion-sensing specialists who have the knowledge to efficiently interact with the 3D data output (e.g., free up time otherwise spent on processing motion-sensing data without the technology) and hence accentuate their cost advantage. In the second case, the reduction in technology cost might level the playing field by making it easier for agents, regardless of their level of focal area expertise, to engage with the algorithms contained in the technology. For example, researchers might find it easier to include motion-sensing data in their research, independent of their ex ante level of motion-sensing expertise. Note that in both cases, total within-area output increases following the reduction in cost, in line with previous literature findings (e.g., Murray and Stern 2007, Furman and Stern 2011, Williams 2013), but the increase is potentially more accentuated when the reduction in cost is democratizing.

In summary, the type of agent that plays an influential role following a technology cost reduction depends on the incidence of cost reduction. Within-area specialists play an influential role when the cost reduction increases the returns to specialization. Conversely, generalists and outside-area specialists play an influential role when the cost reduction is democratizing. Thus, it is theoretically ambiguous how a technology cost reduction might influence team formation, as it depends on who benefits most from the reduction. I empirically explore this mechanism in the context of an unexpected and sudden reduction in the cost of motion-sensing research technology.

3. Kinect

I focus on the events triggered by the launch of Microsoft Kinect on November 4, 2010, as an exogenous shock to academic research, which resulted in a sudden and unexpected cost reduction of motion-sensing research technology. Microsoft positioned its technology as a revolutionary device for the gaming industry, an add-on for the Xbox 360 that allowed users to interact with video games through motion sensing and without the need for a controller. However, no one, including Microsoft, anticipated the wide-reaching effect Kinect would trigger on scholarly research in electrical engineering, computer science, and electronics.

3.1. Kinect as Gaming Technology

Microsoft launched Kinect to compete with Nintendo's Wii Remote and Sony's PlayStation Move gesture-recognition game controllers. Kinect was positioned to take gesture-recognition video gaming one large step further by altogether eliminating the need for a controller.

The Kinect motion sensor comprises an RGB camera, depth sensor, and multiarray microphones, providing full-body 3D motion capture as well as facial, gesture, and voice recognition. The sensor is superior to many other 3D cameras in its movement capturing accuracy and recognition capabilities for multiple simultaneous subjects.

In June 2009, Microsoft announced Project Natal, the development endeavor to create Kinect. Up until November 2010, when Kinect was released, Microsoft fostered excitement among gamers by presenting video game demos at various events. However, nowhere during this period was Microsoft or any other party engaged in promoting, linking, or in any way suggesting the use of the Kinect technology outside its intended purpose as a gaming device.

3.2. Unexpected "Kinect Effect"

On November 4, 2010, Microsoft launched Kinect with an advertising budget of US$500 million. These advertising efforts did not include promoting Kinect outside its intended gaming purpose.

The starting point of the unexpected Kinect Effect in academic research can be traced to the bounty AdaFruit Industries placed on Kinect's launch day. AdaFruit Industries is an electronics hobbyist company led by Limor Fried, an MIT electrical engineering and computer science graduate influential in the open hardware community. AdaFruit placed the bounty, originally in the amount of US$1,000, in search of someone who could develop and distribute an open source driver for Kinect. The driver would make it possible to access data collected by Kinect's motion sensors. In other words, the driver would open the pipeline through which Microsoft had designed motion-sensing data to flow only between Kinect and the Xbox 360 video games. The driver would thus allow researchers and enthusiasts to connect the pipeline to any other project that would benefit from capturing and interpreting motion-sensing data.

Just hours after AdaFruit made the search for an open source driver public, Microsoft voiced its disapproval on CNET, saying that it "does not condone the modification of its products. . . . With Kinect, Microsoft built in numerous hardware and software safeguards designed to reduce the chances of product tampering. Microsoft will continue to make advances in these types of safeguards and work closely with law enforcement and product safety groups to keep Kinect tamper-resistant" (Terdiman 2010).

AdaFruit did not withdraw the contest. Moreover, on the same day of Microsoft's announcement, AdaFruit tripled its bounty to US$3,000. Six days later, on November 10, 2010, a Spanish technology enthusiast, Hector Martin Cantero, released the open source driver and won the bounty. Microsoft reacted within a couple of days after the open source driver's release. First, the company's public rhetoric became less negative toward the events: "what has happened is someone has created drivers that allow other devices to interface with the Kinect for Xbox 360. . . . The creation of these drivers, and the use of Kinect for Xbox 360 with other devices, is unsupported. . . . We strongly encourage customers to use Kinect for Xbox 360 with their Xbox 360 to get the best experience possible" (*BBC News* 2010). A few days later, as the unexpected Kinect Effect continued to unfold, Microsoft dropped all concerns and announced its intention to allow and support the unanticipated developments. Microsoft recognized the benefit to academic research and was on board.[11] From this point on, the gates for creative development opened.

3.3. Kinect in Academia

Kinect appeals to academic research because it provides high-quality, low-price motion-sensing technology.[12] Kinect lowers the cost of employing motion sensing as a tool in the process of scientific research. Prior to Kinect, motion-sensing technologies available for academic research had lower depth-sensing quality, and a price tag in the thousands of dollars. Microsoft priced Kinect at around US$150 at launch and lower thereafter.

As a motion-sensing research technology, Kinect has attracted attention from researchers curious about a variety of research topics. For example, computer science scholars involved in computer learning algorithms targeted at detecting human emotions have been interested in Kinect's advanced facial expression recognition capabilities. Scholars focused on robotics have liked the depth motion-sensing capabilities of Kinect, which have aided in developing robots that can more accurately navigate a complex landscape. Researchers studying the development of technologies for impaired individuals have engaged Kinect in crafting algorithms to allow visually impaired subjects to hear an accurate and timely description of their surrounding environment as they attempt to walk around in a room.

In summary, the broad use and impact of Kinect as a motion-sensing research technology was not anticipated. As such, the setting provides a natural experiment to draw more causal inferences (albeit not without limitations) about observed follow-on research developments triggered by a cost reduction in research technology. Stated differently, the unanticipated Kinect Effect provides an exogenous event that is correlated with a cost reduction of motion-sensing research technology, but not with researchers' characteristics and their research behavior, except indirectly through its effect on researchers' publication trends and propensity to respond to opportunities opened by the cost reduction.

4. Data and Empirical Framework

4.1. Data Collection

I focus on academic publication data from researchers in electrical engineering, computer science, and electronics. I collect data on every publication, early-access publication, and conference proceeding academic paper in electrical engineering, computer science, and electronics during an eight-year period from 2005 to 2012 (inclusive). This sample represents six years of data before and two years of data after Kinect's launch. The longer prelaunch data collection period facilitates a better estimation of researcher types in electrical engineering, computer science, and electronics. The shorter postlaunch period is informative given the publication norms in electrical engineering, computer science, and electronics. The publication cycle is fairly short, and scholars usually make their research known early in conference proceedings.

I collect these data from IEEE *Xplore*, the bibliographical database maintained by the Institute of Electrical and Electronics Engineers (IEEE). IEEE *Xplore* provides access to "full-text documents from some of the world's most highly cited publications in electrical engineering, computer science, and electronics."[13] I collect data on 1,336,866 publications in electrical engineering, computer science, and electronics spanning the period of interest from 2005 to 2012 (inclusive). This represents the full set of journal publications, early-access publications, and conference proceedings available through IEEE *Xplore*.

4.2. Variables of Interest

I am interested in researchers' collaborative behavior relative to collaboration composition between generalists, within-area specialists, and outside-area specialists. My setting is a natural experiment triggered by the launch of Kinect and its unexpected use as a motion-sensing research technology. As such, I distinguish between motion-sensing specialists and non-motion-sensing specialists as within-area specialists and outside-area specialists, respectively. To do so, I first identify the subset of publications within my data set on topics that reference motion sensing. Second, I construct a measure of diversification of research portfolios at the individual level to distinguish between generalists, motion-sensing specialists, and non-motion-sensing specialists.

To isolate these data, I use two features of the IEEE database: (1) its full text search of all publications included in the IEEE bibliographical database and (2) that qualified IEEE personnel assign a limited set of keywords to publications out of a controlled hierarchical vocabulary of about 9,000 words. This taxonomy remains unchanged over the period of interest. I identify 7,276 unique keywords in my data set of publications spanning the period 2005 to 2012 (inclusive). Less than 7% of publications have no keywords, so I drop them from my data set. The remainder have between 1 and 18 keywords per publication. The IEEE taxonomy hierarchically classifies these keywords under 51 main research areas.

4.2.1. Motion-Sensing Academic Publications. I identify the sample set of motion-sensing academic publications by searching the full text of publications included in the IEEE database. I search using a set of key terms that I carefully identify as representative for isolating publications on motion sensing (Appendix C, Table C.2). Specifically, I search for broad as well as more targeted terms referencing motion-sensing technologies. I carefully selected these terms through conversations with experts and cross-referenced them against IEEE's taxonomy. However, for two reasons, I do not restrict mapping the boundaries of motion-sensing to the list of 51 research areas under the IEEE taxonomy. First, I am interested in a more granular identification of this research topic. For example, most publications referencing motion sensing are included under the "Computers and information processing" research area of IEEE's taxonomy. However, this research area includes a variety of other research topics. Second, a premise of the observed phenomenon of interest is that the reduction in research technology cost is an influencing factor for the evolution of knowledge trajectories. As such, it is important to avoid boundaries imposed by a rigid taxonomy developed for rather static classification purposes. In other words, I want to ensure that my definition of motion-sensing research topics captures those publications that reference motion sensing, but are outside the traditional "Computers and information processing" research area. I identify a total of 17,196 academic publications referencing motion-sensing keywords over the period of interest (2005–2012).

