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Generalists, Specialists, and the Direction of Inventive Activity

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Abstract

Due to the cumulative nature of innovation, access to knowledge is important. Although evidence exists concerning the positive impact of increased knowledge access on the rate of inventive activity, less is known about its influence on the direction of inventive activity. I examine how a change in the cost of access to knowledge influences inventive activity by exploiting the hack of Microsoft Kinect as an exogenous event resulting in a sudden and unexpected reduction in the cost of motion-sensing research technology. Specifically, I examine changes in the publication rate of academic papers that use motion-sensing keywords and the composition of authorship on these papers before and after the launch of Kinect relative to other academic publications in selected control subfields of electrical engineering, computer science, and electronics. Despite a growing emphasis on the importance of specialists for knowledge creation, I identify generalists -- researchers with broader exposure to knowledge -- as playing a particularly important role in the process through which this shock influenced inventive activity. First, generalists have a higher propensity than specialists to respond to opportunities for knowledge creation enabled by the reduction in cost of motion-sensing technology. Second, generalists play a central role in connecting non-motion-sensing specialists to these opportunities, thus influencing the direction of inventive activity.

Jelcodes:O31,O33

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JEL: O31, O33, O40

1 Introduction

Knowledge production plays a central role in economic growth. An important aspect of knowledge production is the cumulative nature of knowledge. In order to avoid diminishing returns to investments in knowledge production, research "stands on the shoulders" of prior knowledge (Jones, 1995; Furman and Stern, 2011). Scholars have recognized the salient role of cumulativeness and incorporated it in more recent models of endogenous economic growth (Romer, 1990; Grossman and Helpman, 1991; Jones, 1995). However, the microeconomic foundations of cumulativeness remain less explored.

In particular, the ability to build on the existing stock of knowledge depends on the cost of access to knowledge (Mokyr, 2002). While scholars have documented a positive impact of low-cost conditions on the rate of inventive activity (e.g., Murray and Stern, 2007; Furman and Stern, 2011; Williams, 2012) with implications for the type of follow-on research (e.g., Murray et al., 2009), less is understood regarding the organization of knowledge creation under such conditions as a factor influencing the direction of inventive activity. The organization of knowledge creation informs the process through which reductions in costs of access to knowledge influence the type of follow-on research. Although such an extension would help shed light on the evolution of innovation trajectories, it is empirically difficult to isolate the role of cost conditions from a selection effect, since the knowledge creation process endogenously affects the cost of access to knowledge.

The main contribution of this paper is to empirically explore the organization of knowledge creation following a particular instance of change in the cost of accessing knowledge while also considering the selection effect. Specifically, I focus on an unanticipated reduction in the cost of motion-sensing research technology and its implications.

Mokyr (2002) details the salient influence of technology in general and research technology in particular in significantly lowering the cost of access to knowledge. The cost of research technology influences the pace of inventive activity (Stephan, 2012). For example, reductions in the cost of the processing power and mathematical sophistication of computers have lowered the cost of access to complex statistical analyses. Similarly, reductions in the cost of motion-sensing research technology have lowered the cost of access to complex motion-sensing algorithms necessary for research involving capturing and analyzing 3D data.

However, more often than not, such changes in cost are endogenous to the observed follow-on innovation. For example, funding is selectively injected for high-quality research technologies that are expected to have a significant and positive impact on subsequent innovation (Stephan, 2012). To address such concerns, I leverage a natural experiment as an exogenous event correlated with reductions in the cost of motion-sensing research technology but not correlated with the ex-ante rate and direction of inventive activity. The surprising 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 possible the use of Kinect as a motion-sensing research device. Given Kinect's technological sophistication relative to its low price ($150 at launch and lower thereafter), the consequence has been an unforeseen reduction in the cost of motion-sensing technology in research. Its release marked the start of what Microsoft eventually coined the "Kinect Effect." 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], <u>Kinect is much more than just a cool video game technology</u>... 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 <u>Kinect's inexpensive (but sophisticated) motion-sensing technology</u> 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... (The Gates Notes, 2011) (emphasis mine).