4.2.2. Generalists and Specialists. I distinguish between generalists and specialists based on a measure of diversification of research portfolios across the 51 main areas of research as identified by IEEE. I define generalists as scholars who have a diversification level of research portfolio areas in the top 5% of the sample as identified through an inspection of the set of keywords assigned by IEEE from its taxonomy to scholars' publications in the period 2005–2008. I define specialists as the remainder of scholars in my sample.[14]

I use the period 2005–2008 to characterize the level of diversification of scholars' research portfolios. I use the period 2009–2012 to estimate changes in collaboration levels of these identified researcher types as triggered by the launch of Kinect at the end of year 2010. I refer to the period before Kinect's launch since I focus on estimating the collaborative behavior of researchers following a research technology cost reduction. As such, the relevant individual-level characteristics are observed before Kinect's arrival. Furthermore, I consider 2008 as the cutoff year to allow for a comparison of research outcomes two years before and two years after the launch (2009–2012, inclusive), with researcher types defined based on the research behavior prior to this entire period.

To identify generalists and specialists, I exclusively focus on the IEEE set of keywords, because the taxonomy provides a stable and thus tractable classification of scholars' research portfolio areas. Furthermore, the fact that the research areas defined under the IEEE taxonomy are broader not only does not negatively impact my estimations, but also downplays generalists' breadth of research portfolio areas.

I start by collecting all keywords per author per year from researchers' publication portfolios from 2005 to 2008 (inclusive). Next, I refer to the IEEE's taxonomy to identify each keyword's main research area. I proceed by constructing a list of main research areas per author per publication and their frequency of occurrence as a count of publications from each respective main research area. Next, I convert the count into percentages and calculate the Euclidian distance in the multidimensional space of 51 research areas.[15] Note that, by construction, the measure adjusts for the fact that the probability of diverse keywords increases with the number of publications per author. Specifically, I consider the percentage of academic publications across each of the 51 research areas for each researcher rather than counts of publications within the respective research areas. For example, a researcher with a publication portfolio of 10 papers in 10 different research areas will have the same diversification level as another researcher with 20 publications, two in each of the 10 research areas.

I construct the diversification measure to be equal to 1 minus the calculated Euclidian distance. The higher the value, the higher the diversity of research portfolio areas at the individual level i:

$$DiversificationOfResearchTopics_i = 1 - \sqrt{\sum_{k=1}^{51} CategoryPercentage_{ik}^2}.$$

The diversification measure, by construction, is higher than or equal to 0 and never 1. The highest diversification index is equal to 0.86 and characterizes researchers who publish equal percentages of their publication portfolio across the 51 research areas. The lowest diversification index is equal to 0 and characterizes researchers who publish exclusively in one research area.

Researchers from the bottom 1% of my data have a diversification level of up to 0.37. Researchers in the top 1% of my data have a diversification level of 0.77 or above. The median is 0.65, and the mean is 0.63. I define generalists as researchers with a diversification level in the top 5%, equivalent to values above 0.75. I define specialists as researchers with a diversification level below 0.75. All results remain robust to considering alternative definitions of generalists: top 10% (above 0.73) and top 25% (above 0.69). Furthermore, all results remain robust to considering alternative definitions of specialists as the bottom 5% (below 0.48), bottom 10% (below 0.52), and bottom 25% (below 0.59). In addition, all results remain robust when combining these definitions of generalists and specialists with matching (coarsened exact matching (CEM)) on publication productivity across the entire period before Kinect's launch (from 2005 to 2010).

4.3. Estimation Strategy

I explore changes in collaboration between generalists and specialists following the reduction in cost of motion-sensing research technology guided by the formal model predictions described in Section 2.2.

I start with a preliminary step to confirm the baseline result of an overall increase in output following a reduction in cost of research technology. The test is necessary to establish a solid foundation for my empirical analysis on changes in collaboration composition. The discussion on optimal collaboration behavior informed by the theoretical model notes that in all cases, total within-area output increases following the reduction in cost, with the increase potentially more accentuated when the reduction in cost is democratizing. While the fact that a reduction in cost leads to an increase in output is not surprising (Murray and Stern 2007, Furman and Stern 2011, Williams 2013), confirming this effect in the case of Kinect ensures alignment with the theory used to explicate collaboration behavior consequences.

Next, I follow a two-step estimation strategy exploring changes in collaboration behavior after the reduction in cost. In line with the formal model, I distinguish between generalists, within-area specialists (motion-sensing specialists), and outside-area specialists (non-motion-sensing specialists).[16]

In a first step, I test for changes in the collaboration level of generalists, motion-sensing specialists, and non-motion-sensing specialists relative to one another. I do not directly focus on papers referencing motion sensing since, by definition, non-motion-sensing specialists were not involved in motion-sensing projects before Kinect. However, it is important to note that I interpret these results in the context of the exogenous change in cost of research technology triggered by Kinect's launch. Thus, the estimated changes in collaboration composition are implicitly attributed to coauthorship on motion-sensing academic publications.

Nevertheless, in a second step, I explicitly investigate how the composition of teams varies on projects referencing motion sensing by testing for changes in the fraction of generalists, motion-sensing specialists and non-motion-sensing specialists, as well as collaborating pairs of generalists, motion-sensing specialists, and non-motion-sensing specialists after Kinect. The estimation exploits the fact that researchers' types are set for the two-year prelaunch period. Thus, in isolation, this estimation's results should be interpreted with care. However, in conjunction with the first set of estimations, the results offer additional evidence on changes in collaboration composition on motion-sensing publications after the research technology cost reduction.

4.3.1. Preliminary Step: Changes in Motion-Sensing Output. I compare the number of publications referencing motion-sensing keywords with the number of publications referencing other research topics before and after the launch of Kinect. I follow a difference-in-differences estimation to reduce concerns of systematic differences between publications that do and do not reference motion-sensing keywords driving measured changes in motion-sensing output. Formally, I estimate

$$\begin{aligned}\mathrm{Log}PubCount_{jt} &= \beta(MotionSensingPub_j \times AfterKinectLaunch_t) \\ &\quad + \theta_j + \gamma_t + \epsilon_{jt}. \qquad (1)\end{aligned}$$

$\mathrm{Log}PubCount_{jt}$ is the log count of publications for each research topic j published in year t, $MotionSensingPub_j$ is an indicator variable equal to 1 if research topic j is motion sensing and 0 otherwise, and $AfterKinectLaunch_t$ is an indicator variable equal to 1 if papers in research topic j are listed as published in 2011 or 2012, and 0 otherwise. I include research topic and time fixed effects; hence, the main effects $MotionSensingPub_j$ and $AfterKinectLaunch_t$ drop out of the estimating equation.

I am interested in the estimated coefficient β of the interaction between $MotionSensingPub_j$ and $AfterKinectLaunch_t$. I interpret a positive estimated value of this coefficient as implying that the average number of publications referencing motion-sensing keywords increases disproportionately more relative to the average number of publications referencing other research topic keywords, and that this increase is triggered by the reduction in cost of motion-sensing research technology facilitated by the launch of Kinect. I conduct my analysis on a panel data set of counts of academic publications per year per research topic from 2005 to 2012.

4.3.2. Two-Step Estimation: Changes in Collaboration Composition. I test for changes in the collaboration levels of specialists and generalists after the launch of Kinect. I do so on a panel data set with the individual researcher as the unit of analysis. I focus on two measures of collaboration: (1) the average number of coauthors per period (extensive collaboration level) and (2) the average number of unique coauthors per period (intensive collaboration level). I conduct a difference-in-differences estimation to distinguish between the changes in collaboration composition of researchers relative to the three types that is directly attributable to the reduction in cost of motion-sensing technology from the underlying differences between the three types of researchers over time.

Specifically, I compare the extensive and intensive collaboration levels of generalists with those of specialists two years before and after the launch of Kinect. Formally, I estimate

$$CollaborationLevel_{it} = \beta(Specialist_i \times AfterKinectLaunch_t) + \delta_i + \gamma_t + \epsilon_{it}. \quad (2)$$

$CollaborationLevel_{it}$ is equal to the level of collaboration of researcher i in year t; $Specialist_i$ is an indicator variable equal to 1 if researcher i is, in turn, a motion-sensing specialist or a non-motion-sensing specialist and 0 otherwise; and $AfterKinectLaunch_t$ is an indicator variable equal to 1 if the year of observation t is either 2011 or 2012, namely, after Kinect's launch. This applies to both generalists and specialists. I include time and individual fixed effects; hence, the main effects $Specialist_i$ and $AfterKinectLaunch_t$ drop out of the estimating equation.

I am interested in the estimated coefficient β of the interaction term between $Specialist_i$ and $AfterKinectLaunch_t$. The interaction term equals 1 for collaboration levels of each of the two types of specialists after the launch of Kinect, and 0 for all others. I interpret a positive estimated value of this coefficient as implying that the average collaboration level of each respective type of specialist increases disproportionately more relative to the average collaboration level of the other researchers. Similarly, I interpret a negative estimated value of this coefficient as implying a decrease in the average collaboration level of the respective type of specialist relative to the collaboration level of the other researchers. Furthermore, the estimated increase or decrease is triggered by the reduction in cost of motion-sensing research technology facilitated by the launch of Kinect.

Next, I explicitly test how these changes in collaboration are reflected after launch on publications referencing motion-sensing keywords. I conduct this second part of my analysis on a data set at the academic publication level, rather than at the individual researcher level.