In my empirical analysis, I focus on academic publications in electrical engineering, computer science, and electronics from 2005 to 2012, inclusive, as listed in the IEEE bibliographical database.[1] I start by confirming a positive impact on the rate of inventive activity and then follow by investigating the organization of knowledge creation as a factor influencing the direction of inventive activity.

First and in line with prior studies (e.g., Murray and Stern, 2007; Furman and Stern, 2011; Williams, 2012), I confirm a positive impact of the reduction in cost of access to knowledge on the subsequent publication rate. I add to this body of literature by providing evidence for this effect in a setting where the reduction in cost is triggered by changes in the cost of research technology. Furthermore, the setting allows me to get closer to isolating the marginal impact of motion-sensing research technology costs on the rate of inventive activity. In observational data, the marginal impact is difficult to identify since changes in

[1] I collected the data in December 2012. To the extent there is a lag in adding 2012 publications to the IEEE bibliographical database, my dataset does not capture all 2012 publications. This underestimates the impact of the reduction in cost of motion-sensing technology.

the cost of research technology and founding conditions that lead to such reductions are highly correlated. The unexpected nature of the Kinect event mitigates these concerns. Specifically, I examine changes in the publication rate of academic papers that use motion-sensing keywords before and after the launch of Kinect. I find evidence of up to a 57% increase in publications referencing motion-sensing keywords relative to other publications.

Next, I explore the organization of knowledge creation following the reduction in cost as a factor influencing the direction of inventive activity. I conduct my analysis at the individual level since researchers are at the root of scientific knowledge production. My goals are to identify researchers with a high propensity to respond to opportunities opened by the reduction in cost of motion-sensing research technology and to uncover the impact of their research behavior on the direction of inventive activity. Despite a growing emphasis on the importance of specialists for knowledge creation, I identify generalists – researchers with broader exposure to knowledge – as playing a particularly influential role for knowledge creation following a reduction in cost of access to knowledge. I motivate my analysis with a formal model of knowledge production in which specialists and generalists choose with whom to collaborate (if at all) before and after the reduction in cost of motion-sensing technology. The model demonstrates the usefulness of separating generalists, motion-sensing specialists, and non-motion sensing specialists and shows that the fall in cost can be democratizing, increasing the importance of generalists.

I use the model to sharpen the inferences drawn from empirical findings. First, I find that generalists have a higher propensity than specialists to publish papers that reference Kinect. I interpret this as evidence of generalists playing a central role in responding to opportunities opened by the reduction in cost of motion-sensing research technology. Second, I examine changes in team size and composition of authorship on academic papers referencing motion-sensing keywords before and after the launch of Kinect. I find evidence of an increase in team size on publications referencing motion-sensing keywords after the launch of Kinect driven by collaboration between generalists and non-motion-sensing specialists. Thus, generalists also play an important role in connecting specialists in areas other than motion-sensing to the research opportunities opened by the reduction in cost of motion-sensing technology, thus influencing the type of knowledge created.

Taken together, these results suggest not only a significant impact of research technology costs on the rate of inventive activity but also, and perhaps more importantly, fundamental changes in the organization of knowledge creation that affect the direction of inventive activity. Generalists influence the process of cumulative knowledge creation by connecting specialists to research opportunities opened by the reduction in cost of access to knowledge. More generally, the role of generalists might grow in significance as knowledge accumulation leads to specialization in progressively narrower niches (Jones, 2009).

I structure the remainder of the paper as follows. Section 2 details the concepts of generalists and specialists. Sections 3 and 4 provide the setting and data. I then present and discuss results in Section 5 and conclude in Section 6.

2 Generalists and Specialists

The fact that division of labor, or specialization, has a positive impact on productivity and hence on economic growth is well accepted and goes back to Adam Smith's seminal work (1776). As such, many academic incentives encourage a narrow research focus. For example, scientists target their research for certain journals in response to monetary awards (Franzoni et al, 2011) or reputation benefits associated with such publications or in an attempt to secure grants as urged by universities (Stephan, 2012). Moreover, evidence indicates a trend towards specialization in increasingly narrower niches explained by the growth in knowledge stock and the continuous forward movement of the knowledge frontier (Jones, 2009, 2010, 2011).