In a difference-in-differences estimation, I first focus on identifying changes in the occurrence of generalists, motion-sensing specialists, and non-motion-sensing specialists on papers referencing motion-sensing keywords after the launch of Kinect. Next, I test for changes in coauthorship composition between (1) generalists and non-motion-sensing specialists, (2) generalists and motion-sensing specialists, and (3) non-motion-sensing specialists and motion-sensing specialists. Formally, I estimate

$$\begin{aligned} TeamCompositionDummy_{jt} &= \beta(MotionSensingPub_j \times AfterKinectLaunch_t) \\ &\quad + MotionSensingPub_j + \gamma_t + \epsilon_{jt}. \end{aligned} \quad (3)$$

$TeamCompositionDummy_{jt}$ is a dummy variable equal to 1 if the coauthorship team on publication j includes the researcher types under consideration, and 0 otherwise; $MotionSensingPub_j$ is a dummy equal to 1 if publication j is a paper referencing motion-sensing research keywords, and 0 otherwise; and $AfterKinectLaunch_t$ is an indicator variable equal to 1 if the year of observation t is either 2011 or 2012, namely, after Kinect's launch. This applies to both academic papers referencing motion-sensing keywords and those that do not. I include time fixed effects; hence, the main effect $AfterKinectLaunch_t$ drops out of the estimating equation.

I am interested in the estimated coefficient β of the interaction term ($MotionSensingPub \times AfterKinectLaunch$). I interpret a positive (negative) estimated value of this coefficient as implying that the average collaboration occurrence between the respective researcher types increases (decreases) disproportionately more relative to the average collaboration occurrence between other researchers, and the estimated change is triggered by the cost reduction of motion-sensing research technology facilitated by the launch of Kinect.

Table 1. Descriptive Statistics

	Mean	Std. dev.	Minimum	Maximum	No. of observations
Individual level panel (using 2009–2012 publication data)					
Intensive collaboration	2.522	2.606	0	23	387,196
Extensive collaboration	2.846	2.825	0	23	387,196
After Kinect launch	0.500	0.500	0	1	387,196
Motion-sensing specialist	0.073	0.259	0	1	387,196
Non-motion-sensing specialist	0.438	0.496	0	1	387,196
Motion-sensing specialist × After Kinect launch	0.036	0.187	0	1	387,196
Non-motion-sensing specialist × After Kinect launch	0.438	0.496	0	1	387,196
Publication level panel 2009–2012 (restricted to coauthored)					
With generalists	0.207	0.406	0	1	600,756
With non-motion-sensing specialists	0.985	0.122	0	1	600,756
With motion-sensing specialists	0.203	0.403	0	1	600,756
Generalists and non-motion-sensing specialists	0.159	0.366	0	1	600,756
Generalists and motion-sensing specialists	0.006	0.076	0	1	600,756
Motion-sensing specialists and non-motion-sensing specialists	0.150	0.357	0	1	600,756
After Kinect launch	0.471	0.499	0	1	600,756
Motion-sensing pub	0.014	0.117	0	1	600,756
Motion-sensing pub × After Kinect launch	0.008	0.089	0	1	600,756
Diversification index (using 2005–2008 publication data)					
Diversification index	0.635	0.084	0	0.8	387,196
Publications	2.734	3.922	0.25	141.75	387,196
Diversification index generalist	0.760	0.011	0.75	0.8	19,980
Publications generalist	9.254	10.416	0.5	141.75	19,980
Diversification index motion-sensing specialists	0.676	0.054	0.24	0.74	28,068
Publications motion-sensing specialists	3.974	4.165	0.25	53.25	28,068
Diversification index non-motion-sensing specialists	0.624	0.081	0	0.74	339,148
Publications non-motion-sensing specialists	2.247	2.621	0.25	59.25	339,148

I conduct my analysis on two data sets, both ranging from 2009 to 2012, two years before and two years after the launch of Kinect (at the end of 2010). The fist data set is a panel at the individual author level. The second data set is at the publication level.

The first data set comprises researchers who published throughout the course of my entire period of interest, from 2005 to 2012. I restrict my analysis to this set of researchers since I need the 2005–2008 publication period to construct the diversification index and identify generalists and specialists. I require the 2009–2012 period to estimate changes in the collaboration behavior of generalists and specialists, triggered by the cost reduction of motion-sensing research technology. There are a total of 96,799 distinct researchers in my data set. The second data set is comprised of all academic publications from 2009 to 2012, inclusive of those researchers included in the first data set. There are a total of 748,922 such publications. I estimate Equation (2) using the first data set and Equation (3) using the second data set (descriptive statistics are included in Table 1). Overall, the difference between the two data sets is the unit of analysis, which changes from the individual researcher to the academic publication.

5. Results

5.1. Changes in Motion-Sensing Output

I present results of estimating Equation (1) in Table 2. In columns (1) and (2), I compare changes in motion-sensing output with the publication rate in other research topics (Appendix C, Table C.2). I define the topics using the same keyword approach and rationale used in identifying motion-sensing publications. In column (3), I consider control research areas from IEEE's taxonomy. The mean number of motion-sensing publications per year in the period before Kinect's launch is 989.67. After the launch, this value increases to 2,425.

Table 2. Researchers Publish Disproportionately More on Topics Referencing Motion-Sensing Keywords After the Launch of Kinect

	Dependent variable: Log of count of publications per year per research topic or research area		
	(1) Compared to research topics close in volume before Kinect's launch	(2) Compared to all research topics	(3) Compared to all research areas (IEEE taxonomy)
MotionSensingPub × *AfterKinectLaunch*	0.3919***	0.4727***	0.5651***
	(0.1105)	(0.0690)	(0.1017)
MotionSensingPub			−4.8360***
			(0.1838)
Year fixed effects	Yes	Yes	Yes
Research topic fixed effects	Yes	Yes	
Research area fixed effects			Yes
R-squared	0.980	0.984	0.929
Observations	64	104	725

Notes. The data set is a panel of counts of publications between 2005 and 2012. The unit of analysis is year-research topic or year-research areas. I list all research topics and keywords used to identify them in Appendix C, Table C.2. Research areas are those identified in the IEEE taxonomy. All models are ordinary least squares with robust standard errors clustered by research topic or research area.
***Significant at 1%.

The main result of interest is the estimated coefficient of the interaction term ($MotionSensingPub_j \times AfterKinectLaunch_t$), which is positive and statistically significant across all estimations. This implies that the difference between the number of publications referencing motion-sensing keywords and the number of publications from other research topics is greater after rather than before the reduction in cost of motion-sensing technology triggered by the launch of Kinect. More specifically, I find evidence of up to a 57% increase in publications referencing motion-sensing keywords relative to other publications, after the reduction in cost.

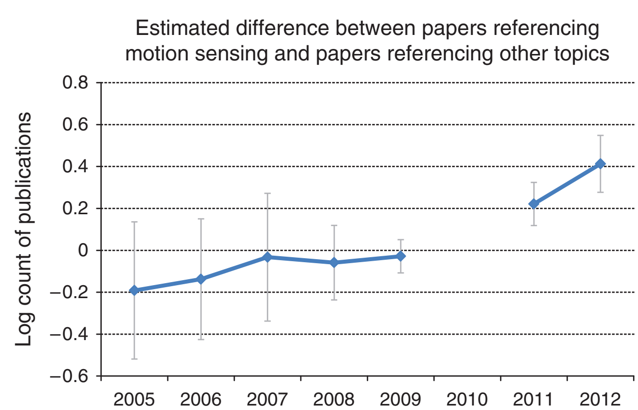
Figure 2 provides further evidence of the timing of this effect. Each point represents the estimated difference in yearly log publication counts between papers referencing motion-sensing keywords and papers referencing other research topics, all relative to the base year of 2010. The graph shows that the difference in publication rates between papers that reference motion-sensing keywords and those that do not is small and stable until the launch of Kinect at the end of 2010. Thereafter, the difference increases, as evidenced by the higher coefficients.

5.2. Changes in Collaboration Composition

Having established the baseline effect of overall changes in output rate, I now explore changes in collaboration between generalists and specialists following the reduction in cost of motion-sensing research technology, guided by the formal model predictions described in Section 2.2. First, I observe that researchers' collaboration and diversification levels are codetermined. Indeed, before the launch of Kinect, generalists collaborate more than specialists both at the intensive (number of distinct collaborators per period) and extensive (number of collaborators per period) levels (Table 3). Thus, while it is unclear if diversity of individual research portfolio areas results from increased collaboration or vice versa, the data confirm collaboration as an influential factor relative to generalists' role in the organization of knowledge creation.

Next, I test for changes in the collaboration levels of generalists, motion-sensing specialists, and non-motion-sensing specialists relative to one another after the launch of Kinect. As before, I focus on two measures of collaboration: extensive and intensive. I start by comparing mean collaboration levels of generalists,

Figure 2. (Color online) Disproportionate Increase in Motion-Sensing Publications After Kinect



Notes. I base this figure on six years of publication data before the launch of Kinect (2005–2010) and two years of publication data after the launch of Kinect (2011–2012). Each point on the graph represents the coefficient value on the covariate *MotionSensingPub* × *Year* and thus describes the relative difference in log publication rates between papers referencing motion-sensing keywords and other papers that year (research topics close in volume as controls). The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 2010. I include the same results in table format in Appendix C, Table C.1.

Table 3. Mean Differences in Collaboration Rates Between Generalists, Motion-Sensing Specialists, and Non-Motion-Sensing Specialists Before and After Kinect's Launch

		Collaboration—Intensive (mean)		Collaboration—Extensive (mean)	
	Observations	Before	After	Before	After
Generalist	4,995	3.251	3.404	3.765	3.836
Motion-sensing specialist	7,017	2.544	2.707	2.992	3.065
Non-motion-sensing specialist	84,787	2.208	2.722	2.532	3.016

Notes. The data set is a panel at the author level based on publication data between 2009 and 2012. The number of observations indicates the number of researchers of each type in the sample. "Before" values refer to the period before Kinect's launch (2009–2010). "After" values refer to the period after Kinect's launch (2011–2012).

motion-sensing specialists, and non-motion-sensing specialists to one another, before and after the research technology cost reduction (Table 3). I observe that while all researchers increase their mean collaboration level after the launch of Kinect, the increase is highest for non-motion-sensing specialists. This increase aligns with the formal model proposition, in which the decrease in cost is democratizing, leading to an increased involvement of non-motion-sensing specialists in team knowledge production.