Specifically, Jones (2009) emphasizes the "knowledge burden" hypothesis in which successive generations of innovators face an increasing education burden due to the advancing knowledge frontier. As a consequence, time in education is lengthening and the domain of individual level expertise is narrowing. In turn, this leads to an increased need for collaborative work in order to move knowledge forward by combining the increasingly narrower niches of specialization (Jones, 2009; Agrawal et al., 2013). 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 require spanning 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 difficult to coordinate efficient teams of specialists who work on topics bridging knowledge areas (Jones, 2010). This matters because teams play an increasingly salient role in combining knowledge and facilitating innovation (Wuchty et al., 2007, Singh and Fleming, 2010). This search problem is indicative of a potential demand for researchers who have enough exposure to broad knowledge to recognize opportunities for knowledge creation that requires bridging across knowledge areas and to lower coordination costs between collaborating specialists required to execute on the opportunities (Jones, 2010). The role seems to increase in importance as research specialization niches become increasingly narrower.

Broad exposure to knowledge is a consequence of involvement in a wide variety of research topics. Whether or not if 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 differ from specialists in that they do not have a narrow, well-defined research topic. In what follows, I refer to these researchers as *generalists* in order to distinguish them from *specialists*.

2.1 Breadth of Knowledge: The Role of Generalists

Generalists have sufficient broad exposure to knowledge to recognize opportunities for knowledge creation that require spanning knowledge areas as well as to identify and coordinate connections among specialists. In turn, specialists have the depth of knowledge required to push the knowledge creation process further.

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, 2009). Similarly, organizational theory highlights the salient role of networks in facilitating diverse knowledge creation both at the individual and firm levels. For instance, innovators broker between otherwise disconnected contacts with diverse knowledge (Burt, 1992) to generate innovations (Hargadon and Sutton, 1997; Regans and Zuckerman, 2001). Emergent network literature extends these insights to explicitly consider individuals who identify innovative opportunities by bridging between contacts with diverse knowledge (Tortoriello et al., 2013). At the organization level, diversity of knowledge enables firms to recognize the value of new knowledge for innovation (Cohen and Levinthal, 1990). More generally, scholars have identified investments in diversity to be salient for technological and economic progress (Acemoglu, 2012). I draw on these insights to consider the role of generalists in the context of the scientific innovative landscape. In particular, I consider the role of generalists – researchers with broad exposure to knowledge – in the organization of creative activity following reductions in cost of access to knowledge.

2.2 Generalists and Specialists in the Context of Reductions in Cost of Access to Knowledge

It is unclear ex-ante how the role of generalists and specialists in knowledge creation might influence the type of knowledge created following a reduction in cost of access to knowledge. In the process of cumulative innovation, access to knowledge is a necessary condition to facilitate follow-on innovation. However, this is not a sufficient condition, since the knowledge creation process also depends on the ability to build on knowledge (Murray and O'Mahony, 2007).

First, researchers need to have the necessary expertise to recognize and execute opportunities for follow-on innovation opened by reductions in cost of access to knowledge. Generalists and specialists, by definition, are heterogeneous in their level of knowledge. As such, generalists and specialists vary in their abilities to recognize and execute on opportunities opened by the reduction in cost of motion-sensing technology. Generalists and motion-sensing specialists might have a higher propensity than specialists in other domains to recognize opportunities for knowledge creation opened by the reduction in cost. Furthermore, while motion-sensing specialists have the expertise to execute on some opportunities, generalists' breadth of exposure to knowledge facilitates execution on opportunities spanning knowledge areas as generalists identify and coordinate connections among various specialists.

Second, the reduction in cost of motion-sensing technology alters the cost of engagement with motion-sensing in research and with it the productivity of researchers. However, it is unclear if the reduction in cost of motion-sensing research technology makes it easier for researchers, regardless of their previous exposure to motion-sensing, to engage with motion-sensing in research or disproportionally benefits researchers with an ex-ante focus on motion-sensing research, that is motion-sensing specialists.