However, there may be systematic differences between generalists, motion-sensing specialists, and non-motion-sensing specialists that are unaccounted for when comparing these simple means. As such, I turn to the regression estimate described by Equation (2). I document the results of this estimation in Table 4. Columns (1) and (3) report results for non-motion-sensing specialists, while columns (2) and (4) report results for motion-sensing specialists. The result supports the observation that non-motion-sensing specialists increase their collaboration level disproportionately more than generalists and motion-sensing specialists after the launch of Kinect, while motion-sensing specialists decrease it. Specifically, non-motion-sensing specialists disproportionately increase their intensive and extensive collaboration levels by 17% relative to other researchers, after the launch of Kinect. At the same time, motion-sensing specialists decrease their intensive and extensive collaboration levels by 13% relative to all other researchers, after the launch of Kinect.

Next, I explicitly test whether the mechanism described by the theoretical model explains the increase. Specifically, when the reduction in cost is democratizing, the proposition predicts an increased involvement of non-motion-sensing specialists on motion-sensing projects after the launch of Kinect through collaboration with generalists. Furthermore, the model predicts a decrease in collaboration of generalists and motion-sensing specialists. I test for this mechanism using Equation (2) on the individual-level panel, restricted to collaborations that include generalists.

Table 5 presents results of the estimated changes in collaboration with generalists. In line with the model's prediction of reductions in cost that democratize, I find evidence of a disproportionate increase in collaboration between generalists and non-motion-sensing specialists, relative to collaboration between generalists and motion-sensing specialists or other generalists, after the launch of Kinect. Specifically, non-motion-sensing specialists disproportionately increase their intensive collaboration level with generalists by 22%, and their extensive collaboration level by 23%,

Table 4. After Kinect's Launch, Non-Motion-Sensing (Motion-Sensing) Specialists Increase (Decrease) Collaboration

	Dependent variable: Count of collaboration per author per year			
	(1) Intensive (incidence ratio)	(2)	(3) Extensive (incidence ratio)	(4)
NonMotionSensingSpecialist × *AfterKinectLaunch*	1.1673*** (0.0074)		1.1656*** (0.0068)	
MotionSensingSpecialist × *AfterKinectLaunch*		0.8738*** (0.0077)		0.8704*** (0.0070)
Year fixed effects	Yes	Yes	Yes	Yes
Author fixed effects	Yes	Yes	Yes	Yes
Log likelihood	−530,866.74	−531,070.02	−557,518.65	−557,732.45
Observations	387,196	387,196	387,196	387,196

Notes. The data set is a panel at the author level based on publication data between 2009 and 2012. I define generalist and specialist types using publication data between 2005 and 2008. The comparison group for non-motion-sensing specialists is comprised of motion-sensing specialists and generalists. The comparison group for motion-sensing specialists is comprised of non-motion-sensing specialists and generalists. The unit of analysis is the author-year. All models are Poisson with robust standard errors clustered at the level of fixed effects.

***Significant at 1%.

Table 5. After Kinect's Launch, Non-Motion-Sensing (Motion-Sensing) Specialists Increase (Decrease) Collaboration *with Generalists*

Dependent variable: Count of collaboration per author per year				
	(1)	(2)	(3)	(4)
	Intensive (incidence ratio)		Extensive (incidence ratio)	
NonMotionSensingSpecialist × AfterKinectLaunch	1.2190***		1.2294***	
	(0.0226)		(0.0216)	
MotionSensingSpecialist × AfterKinectLaunch		0.7609***		0.7531***
		(0.0209)		(0.0192)
Year fixed effects	Yes	Yes	Yes	Yes
Author fixed effects	Yes	Yes	Yes	Yes
Log likelihood	−48,497.91	−48,498.44	−53,082.52	−53,082.93
Observations	168,844	168,844	168,844	168,844

Notes. The data set is a panel at the author level based on publication data between 2009 and 2012. I define generalist and specialist types using publication data between 2005 and 2008. The comparison group for non-motion-sensing specialists is comprised of motion-sensing specialists and generalists. The comparison group for motion-sensing specialists is comprised of non-motion-sensing specialists and generalists. The unit of analysis is the author-year. All models are Poisson with robust standard errors, clustered at the level of fixed effects.

***Significant at 1%.

relative to other researchers collaborating with generalists, after the launch of Kinect. Moreover, and also in line with the model's predictions, motion-sensing specialists decrease their intensive and extensive collaboration levels with generalists by 24%, relative to generalists collaborating with other researchers, after the launch of Kinect.

Next, I test whether this main result remains robust to alternative specifications for identifying generalists and specialists. Thus far, I have identified generalists as researchers with a diversification level in the top 5% (above 0.75), and specialists as the remainder. While the results remain robust to considering definitions of generalists as researchers with diversification levels in the top 10% and top 25%, there might be concerns that the findings are not driven by heterogeneity in exposure to knowledge between specialists and generalists, since the specialists group remains quite diversified. To address this concern, I provide results (Table 6, columns (5)–(8)) using an alternative definition of specialists as individuals with a diversification level in the bottom 5% (below 0.48), while continuing to define generalists as researchers with a diversification level in the top 5% (above 0.75). Under this specification the results not only continue to hold, but the magnitude increases in line with the build-in increased gap in diversification level between generalists and specialists, as informed by the mechanism described in the theoretical model. Specifically, non-motion-sensing specialists disproportionately increase their intensive

Table 6. Robustness of Non-Motion-Sensing (Motion-Sensing) Specialists' Increased (Decreased) Collaboration *with Generalists*

Dependent variable: Count of collaboration per author per year								
	Specialists as bottom 5 percentile				CEM: Matching by publication count in the before period			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Intensive (incidence ratio)		Extensive (incidence ratio)		Intensive (incidence ratio)		Extensive (incidence ratio)	
NonMotionSensingSpecialist × AfterKinectLaunch	1.4961***		1.5410***		1.0757***		1.0950***	
	(0.0983)		(0.1004)		(0.0144)		(0.0130)	
MotionSensingSpecialist × AfterKinectLaunch		0.3914***		0.3367***		0.8941***		0.8709***
		(0.1275)		(0.1130)		(0.0124)		(0.0105)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Author fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	−6,825.29	−6,843.28	−7,489.87	−7,512.02	−57,498.63	−57,492.87	−66,718.94	−66,707.73
Observations	22,468	22,468	22,468	22,468	163,656	163,656	163,656	163,656

Notes. The data set is a panel at the author level based on publication data between 2009 and 2012. I define generalist and specialist types using publication data between 2005 and 2008. The comparison group for non-motion-sensing specialists is comprised of motion-sensing specialists and generalists. The comparison group for motion-sensing specialists is comprised of non-motion-sensing specialists and generalists. The unit of analysis is the author-year. All models are Poisson with robust standard errors clustered at the level of fixed effects.

***Significant at 1%.

collaboration level with generalists by 50%, and their extensive collaboration level by 54%, relative to other researchers collaborating with generalists, after the launch of Kinect. Furthermore, motion-sensing specialists decrease their intensive collaboration level with generalists by 61%, and their extensive collaboration level with generalists by 66%, relative to generalists collaborating with other researchers, after the launch of Kinect. The results remain robust to considering alternative definitions of specialists as researchers with diversification levels in the bottom 10% (below 0.52) and bottom 25% (below 0.59).

However, concerns remain that the definitions of generalists and specialists capture unequal productivity levels rather than diversification across knowledge areas. Indeed, during the period used to calculate the diversity index (2005–2008), generalists (researchers in the top 5%) published an average of 36.99 papers, whereas specialists (all other) published an average of 9.48 papers. While the difference could be a direct result of the higher mean levels of collaboration of generalists, rather than knowledge creation ability—when considering a number of publications weighted by the number of coauthors per publication, the difference in count is reduced—the concern remains. I take two approaches to address it. First, I account for the difference in the diversification measure calculation. Specifically, the calculation considers percentages of academic papers across the 51 research areas rather than counts of publications. Nevertheless, systematic differences between high and low productive individuals could drive the results. As such, I repeat the estimation of Equation (2) using CEM (Iacus et al. 2011, 2012). I match on productivity—counts of academic publications per researcher—for the 2005–2008 period as well as for the period before Kinect's launch (2009–2010), per year. I present results of this estimation in Table 6 (columns (5)–(8)). The direction of changes in collaboration levels persists, while, not surprisingly, the magnitude decreases. Specifically, non-motion-sensing specialists disproportionately increase their postlaunch intensive collaboration level with generalists by 8%, and their extensive collaboration level by 10%, relative to other researchers collaborating with generalists. At the same time, motion-sensing specialists decrease their intensive collaboration level with generalists by 10%, and their extensive collaboration level with generalists by 13%, relative to generalists collaborating with other researchers, after the launch of Kinect. Table 7 shows the balance in productivity rates between matched specialists and generalists. While, as anticipated, large disparities characterize the full sample (columns (1)–(3)), the CEM procedure balances the productivity rates (columns (4)–(6)) and thus ensures the results on changes in collaboration composition are not driven by unequal productivity levels, but rather by heterogeneity in diversification across knowledge areas.

Overall, the results indicate an increase in collaboration between non-motion-sensing specialists and generalists, and a decrease in collaboration between motion-sensing specialists and generalists. Under the most conservative estimation, the results indicate the effect occurs for 1 in 10 papers.

Thus far, I have not directly focused on papers referencing motion sensing since, by definition, non-motion-sensing specialists were not involved in motion-sensing projects before Kinect. As described in Section 4.3, I interpret these results in the context of the exogenous change in cost of research technology triggered by Kinect's launch. Thus, the estimated changes in collaboration composition are implicitly attributed to motion-sensing publications. Additionally, I follow the estimation strategy described in Equation (3) and test how these changes in collaboration are reflected in publications referencing motion-sensing keywords after the launch of Kinect.

I turn to the data set at the publication level and estimate how the composition of collaboration changes on publications referencing motion-sensing keywords after the launch of Kinect, relative to other publications. I restrict my analysis to academic publications with at least two authors. I investigate how the composition of teams varies on projects referencing motion-sensing keywords by explicitly testing for changes in the fractions of generalists, motion-sensing specialists,

Table 7. Matching Ensures the Results Are Not Driven by Productivity Differences Between Generalists and Specialists Before Kinect's Launch

	Full sample			Matched sample (CEM)		
	(1) Generalists	(2) Specialists	(3) *t*-stat.	(4) Generalists	(5) Specialists	(6) *t*-stat.
Publication count 2005–2008	36.99	9.48	185.75	25.99	25.61	1.46
Publication count 2009	12.33	2.54	183.47	7.87	7.83	0.49
Publication count 2010	14.14	2.70	186.97	8.69	8.56	1.24
Observations	17,596	151,248		15,028	148,628	

Notes. The full sample refers to the data used in estimating the results in Table 5. The matched sample refers to the data used in estimating the results in Table 6, columns (5)–(8).

Table 8. Changes in Authorship Composition for Papers Referencing Motion Sensing After Kinect

	Dependent variable: Dummy for collaboration instances		
	(1) With non-motion-sensing specialists	(2) With generalists	(3) With motion-sensing specialists
MotionSensingPub × *AfterKinectLaunch*	0.3378***	−0.0021	−0.3605***
	(0.0106)	(0.0061)	(0.0177)
MotionSensingPub	−0.4107***	0.0073	0.7421***
	(0.0101)	(0.0044)	(0.0175)
Year fixed effects	Yes	Yes	Yes
Research area fixed effects	Yes	Yes	Yes
R-squared	0.074	0.003	0.044
Observations	600,756	600,756	600,756

Notes. The data set is a panel of publication data between 2009 and 2012. I define generalist and specialist types using publication data between 2005 and 2008. The unit of analysis is the publication. I restrict the sample to publications with more than one author. All models are ordinary least squares with robust standard error clustered by research area.

***Significant at 1%.

and non-motion-sensing specialists (Table 8), as well as collaborating pairs of generalists, motion-sensing specialists, and non-motion-sensing specialists, after Kinect (Table 9).

Table 8 indicates an increase in the occurrence of non-motion-sensing specialists on coauthored papers referencing motion-sensing keywords after the launch of Kinect (column (1)), no significant change in the occurrence of generalists (column (2)), and a decrease in the occurrence of motion-sensing specialists (column (3)). These results align with the mechanism described by the theoretical model. Specifically, when the reduction in cost of research technology is democratizing, the optimal collaboration changes from motion-sensing specialists working with generalists to generalists working with non-motion-sensing specialists. In Table 9, I present results that further support this result at the pair level. Column (1) shows a positive and statistically significant increase in the frequency of teams comprised of generalists and non-motion-sensing specialists, and a decrease in the frequency of teams comprised of generalists and motion-sensing specialists (column (2)) on publications referencing motion-sensing keywords after the launch of Kinect relative to other academic publications. There is an 8% increase in the occurrence of collaboration between generalists and non-motion-sensing specialists on motion-sensing papers after the launch of Kinect, relative to before, a 3% decrease in the occurrence of collaboration between motion-sensing specialists and non-motion-sensing specialists, and a 9% decrease in the occurrence of collaboration between generalists and motion-sensing specialists.

I interpret these results as offering strong evidence of a disproportionately greater increase in collaboration between generalists and non-motion-sensing

Table 9. Changes in Authorship Composition (Collaboration Between Generalists, Non-Motion-Sensing Specialists, and Motion-Sensing Specialists) for Papers Referencing Motion Sensing After Kinect

	Dependent variable: Dummy for collaboration instances between generalists and specialists		
	(1) Generalist and non-motion-sensing specialist	(2) Generalist and motion-sensing specialist	(3) Motion-sensing and non-motion-sensing specialists
MotionSensingPub × *AfterKinectLaunch*	0.0802***	−0.0861***	−0.0306+
	(0.0038)	(0.0061)	(0.01933)
MotionSensingPub	−0.1432***	0.1076***	0.2919***
	(0.0036)	(0.0045)	(0.0151)
Year fixed effects	Yes	Yes	Yes
Research area fixed effects	Yes	Yes	Yes
R-squared	0.004	0.014	0.019
Observations	600,756	600,756	600,756

Notes. The data set is a panel of publication data between 2009 and 2012. I define generalist and specialist types using publication data between 2005 and 2008. The unit of analysis is the publication. I restrict the sample to publications with more than one author. All models are OLS with robust standard error clustered by research areas.

+Significant at 15%; ***significant at 1%.

specialists relative to other collaborating types after the launch of Kinect. The effect aligns with the mechanism described by the theoretical model's predictions where the cost reduction is democratizing. Specifically, following the reduction in cost, generalists play an influential role in facilitating involvement of non-motion-sensing specialists, as reflected in team formation changes. The estimated variance in magnitudes of the collaboration effect also aligns with the theorized role of breadth of knowledge exposure as an influential factor in team formation.

A comparison of output values as measured by citations further strengthens this interpretation and alignment with the theoretical model. Specifically, motion-sensing publications authored by generalists and non-motion-sensing specialists after Kinect receive an average of 2.72 citations, while all other collaborations receive an average of 1.84 citations, conditional on being cited. The difference is statistically significant at the 2.5% level. I interpret this result as additional evidence of the optimal change in collaboration composition triggered by the reduction in cost of motion-sensing research technology.

6. Discussion and Conclusion

I examine implications of technology cost reductions on team formation by exploiting the launch of Kinect as an exogenous event that suddenly and unexpectedly reduced motion-sensing technology costs. I find evidence of an increase in collaboration between generalists and non-motion-sensing specialists driven by coauthorship on publications referencing motion-sensing keywords after Kinect's launch. The empirical results indicate the effect occurs for 1 in 10 papers. The shift in collaboration composition is consistent with the mechanism emphasized in the formal model where the reduction in cost is democratizing and the optimal collaboration composition is altered to reduce ex ante optimal involvement of within-area specialists and to facilitate involvement of outside-area specialists through collaboration with generalists. Stated differently, with great cost reductions, the technology substitutes for the need to include within-area specialists in coauthorship teams when the knowledge required is embedded in the technology. The consequence is an increase in coauthorship capacity, otherwise limited by collaboration costs (Bikard et al. 2015), to include specialists from other research areas. Generalists appear to act as intermediaries in the process.

The results are not without limitations. While the launch of Kinect offers a plausible natural experiment to draw more causal inferences regarding the impact of research technology costs on team formation, the general limitations of a natural experiment apply. Furthermore, Kinect represents only one instance of research technology cost reduction, subject to the idiosyncrasies of computer science, electrical engineering, and electronics research and domain-specific reliance on research equipment.

At the same time, by and large, team formation is difficult to study with observational data because of selection concerns, which constrains most studies to lab experiments. The case of Kinect offers an opportunity to study team formation in a setting that is otherwise difficult to simulate in the lab. While there are uncontested advantages of lab experiments, limitations remain, particularly relative to the generalizability to complex practical settings. This study extends efforts in this direction.

All in all, the results suggest a potentially significant impact of the relationship between human capital and technology costs on inventive activity. The findings contribute to the literature on team formation, the literature on productivity in knowledge creation, and the emerging literature on the role of research equipment in knowledge production (e.g., Ding et al. 2010, Furman and Stern 2011, Murray et al. 2016).

First, reducing technology costs might be a productive strategy for decreasing collaboration costs and enabling knowledge creation that combines more broadly across the frontier. Specifically, reductions in cost of technology might lessen the "knowledge burden" (Jones 2009) resulting from continuous knowledge accumulation by substituting the need for within-area expertise with availability of technology. Furthermore, as a consequence, within-area scientific discoveries might be propelled forward. For example, after the reduction in cost, motion-sensing specialists turn to optimal outside options that might involve creating the new generation of motion-sensing technology.

These findings suggest implications for domains in which collaboration decisions are discretionary, such as scientific research and entrepreneurship, as well as settings where managers coordinate team formation. Understanding factors that influence innovation is crucial for both organizational performance and for informing policy. For example, prior work has emphasized the strategic importance of R&D engagement as a channel for firms to gain new knowledge and increase productivity (e.g., Cockburn and Henderson 1998, Owen-Smith and Powell 2004). Firms could consider subsidies to certain technologies as strategies to influence these outcomes. Similarly, policy could strategically evaluate the funding of research technologies to achieve the most efficient levels of diversity in knowledge creation required for economic growth (e.g., Aghion et al. 2008, Acemoglu 2012).

Second, the role of generalists suggests changes in the organization of inventive activity relative to the division of labor in knowledge creation. Specifically, individuals with broader exposure to knowledge play an important role in team formation in environments with democratizing technology cost reductions. Moreover, the role of generalists in the organization of knowledge creation might grow in significance, as knowledge accumulation leads to specialization in progressively narrower niches (Jones 2009). This observation suggests a departure from incentives designed to encourage specialization in knowledge creation and toward incentives that also encourage diversification, with implications for private and public institutions, as well as for policy makers.