Third, it is unclear how the reduction in cost of motion-sensing technology might alter collaboration as a mechanism of knowledge creation. Scholars have investigated the relationship between specialization and collaboration in the context of cumulative innovation and found that knowledge accumulation leads to an increase in research team size (Jones, 2009; Agrawal et al., 2013). However, these findings do not account for sudden reductions in the cost of access to knowledge and for heterogeneity in the level of specialization. On the one hand, the reduction in cost of access to knowledge might alter the knowledge accumulation pressure on the need for collaborative work. On the other hand, the reduction in cost might enable the realization of collaborative projects too costly to undertake before the drop in cost. Furthermore, the heterogeneity in the level of specialization and in the propensity to respond to opportunities opened by the reduction in cost might differentially affect the collaborative behavior of researchers. For example, generalists have a lower cost of coordinating collaboration when compared to specialists. This is important because the cost of coordination is directly reflected in the cost of collaboration (Bikard et al., 2013), and in turn the cost of collaboration influences the size of collaborative teams.

To shed light on these potential tradeoffs I have developed a simple formal model that explicitly considers the impact of the reduction in cost of a motion-sensing research technology on researchers' choices of authorship (single or collaborative) in executing on opportunities for knowledge creation. Researchers' choices with regards to their collaborators, both in terms of type and number, inform on the type of knowledge created following the reduction in cost. I use the model not only to inform my empirical approach, but also to sharpen the inferences that might be drawn from my empirical 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 cost of research technology on knowledge production, particularly with respect to the behavior of generalists and specialists.

2.3 Formal Model

Consider a set of researchers $i(c, C)$ where c is a cost of engagement with motion-sensing in research and C is a cost of collaboration. Opportunities for knowledge creation involving motion-sensing can arrive to any researcher i.[2] This applies to both the period before and after the reduction in cost of motion-sensing research technology. The approach acknowledges not only the fact that opportunities can be born in any situation but also that Kinect has a wide reach outside academia, hence ideas might be born while observing Kinect in settings other than academia.

Researcher i has the option to work alone or collaborate in executing on the opportunity. If researcher i chooses to collaborate, the team will incur a collaboration cost C which varies with the type of the collaborator. If the collaboration occurs only between specialists, the cost will be higher than in situations in which the collaboration includes a generalist. 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.[3]

Researcher i also pays c, a cost of engagement with motion-sensing that varies with the researcher's ex-ante exposure to motion-sensing knowledge. Motion-sensing specialists incur a cost c_{MS}, generalists incur c_{GEN}, and non-motion-sensing specialists incur c_{OTH}. I assume that:

$$c_{MS} < c_{GEN} << c_{OTH}$$

In other words, it is easiest for motion-sensing specialists to engage with motion-sensing in research, while it is most costly for non-motion-sensing specialists to do so. These costs are denoted by $c_{MS}(0)$, $c_{OTH}(0)$, and $c_{GEN}(0)$ for the period before the reduction in cost of motion-sensing technology and by $c_{MS}(1)$, $c_{OTH}(1)$, and $c_{GEN}(1)$ for the period after.

Figure 1 displays researcher's i options and payoffs. I review changes in optimal research behavior and how these are reflected in the composition and level of collaboration for the

[2] I consider the value of an opportunity to be V, distributed with $cdf\, F(V)$. The variation in researchers' choice of executing on the opportunity is given by the cost incurred during execution.

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

period before and after the reduction in cost of motion-sensing research technology.

First, I consider the period before the reduction in cost of motion-sensing technology.

1. Consider the opportunity comes to a motion-sensing specialist. If the researcher pursues the opportunity alone, then he will pay $c_{MS}(0)$. If the researcher collaborates with a non-motion-sensing specialist, the cost will be $(c_{MS}(0) + C)$, and if he collaborates with a generalist, the cost will be $c_{MS}(0)$. It follows that the motion-sensing specialist is indifferent between single-authorship and collaborating with a generalist.