More generally, the observations open questions for future research regarding the interrelated roles of technology costs and breadth of expertise in influencing innovation not only at the individual level, but also at the institutional and field levels. For example, does variation in technology costs altering researchers' topics lead to more diversification or convergence in research domains? What is the relationship between the frequency of technological advancements and the optimal distribution of individual- and field-level diversification? Related, to what extent does the cost regime influence entry and exit into research domains or scientific careers? Does variation in costs of technology accentuate or decrease the gap between high- and low-performing institutions and regions?

Overall, the findings of this study suggest a nuanced relationship between human capital and technology in the process of cumulative knowledge creation. Sufficiently large reductions in technology costs carry the potential to lead to more diverse teams, and hence to generate more impactful discoveries (e.g., Weitzman 1998, Wuchty et al. 2007, Uzzi et al. 2013). More broadly, technology costs emerge as an influential factor in enriching diversity in knowledge creation, an outcome that has been shown to fuel economic progress (Acemoglu 2012).

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Appendix A. Formal Model Extensions

A.1. Collaborative Projects That Include a Generalist Have the Highest Value V_{GEN}

Agents' Optimal Choices. I review the optimal choice of each agent i who seeks to maximize his or her payoff given the assumed costs and values. I do so to identify the conditions under which each type will collaborate with another type and when they will not. I assume a collaboration occurs only if the action is value maximizing for each party.

OAS. Consider that the opportunity comes to an outside-area specialist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{OAS}. Otherwise, if the agent chooses to collaborate with a within-area specialist, the net value will be $V_{WAS}^{OAS} - (c_{WAS} + C)$; if the agent collaborates with a generalist, the net value will be $V_{GEN}^{OAS} - c_{GEN}$; and if the agent collaborates with another outside-area specialist, the net value will be $V_{OAS}^{OAS} - (c_{OAS} + C)$. It follows that it is optimal for outside-area specialists to collaborate with generalists if $V_{GEN} - V_{OAS} > c_{GEN} - (c_{WAS} + C)$, and to otherwise collaborate with within-area specialists. In other words, it is optimal for outside-area specialists to collaborate with within-area specialists as long as within-area specialists provide a large enough cost advantage to offset the premium value otherwise captured from collaborating with generalists. Outside-area specialists find it optimal to pursue their outside options if the average net value of collaborating with generalists or within-area specialists is lower than V_O^{OAS}.

GEN. Consider that the opportunity comes to a generalist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{GEN}. Otherwise, if the agent chooses to collaborate with an outside-area specialist, the net value will be $V_{OAS}^{GEN} - c_{GEN}$; if the agent collaborates with a within-area specialist, the net value will be $V_{WAS}^{GEN} - c_{WAS}$; and if the agent collaborates with another generalist, the net value will be $V_{GEN}^{GEN} - c_{GEN}$. It follows that it is optimal for generalists to collaborate with within-area specialists if $c_{GEN} - c_{WAS} > 0$, and to otherwise collaborate with outside-area specialists. Generalists find it optimal to pursue their outside options if the average net value of collaborating with either outside-area specialists or within-area specialists is lower than V_O^{GEN}.

WAS. Consider that the opportunity comes to a within-area specialist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{WAS}. Otherwise, if the agent chooses to collaborate with an outside-area specialist, the net value will be $V_{OAS}^{WAS} - (c_{WAS} + C)$; if the agent collaborates with a generalist, the net value will be $V_{GEN}^{WAS} - c_{WAS}$; and if the agent collaborates with another within-area specialist, the net value will be $V_{WAS}^{WAS} - (c_{WAS} + C)$. It follows that it is optimal for within-area specialists to collaborate with generalists if $V_O^{WAS} < V_{GEN}$, and to otherwise pursue their outside options.

Proposition A1. *The equilibrium outcome depends on the difference between costs c_i such that* (a) *if the difference is sufficiently large, then, in equilibrium, within-area specialists and generalists collaborate on the opportunity as long as the values of their respective outside options are lower than the net value captured through this collaboration;* (b) *if the difference is sufficiently small, approaching* 0, *then, in equilibrium, generalists and outside-area specialists collaborate on the opportunity, while within-area specialists are left to pursue their outside options.*

Proof. Consider the optimal choice of each agent i who seeks to maximize his or her payoff. It follows that when the difference between c_{WAS} and c_{GEN} is sufficiently large ($c_{WAS} \ll c_{GEN}$), within-area specialists match with generalists if $V_O^{WAS} < V_{GEN}$, and otherwise pursue their outside options. Similarly, generalists with outside options valued higher than the net value of collaborating with within-area specialists pursue their outside options. Absent the cost advantage of within-area specialists (i.e., the difference between costs c_{WAS} and c_{GEN} is sufficiently small, approaching 0), in equilibrium, generalists and outside-area specialists match, while within-area specialists are left to pursue their outside options. Note that in this case, as a consequence, total within-area output increases since generalists always prefer to collaborate on the opportunity over pursuing their outside options, and outside-area specialists join in. □

A.2. Collaborative Projects That Include an Outside-Area Specialist Have the Highest Value V_{OAS}

Agents' Optimal Choices. I review the optimal choice of each agent i who seeks to maximize his or her payoff given the assumed costs and values. I do so to identify the conditions under which each type will collaborate with another type and when they will not. I assume a collaboration occurs only if the action is value maximizing for each party.

OAS. Consider that the opportunity comes to an outside-area specialist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{OAS}. Otherwise, if the agent chooses to collaborate with a within-area specialist, the net value will be $V_{WAS}^{OAS} - (c_{WAS} + C)$; if the agent collaborates with a generalist, the net value will be $V_{GEN}^{OAS} - c_{GEN}$; and if the agent collaborates with another outside-area specialist, the net value will be $V_{OAS}^{OAS} - (c_{OAS} + C)$. It follows that it is optimal for outside-area specialists to collaborate with generalists if $c_{WAS} + C > c_{GEN}$, and to otherwise collaborate with within-area specialists. Outside-area specialists find it optimal to pursue their outside options if the average net value of collaborating with generalists or within-area specialists is lower than V_O^{OAS}.

GEN. Consider that the opportunity comes to a generalist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{GEN}. Otherwise, if the agent chooses to collaborate with an outside-area specialist, the net value will be $V_{OAS}^{GEN} - c_{GEN}$; if the agent collaborates with a within-area specialist, the net value will be $V_{WAS}^{GEN} - c_{WAS}$; and if the agent collaborates with another generalist, the net value will be $V_{GEN}^{GEN} - c_{GEN}$. It follows that it is optimal for generalists to collaborate with outside-area specialists if $V_{OAS} - V_{GEN} > c_{GEN} - c_{WAS}$, and to otherwise collaborate with within-area specialists. Generalists find it optimal to pursue their outside options if the average net value of collaborating with outside-area specialists or within-area specialists is lower than V_O^{GEN}.

WAS. Consider that the opportunity comes to a within-area specialist. If the agent chooses to pass on the opportunity, the net value accruing will be V_O^{WAS}. Otherwise, if the agent chooses to collaborate with an outside-area specialist, the net value will be $V_{OAS}^{WAS} - (c_{WAS} + C)$; if the agent collaborates with a generalist, the net value will be $V_{GEN}^{WAS} - c_{WAS}$; and if the agent collaborates with another within-area specialist, the net value will be $V_{WAS}^{WAS} - (c_{WAS} + C)$. It follows that it is optimal for within-area specialists to collaborate with generalists if $(V_{OAS} - V_{GEN}) < C$ and to otherwise collaborate with outside-area specialists. Within-area specialists find it optimal to pursue their outside option if its value is higher than both $V_{OAS} - C$ and V_{GEN}.

Proposition A2. *The equilibrium outcome depends on the difference between costs c_i such that* (a) *if the difference is sufficiently large, then, in equilibrium, within-area specialists and either generalists or outside-area specialists collaborate on the opportunity, with the realization being determined by the difference between* ($V_{OAS} - V_{GEN}$) *and* C; (b) *if the difference is sufficiently small, approaching* 0, *then, in equilibrium, generalists and outside-area specialists collaborate on the opportunity, while within-area specialists are left to pursue their outside options.*

Proof. Consider the optimal choice of each agent i who seeks to maximize his or her payoff. It follows that when the difference between c_{WAS} and c_{GEN} is sufficiently large ($c_{WAS} \ll c_{GEN}$), within-area specialists match with either generalists or outside-area specialists. Within-area specialists with outside options valued higher than $V_{OAS} - C$ and V_{GEN}, and generalists and outside-area specialists with outside options valued higher than the average net value of collaborating with within-area specialists, pursue their outside options. Absent the cost advantage of within-area specialists (i.e., the distance between costs c_{WAS} and c_{GEN} is sufficiently small, approaching 0), in equilibrium, generalists and outside-area specialists match, while within-area specialists are left to pursue their outside options. Note that in this case, as a consequence, total within-area output increases since both generalists and outside-area specialists always prefer to collaborate on the opportunity over pursuing their outside options. □

Appendix B. Quotes from Personal Email Exchanges with Researchers

1. "Image (video) analysis tasks are widespread nowadays. This is mainly because a multitude of image sensors abound (they have become a commodity) and all the captured content cannot be analyzed by human eyes. . . . So image analysis (computer vision) tasks have become, in turn, in great demand themselves.

But something fundamental makes automated vision tasks a difficult endeavor: projection. Analysis algorithms are not analyzing the actual (3D + time) scene but a (2D + time) projection of the scene on the camera sensor. Thus, we lose a dimension. And this means that higher intelligence is needed in automatic analysis to avoid mistakenly detect, say, a fly at a short distance from the sensor by (let's say) an elephant at the far background. . . . And this is due to the effect of the "apparent" size of objects in a projected image (smaller when farther away). Basically, we don't know the scale (i.e., the actual size) of an N-pixels wide dark spot, because we don't know the distance at which it is placed from the sensor.