2. Consider the opportunity comes to a non-motion-sensing specialist. If the researcher pursues the opportunity alone, then he will pay $c_{OTH}(0)$. If the researcher collaborates with a motion-sensing specialist, the cost will be $(c_{MS}(0) + C)$, and if he collaborates with a generalist, the cost will be $c_{GEN}(0)$. It follows that it is optimal for the non-motion-sensing specialist to collaborate with a motion-sensing specialist if:

$$c_{GEN}(0) - c_{MS}(0) > C,$$

and collaborate with a generalist otherwise.

3. Consider the opportunity comes to a generalist. If the researcher pursues the opportunity alone, then he will pay $c_{GEN}(0)$. If the researcher collaborates with a non-motion-sensing specialist, the cost will be $c_{GEN}(0)$, and if he collaborates with a motion-sensing specialist, the cost will be $c_{MS}(0)$. It follows that it is optimal for the generalist to collaborate with a motion-sensing specialist.

Next, I consider the period after the cost reduction and analyze how changes in costs, as reflected in changes in payoffs, influence the composition and level of collaboration of researchers. The reduction in cost of motion-sensing technology affects the cost of engagement with motion-sensing in research, namely c_{MS}, c_{GEN}, and c_{OTH}. However, it is unclear how this change might affect the distance between these costs, and in particular the distance between c_{MS} and c_{GEN}, since by assumption c_{OTH} is very high. On the one hand the reduction in cost of motion-sensing technology might level the playing field by making it easier for researchers to engage with motion-sensing in research. In other words, the costs might change such that:

$$c_{GEN}(1) - c_{MS}(1) < c_{GEN}(0) - c_{MS}(0)$$

and $(c_{GEN}(1) - c_{MS}(1))$ small. On the other hand, the reduction in cost might disproportionally benefit those researchers focused on motion-sensing ex-ante, namely motion-sensing specialists. In other words, the costs might changes such that:

$$c_{GEN}(1) - c_{MS}(1) > c_{GEN}(0) - c_{MS}(0).$$

This leads to the following set of competing propositions regarding changes in the composition of collaboration (1a, 1b) and changes in the level of collaboration (2a, 2b).

Proposition 1a: If after the reduction in cost of motion-sensing research technology $c_{GEN}(1) - c_{MS}(1) > c_{GEN}(0) - c_{MS}(0)$ and $(c_{GEN}(1) - c_{MS}(1))$ small, then the likelihood of collaboration between non-motion-sensing specialists and generalists increases, while the likelihood of collaboration between non-motion-sensing specialists and motion-sensing specialists as well as generalists and motion-sensing specialists decreases. (Proof in Online Appendix A.)

Proposition 1b: If after the reduction in cost of motion-sensing research technology $c_{GEN}(1) - c_{MS}(1) > c_{GEN}(0) - c_{MS}(0)$, the likelihood of collaboration between non-motion-sensing and motion-sensing specialists increases, while the likelihood of collaboration between non-motion-sensing specialists and generalists decreases. (Proof in Online Appendix A.)

Proposition 2a: If after the reduction in cost of motion-sensing research technology $c_{GEN}(1) - c_{MS}(1) < c_{GEN}(0) - c_{MS}(0)$ and $(c_{GEN}(1) - c_{MS}(1))$ small, non-motion-sensing specialists increase their collaboration level the most, followed by generalists and motion-sensing specialists. (Proof in Online Appendix A.)

Proposition 2b: If after the reduction in cost of motion-sensing research technology $c_{GEN}(1)-c_{MS}(1) > c_{GEN}(0)-c_{MS}(0)$, non-motion-sensing specialists and generalists increase their collaboration level the most, followed by motion-sensing specialists. (Proof in Online Appendix A.)

In summary, the type of researcher that plays an influential role following a reduction in cost of research technology depends on the incidence of cost reduction. Generalists play an influential role when the cost reduction is democratizing. Conversely, motion-sensing specialists play an influential role when the cost reduction increases the returns to specialization. Thus, it is theoretically ambiguous how the role of generalists and specialists might influence the type of knowledge created in response to opportunities for knowledge creation opened by the reduction in cost of research technology. The ambiguity depends on who benefits most from the cost reduction, since this is reflected in researchers' knowledge creation behavior through collaboration. I explore this mechanism empirically in the context of the unexpected and sudden reduction in cost of motion-sensing research technology provided by the launch of Kinect.