For many years, stereo (and multi-view) sensor arrangements have tried to introduce the third dimension (distance to the sensor) by triangulating scene features from different viewpoints. Fairly good results have been reported, but the higher computation load, the difficulties of managing several sensors simultaneously, and the imprecision of the result (one should find the corresponding features across the sensors to be able to triangulate) have put multi-view approaches on the top list of the most CPU-hungry image analysis tasks (difficult to run in real-time or on normal computers, not to say in mobile environments). . . .

Some years ago, Time-of-Flight (ToF) sensors made an interesting introduction of sensors contributing not only the light value for each pixel but also its depth (distance from the camera) . . . but (1) at a cost on the several thousand USD and (2) with very poor image resolution. The price tag made ToF sensors only available to well-funded research facilities. . . .

And in fall 2010, MS Kinect was launched. It was not the product itself (a peripheral of the MS XBox console, with several gaming apps) that made the eyes of all researchers wide open. . . . It was the sensor itself, a camera-projector pair plus a VGA [video graphics array] camera, providing VGA resolution RGB plus depth information . . . at a cost much less than one-tenth of the ToF sensors mentioned above.

In my group alone, three out of four Ph.D. students having started their thesis in a multiview capture facility (a Smart Room equipped with a dozen cameras) for body tracking and gesture analysis, then changed to a single Kinect sensor to continue the same applications and already defended their thesis (or are about to) with nice results, having forgotten about all the hurdles of their starting research pains with multiple cameras."

2. "As per my opinion, the advent of Kinect has led to an unprecedented revolution in the field of (3D) computer vision, 3D robotic perception, and image processing. The main factors of the phenomenon have been on one side the cost (as it was originally sold at just 150$) and on the other the fact it provided dense 3D frames in real-time. These two aspects suddenly allowed researchers to have direct access to high volumes of 3D data acquired at 25 frames per second, thus extremely speeding up the testing and experimental stage of their algorithms. Indeed, several methods in the field of 3D computer vision and 3D robotic perception have real-time requirements and couldn't work well on top of previous technologies such as laser scanners (too slow), stereo cameras (not dense enough), and Time-of-Flight cameras (too low resolution). Furthermore, Microsoft Kinect (and similar products, such as the Asus Xtion) started to push forward applications developed for the mass market and based on computer vision, the first example of this list being the videogames and joypad-free applications developed by Microsoft on the Xbox. This has led to more attention and importance to the field of computer vision, motivating and increasing the amount of research projects, grants and funds on these topics. Thanks to these new devices, a lot of research focus has switched to 3D computer vision-related research, as witnessed by several research groups traditionally working on related fields (virtual reality, robotics, biomedical engineering) that have now turned their heads towards using Microsoft Kinect within their research."

3. "The Microsoft Kinect sensor is the first depth camera that provides the depth images with sufficient resolutions for typical computer vision (CV) tasks at an affordable price to most people. Before the advent of Kinect, the typical depth cameras cost far more than the Kinect and could usually be used in only some laboratories. The Kinect makes it possible for the common researchers to gain insight into CV tasks with the depth camera.

There are some CV tasks in which the depth images are especially useful, such as human pose estimation, hand motion capture, and gesture recognition. However, partly due to the high price of previous depth cameras, researchers in computer vision heavily relied on color cameras before the Kinect. The lighting condition variations, background clutters, and similarity in appearance of different objects in the color images make the above tasks difficult and cause ambiguity in object segmentation, detection, or recognition in the input images. Compared to the color cameras, these tasks are easier for the depth cameras. The objects with similar colors can be differentiated based on their different distances to the camera. Also, the contrast in depth images describes the 3D surface of the objects and is generally more discriminative for feature extraction. For instance, the depth difference feature adopted by the Kinect is capable of recognizing the individual body parts with high accuracy, and thus presents a practical solution for human pose estimation. The recent results on hand motion capture and gesture recognition also show better accuracy can be obtained with the depth cameras like the Kinect."

4. "We work in two fields related to the Kinects: telepresence and object tracking.

For telepresence, the idea is to immerse a user into a simulated environment (similar to virtual reality), in order to give him or her the impression of being in a completely different place. Kinect devices allow us to fuse simulated and real data, increasing the realism of the simulation. For example, one of our demos consists of "teleporting" a user to our laboratory, where the user is able to navigate freely, while integrating information from the real world (such as our colleagues walking around) in real-time.

The other field is object tracking, where we aim to simultaneously estimate the shape and position of a given object. The advantage of a Kinect device is that it provides real-time depth information with reasonable accuracy. Its low price and small size also allow us to deploy multi-camera networks with little effort. These networks are capable of covering a large area and observing a given object from many angles simultaneously. We are not alone in working with Kinect; in fact, the use of Kinect in the field of object tracking has exploded in the last few years. In conferences and journals, presentations casually mentioning Kinect have become the norm.

In conclusion, Kinect devices have definitively changed how we work, both in telepresence and in object tracking."

5. "Indeed, for a few years I have work with the Kinect in biomedical engineering development. I use it in motion analysis, especially for gait. The use that I am doing is not the designated one from Microsoft. It is not a gaming one. This is because the depth measurement done by this camera is so affordable it is a breakthrough for computer vision and particularly motion analysis domain.

I used it for gait motion analysis in order to measure gait asymmetry. We have developed a system really efficient for gait asymmetry measurement, especially lower limb movement. Its aim is the screening of disease like leg length discrepancy (1 person in 1,000 has a leg length difference over 2 cm) and hip and knees prosthesis surgery follow up. I used it too for fall detection research.

Moreover, something very interesting in the Kinect story is the position of Microsoft. Normally such a huge company is used to dictating its view on the domain (closed sources, user information limitation, . . .). But in the Kinect story, due to the involvement of communities, both academic, company, and geek ones, Microsoft decided to adapt the Kinect to Windows and the library of motion capture that they developed. But at the release of the version for Xbox, they said that their library and sensor are very protected and would not be hacked and they would refuse any uses other than gaming on Xbox."

6. "Kinect has been an important game changer in the field of robotics. The availability of a RGB-D (color and depth) sensing device at low cost with a high depth resolution made possible new or improved approaches in different mobile robotics fields. This includes environment mapping, object detection, tracking, and more in general robot navigation.

Nowadays, Kinect can be considered a standard robot sensing equipment. It is worthwhile to note that the Kinect sensor made possible the access of high-resolution depth sensing to small or less-funded research groups that before had no possibility of having access to such kind of a device."

7. "Since I'm not a gamer, I'm not sure how many gamers play with Kinect, but many researchers in computer vision and robotics started to use it as the sensor replacing cameras and other range finders. Similar sensors have already existed before Kinect, but they are expensive, which is an economic impact. The most important thing is it is easy to use."

8. "It's incredibly powerful to have a cheap way to obtain even a noisy estimate of a user's pose. $200 is zero dollars for a research lab, while $2,000 and $20,000 are $2,000 and $20,000—a lot of money! Rehabilitation researchers and robotics researchers love the Kinect because of all the new types of applications it enables. It just works! That is great."

9. "For us, Kinect had a game-changing effect on the research possibilities. We work in robotics perception, i.e., how can robots perceive and act in the environment. Since our world is 3D and Kinect gives 3D information, the data becomes extremely powerful. This has enabled significant advances in applications such as object detection, human activity recognition, and anticipation for robots, as well as robotic grasping and path planning. This also required very creative new algorithmic ideas to make Kinect actually useful."

10. "Kinect has been driving our research for the last 1.5–2 years and, if not for Kinect, I am not sure we would be working right now on our gesture-based authentication project supported by the National Science Foundation (NSF). Also, looking around computer vision conferences, one can see many papers that use Kinect for data collection. I believe Kinect has been a significant driver in computer vision research in the last few years."

Appendix C. Additional Details to Results in the Main Analysis

Table C.1. Estimation Coefficients Displayed in Figure 2

Dependent variable: Log of count of publications per year per research topic	
	Compared to research topics close in volume to motion sensing before Kinect's launch
MotionSensingPub × 2005	−0.1915 (0.1383)
MotionSensingPub × 2006	−0.1377 (0.1217)
MotionSensingPub × 2007	−0.0327 (0.1291)
MotionSensingPub × 2008	−0.0587 (0.0752)
MotionSensingPub × 2009	−0.0282 (0.0335)
MotionSensingPub × 2011	0.2214*** (0.0436)
MotionSensingPub × 2012	0.4127*** (0.0575)
Year fixed effects	Yes
Research topic fixed effects	Yes
R-squared	0.980
Observations	64

Notes. The data set is a panel of count of publications between 2005 and 2012. The unit of analysis is year-research topic. All models are OLS with robust standard errors clustered by research topic.
***Significant at 1%.

Table C.2. Set of Keywords Used to Identify Publications Referencing Certain Research Topics

Research topic	Close in volume to motion sensing before Kinect's launch	List of key terms
1 Motion sensing	N/A	motion sensing, motion tracking, motions tracking, motion recognition, motion sensor, motion capture, 3D tracking, three-dimentional tracking, 3D imaging, three-dimentional imaging, depth camera, depth cameras, ranging camera, ranging cameras, flash LIDAR, time of flight camera, time-of-flight camera, time of flight cameras, time-of-flight cameras, RGB-D camera, RGB-D cameras, 3D camera, 3D cameras, Kinect

Table C.2. (Continued)

Research topic	Close in volume to motion sensing before Kinect's launch	List of key terms
2 Speech and voice recognition	Yes	speech recognition, voice recognition, speech processing, linguistics, natural language communication, natural voice communication, speech signal, voice technology, voice-controlled interface, speech interface, voice interface, speech coding, spoken language technology, spoken language technologies, speech technology, voice technology, HMM, hidden Markov model, VQ, vector quantization, ANN, artificial neural network, SVM, support vector machine, VQ/HMM
3 Green energy	Yes	green energy, greenhouse gas, greenhouse gases, renewable energy, environmentally friendly, green technologies, biofuel, biofuels, bio-fuel, bio-fuels, global warming, fossil fuel, climate change, climate changes, green technology, renewable technology, renewable technologies, wind energy, solar energy, tidal energy, geothermal energy, solar power
4 Aerospace and electronic systems	Yes	aerospace, air traffic control, air safety, Earth Observing System, orbit satellite, orbit satellites, moon, space station, space stations, space exploration, space technology, aircraft, propeller, electronic warfare, electronic countermeasure, electronic countermeasures, radar countermeasure, radar countermeasures, military satellite, military satellites, weapon, weapons, gun, guns, missile, missiles, airborne radar, bistatic radar, doppler radar, ground penetrating radar, laser radar, meteorological radar, millimeter wave radar, multistatic radar, MIMO radar, passive radar, radar countermeasure, radar countermeasures, radar detection, radar imaging, radar measurements, radar polarimetry, radar remote sensing, radar tracking, radar clutter, spaceborne radar, spread spectrum radar, synthetic aperture radar, synthetic aperture radar, sonar
5 Antennas and propagation	No	antennas, antenna, Butler matrix, phased arrays, planar arrays, diffraction, propagation, electromagnetic reflection, optical reflection, optical surface wave, optical surface waves, optical waveguide, optical waveguides, radio propagation, radiowave propagation, radio astronomy
6 Broadcast technology	Yes	broadcast, broadcasting, Digital Radio Mondiale, digital audio player, digital audio players, frequency modulation, radio network, radio networks
7 Packaging and manufacturing technology	No	capacitor, capacitors, varactor, varactors, coil, coils, diode, diodes, electrode, electrodes, anode, anodes, cathode, cathodes, microelectrode, microelectrodes, fuse, fuses, active inductor, active inductors, thick film inductor, thick film inductors, thin film inductor, thin film inductors, resistor, resistors, memristor, memristors, varisor, varistors, optical switch, optical switches, transducer, transducers, damascene integration, micromachining, radiation hardening, flip chip, high-K gate dielectrics, quasi-doping, semiconductor device doping, semiconductor epitaxial layer, semiconductor epitaxial layers, semiconductor growth, silicidation, wafer bonding, electronic packaging, electronics packaging, chip scale packaging, environmentally friendly manufacturing technique, environmentally friendly manufacturing techniques, surface-mount technology, multichip module, multichip modules, integrated circuit packaging, semiconductor device packaging
8 Dielectrics and electrical insulation	No	dielectric, dielectrics, capacitor, capacitors, ferroelectric, piezoelectric, pyroelectric, dielectrophoresis, electrohydrodynamics, electrokinetics, electrostriction, electric breakdown, avalanche breakdown, corona, arc discharge, arc discharges, electrostatic discharge, flashover, glow discharge, glow discharges, partial discharges, partial discharge, surface discharge, surface discharges, cable insulation, gas insulation, sulfur hexafluoride, insulator, insulators, trees-insulation, isolation technology, oil insulation, oil filled cable, oil filled cables, plastic insulation
9 Electromagnetic compatibility and interference	No	electromagnetic, reverberation chamber, spark gap, spark gaps, mutual coupling, optical coupling, Eddy currents, inductive power transmission, Gamma ray, Gamma rays, line-of-sight propagation, cable shielding, magnetic shielding, EMP, EMTDC, EMTP, power system transient, power system transients, crosstalk, diffraction, echo interference, radiofrequency interference, specific absorption rate, radiative interference, electrostatic interference, interchannel interference, interference cancellation, interference channel, interference channels, interference elimination, interference suppression, intersymbol interference, TV interference

Table C.2. (Continued)

Research topic	Close in volume to motion sensing before Kinect's launch	List of key terms
10 Imaging technology	No	imaging, angiocardiography, angiography, cardiography, echocardiography, electrocardiography, DICOM, encephalography, mammography, ground penetrating radar, holography, image converter, image converters, active pixel sensor, active pixel sensors, CCD image sensor, CCD image sensors, CMOS image sensor, CMOS image sensors, charge-coupled image sensor, charge-coupled image sensors, infrared image sensor, infrared image sensors, magnetic resonance, diffusion tensor, magneto electrical resistivity, atomic force microscopy, electron microscopy, photoelectron microscopy, scanning electron microscopy, transmission electron microscopy, scanning probe microscopy, Talbot effect, thermoreflectance, radiography, tomography, ultrasound
11 Microwave technology	Yes	microwave, beam steering, maser, masers, gyrotron, gyrotrons, K-band, L-band, rectenna, rectennas, millimeter wave, MIMIC, MIMICs, submillimeter wave
12 Oceanic engineering and marine technology	Yes	marine, underwater, rebreathing, ocean, oceanographic
13 Resonance theory and technology	Yes	ferroresonance, magnetic resonance, nuclear magnetic resonance, paramagnetic resonance, resonance light scattering, stochastic resonance

Notes. I calculate volume as the number of publications per research topic per period of interest. I define research topics close in volume to motion sensing as research topics with up to 10 times the number of publications in motion sensing over the period of interest. The remaining research topics have a number of publications 20 times or higher than the number in motion sensing over the period of interest. All results remain robust to matched research topics based on yearly growth rate before 2010.

Endnotes

[1] For example, attributes such as gender, cohort, age, ethnicity, and geography were found to influence team formation relative to similarity of knowledge domains (e.g., Ding et al. 2010, Stephan 2012, Baccara and Yariv 2013, Boudreau et al. 2016, Freeman et al. 2015, Freeman and Huang 2015).

[2] See CERN, Atlas, "The collaboration," https://atlas.cern/discover/collaboration (accessed July 2017).

[3] Bill Gates explains, "Kinect is a motion-sensing input device that's a revolutionary new way to play games using your body and voice instead of a controller.... Kinect is a remarkable technical achievement. The ability to take video cameras, multi-array microphones and depth sensors, and bring them all together in order to recognize people, understand and anticipate how they move, incorporate voice recognition, and insert them into games ... is phenomenal.... [However], *Kinect is much more than just a cool video game technology.*... I'm convinced this is a transformational technology.... A surprising number of academic researchers and others are exploring using Kinect in ways we never imagined. In the UK, for example, scientists are developing robots using *Kinect's inexpensive (but sophisticated) motion-sensing technology* to search for survivors in potentially unstable buildings after an earthquake. Researchers in Seattle are exploring how Kinect can give surgeons a "virtual" sense of touch during remote surgical procedures...." (Gates 2011, emphasis added).

[4] It is important to note that the scope of this substitution is limited to the knowledge captured by the algorithms embedded in the research technology.

[5] In organizational settings, scholars have identified generalists as playing an important role in solving complex problems (Garicano 2000) that require specialist expertise. Furthermore, others have found this role to grow in importance in environments that necessitate a multifaceted set of specialists (Ferreira and Sah 2012). Similarly, organizational theory highlights the salient role of networks in facilitating diverse knowledge creation both at the individual and firm levels (e.g., Burt 1992, Hargadon and Sutton 1997, Reagans and Zuckerman 2001). Furthermore, knowledge diversity enables firms to recognize the value of new knowledge for innovation (Cohen and Levinthal 1990). More generally, scholars have identified investments in diversity to fuel technological and economic progress (Acemoglu 2012).

[6] See National Institutes of Health (NIH), National Human Genome Research Institute. "The cost of sequencing a human genome," http://www.genome.gov/sequencingcosts/ (accessed July 2014).

[7] The approach acknowledges not only the fact that opportunities can be born in any situation but also that Kinect in particular has a wide reach outside academia; hence, ideas might be born while observing Kinect in settings other than academia.

[8] The results persist when considering single authorship as an option in addition to collaboration.

[9] The results persist when considering either V_{GEN} or V_{OAS} to have the highest value (Appendix A).

[10] The results persist when considering the cost of collaborating with generalists to be equal to ϵ, small.

[11] In his blog, Johnny Lee provides further evidence that Microsoft did not intend for Kinect's use outside its gaming purpose. Lee is a former Microsoft Kinect team member who subsequently moved to Google. Lee states, "I actually have a secret to share on this topic. When my internal efforts for a [Kinect] driver stalled, I decided to approach AdaFruit to put on the Open Kinect contest. For obvious reasons, I couldn't run the contest myself.... Without a doubt, the contest had a significant impact in raising awareness about the potential for Kinect beyond Xbox gaming both inside and outside the company. Best $3,000 I ever spent" (Lee 2011).

[12] Appendix B includes quotes from researchers attesting to these facts. I collected these quotes through personal email exchanges with researchers from top universities in Europe and North America.

[13] "About IEEE *Xplore*® Digital Library," http://ieeexplore.ieee.org/xpl/aboutUs.jsp (accessed July 2014).

[14] Broad knowledge exposure results from involvement in a wide variety of research topics. Whether or not this is driven by involvement in contributing to different research topics or by bringing the same knowledge to a variety of research topics, researchers with broad exposure to knowledge—generalists—differ from specialists in that they do not have a narrow, well-defined research topic.

[15] By definition, Euclidian distance is equal to the square root of the Herfindahl index. The results remain robust when considering a diversification measure based on the Herfindahl.

[16] There is no evidence of systematic difference in the propensity of collaborating author types to publish journal or conference proceeding academic papers.

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