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 that resulted in a sudden and unexpected reduction in the cost 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 allows users to interact with video games without the need of a controller but instead through motion-sensing. However, nobody, including Microsoft, anticipated the wide-reaching impact 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 Wii Remote and PlayStation Move, gesture-recognition game controllers developed by Nintendo and Sony, respectively. Kinect was positioned to take the gesture-recognition approach to video gaming one large step further by completely eliminating the need for a controller and instead using motion-sensing technology.

The Kinect sensor is comprised of an RGB camera, depth sensor, and multi-array microphones. It provides full-body 3D motion capture as well as facial, gesture, and voice recognition. The sensor is superior to many other 3D cameras in the accuracy of capturing movement and the recognition capabilities of multiple simultaneous subjects.

Microsoft announced Project Natal, the development endeavor that was to create Kinect, in June 2009. Up until November 2010, when Kinect was released, Microsoft made sure to instill 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 didn't include a plan or action for promoting Kinect as a technology of interest outside its intended gaming purpose.

The starting point of the unexpected Kinect Effect in academic research can be traced back to the bounty placed by AdaFruit Industries on the very day of Kinect's launch. 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 possible access to data collected by Kinect through its motion sensors. In other words, the driver would open the pipeline through which Microsoft had motion-sensing data flowing only between Kinect and the Xbox 360 video games. This would allow scientists and enthusiasts to connect the pipeline to any other project that would benefit from capturing and interpreting motion-sensing data.

Only 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, CNET News, 2010)

AdaFruit did not withdraw the contest. Moreover, within 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 following the release of the open source driver. First, the company's public rhetoric became less negative towards 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. [4] From this point, the gates for creative development opened.

3.3 Kinect in Academia

Kinect appeals to academic research because it provides high-quality motion-sensing technology at a low price. Kinect as a motion-sensing research technology 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 for a price tag in the thousands of dollars. Microsoft priced Kinect at around US$150 at launch and lower thereafter.

Kinect as a motion-sensing research technology has attracted attention from researchers

[4] Johnny Lee in his blog provides further evidence that Microsoft did not intend Kinect to be used outside its gaming purpose. Johnny Lee is a former Microsoft Kinect team member who subsequently moved to Google. "*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.*"

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 that have aided in developing better 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 within 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 the reduction in cost of research technology. Stated differently, the unanticipated Kinect Effect provides an exogenous event that is correlated with a reduction in the cost 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 represents six years of data before the launch of Kinect and two years of data after. The period before Kinect's launch is longer to facilitate a better estimation of pre-trends in academic research in electrical engineering, computer science, and electronics. The period after is not as long; however, I argue it is still informative given the publication norms in electrical engineering, computer science, and electronics. The publication cycle is fairly short, and scholars are usually making their research known early in conference proceedings.

I collect these data from IEEE *Xplore*, the bibliographical database maintained by IEEE (Institute of Electrical and Electronics Engineers). IEEE *Xplore* is described as providing access to "full-text documents from some of the world's most highly cited publications in electrical engineering, computer science, and electronics." 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

First, I identify the set of publications on topics that reference motion-sensing. I require this data in order to estimate the impact of the reduction in cost of motion-sensing research technology on the subsequent rate of scholarly publication. Second, I focus on data that identifies generalists and specialists. I require this data to estimate the propensity of researchers to respond and execute on opportunities opened by the reduction in cost of motion-sensing research technology.

To isolate these data, I make use of two features of the IEEE database: 1) the ability to search the full text of all publications included in the IEEE bibliographical database and 2) the fact that IEEE assigns 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 (2005-2012, inclusive).

4.2.1 Research Topics

I identify research topics 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 topics of interest. Table 1 lists the set of key terms used to identify research topics. For example, to identify the set of publications referencing motion-sensing topics, I search for broad terms as well as more targeted terms referencing motion-sensing technologies. I have carefully selected these terms through conversations with experts and cross-reference them against IEEE's taxonomy, which includes a total of 51 main research areas (Table 2, Column 2). However, for two reasons, I do not restrict mapping the boundaries of research topics to the list of 51 research areas. First, I am interested in a more granular set of research topics. For example, most publications referencing motion-sensing are included under the "Computers and Information Processing" research area from 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 cost of research technology is an influencing factor for the direction of research 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 in my definition of, for example, motion-sensing research topics, I capture those publications that are outside the traditional "Computers and Information Processing" research area but reference motion-sensing.

4.2.2 Generalists and Specialists

I define generalists as scientists 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 scientists' publications before the launch of Kinect. I define specialists as the remainder of scholars in my sample.

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

The IEEE taxonomy includes approximately 9,000 keywords. I identify 7,276 unique keywords in my dataset of publications spanning the period 2005 to 2012, inclusive. Less than 7% of publications have no keywords, so I drop them from my dataset. The remainder have between one and 18 keywords per publication.

I start by collecting all keywords per author per year. Next, I refer to the IEEE's taxonomy in order to identify the main research area for each keyword. I proceed by constructing a list of main research areas per author per year. With this data, I build a measure of diversification of research portfolio areas at the individual level that adjusts for the fact that the probability of diverse keywords increases with the number of publications per author.

First, I count the occurrence of each research area at the author level for publications between 2005 and 2008. I refer to the period before Kinect's launch since the focus is on estimating the propensity of generalists to respond to opportunities such as the ones brought by the launch of Kinect. As such, the relevant individual level characteristics are the ones observed before the arrival of Kinect. Furthermore, I consider 2008 as the cut-off year to allow for a comparison of research outcomes two years before and two years after the launch of Kinect (2009-2012, inclusive), with researcher type defined based on the research behavior prior to this entire period. All results remain robust to constructing the diversification measure using the entire period before Kinect's launch (2005-2010, inclusive).

Next, I convert the count in percentages and calculate the Euclidian length in the multi-dimensional space of 51 research areas.[5] Note that the length, by construction, is less than or equal to 1 and never 0. The length is shortest when the percentages per research area are equally spread or when the level of diversification of research portfolio areas is highest. Thus, for mathematical convenience, I construct the diversification measure to be equal to 1 minus the calculated Euclidian length. The higher the value, the higher the diversity of

[5]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.

research portfolio areas at the individual level i:

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

Scientists from the bottom 1% of my data have a diversification level of up to 0.37. Scientists in the top 1% of my data have a diversification level of 0.77 and above. The median is 0.65, and the mean is 0.63. I define generalists as scientists with a diversification level in the top 5%, equivalent to values above 0.75. I define specialists as scientists with a diversification level below 0.75. All results remain robust to considering alternative definitions of generalists: top 25% (above 0.69) and top 10% (above 0.73).

5 Results

First, I confirm a positive impact of the reduction in cost of motion-sensing technology on the rate of inventive activity. I do so using a difference-in-differences estimation. Second, I explore the organization of knowledge creation after the reduction in cost with a focus on generalists and specialists. I start by comparing the propensity of generalists and specialists to respond to opportunities opened by the cost reduction. I do so using a cross-section probability model. Next, I test for changes in team size and composition of authorship on academic papers referencing motion-sensing keywords before and after the launch of Kinect. I do so in a multistep set of difference-in-differences estimations.

5.1 Evidence of a Disproportionate Increase in Publications Referencing Motion-Sensing

I start by comparing the normalized mean growth rates in the number of publications referencing motion-sensing relative to other research topics that are similar in volume to motion-sensing (calculated as the number of publications per research topic per period of interest) as identified in Table 1, Column 3, before and after the launch of Kinect. I find evidence of a disproportionate increase in the mean growth rate of publications referencing motion-sensing after the launch, as represented in Figure 2.

However, there may be concerns that systematic differences between publications that do and do not reference motion-sensing are driving the observed difference in normalized mean growth rates. For instance, the publication rate of motion-sensing research topics might have been on the rise relative to other research topics even before the arrival of Kinect. Thus, I turn to a difference-in-differences estimation to distinguish between the rise in the number of publications directly attributable to the reduction in cost of motion-sensing technology from the underlying differences between the various research topics as well as the underlying changes in publication rate in electrical engineering, computer science, and electronics over time.

I compare the number of publications referencing motion-sensing keywords ("treated") with the number of publications referencing other research topics ("controls") before and after the launch of Kinect ("the treatment"). In other words, I estimate the difference in the number of publications between treated and control research topics in two periods, before and after the treatment. Formally, I estimate:

$$LogPubCount_{jt} =$$
$$\beta(MotionSensingPub_j \times AfterKinectLaunch_t) + ResearchTopic_j + \gamma_t + \epsilon_{jt}.$$

$LogPubCount_{jt}$ is the 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. $AfterKinectLaunch_t$ is an indicator variable equal to 1 if papers in research topic j are listed as published in 2011 or 2012, and 0 otherwise. This applies to publications from both the treated and control research topics. 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 $AfterKinectLaunch_t$. The interaction term equals 1 for counts of papers referencing motion-sensing keywords published after the reduction in cost of motion-sensing research technology triggered by the launch of Kinect, and 0 for all others. 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; this increase is triggered by the reduction in cost of motion-sensing research technology facilitated by the launch of Kinect.

I present results of this estimation in Table 3. In Column 1, I consider control research topics that are similar in volume with motion-sensing before the launch of Kinect. In Column 2, I include all research topics listed in Table 1 as controls. I identify treated and control publications through a search on terms as described in Section 3.2.1. Column 3 includes all other publications as controls. Since I do not classify the full set of publications under research topics but rather under the IEEE taxonomy research areas, I include research areas fixed effects in Column 3. 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 referencing other research topic keywords is greater after rather than before the reduction in cost of motion-sensing technology triggered by the launch of Kinect.

To ensure that underlying time trends are not driving this result, I also examine the timing of this effect by estimating and plotting the interaction coefficients between year dummies and $MotionSensingPub_j$, which is equal to 1 if research topic j is motion-sensing, and 0 otherwise:

$$LogPubCount_{jt} = \sum_{s=0}^{t} \beta_s(\gamma_s \times MotionSensingPub_j) + ResearchTopic_j + \gamma_t + \epsilon_{jt}.$$

I report results using research topics that are close in volume before the launch of Kinect as controls in Figure 3.[6] Each point represents the coefficient value of the covariate ($Year \times MotionSensingPub$), which describes the relative difference in yearly publication counts between papers referencing motion-sensing keywords and papers referencing other research topic keywords. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 2005. 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 end of 2010, the time of Kinect's launch. Thereafter, the difference increases, as evidenced by the higher coefficients.

5.2 Generalists, Specialists, and the Propensity to Respond to Reductions in the Cost of Research Technology

Having established that the reduction in cost of motion-sensing research technology triggered by the launch of Kinect has a positive impact on the rate of inventive activity, I turn to investigating the organization of knowledge creation following the reduction in cost. I start by identifying the type of researcher most likely to respond to opportunities opened by the reduction in cost of motion-sensing technology. Since Kinect is the technology to lower the cost of engagement with motion-sensing and consequently triggers the set of opportunities for research referencing motion-sensing keywords, I interpret the existence of publications referencing the word "Kinect" in a publication portfolio as indicative of responding to opportunities opened by the cost reduction.

I identify 1,271 researchers who publish at least one paper referencing Kinect during 2011 or 2012. These researchers are heterogeneous with regards to their main domain of expertise before the launch of Kinect. I identify an individual' main domain of expertise based on the set of keywords assigned by IEEE to each scientist's set of publications. It represents the

[6] The results remain robust to the two other control groups.

research area (out of 51) with the highest count of keywords assigned to said researcher's publication portfolio between 2005 and 2008.[7] Table 2 (Column 2) lists the number of researchers per domain of expertise who publish at least one Kinect paper during 2011-2012. About 53% of these researchers do not publish papers referencing motion-sensing keywords before the launch of Kinect (Table 2, Columns 3 and 4). Next I examine engagement with Kinect in research using publication output that references the word "Kinect". The mean number of Kinect publications among the 2,950 generalists in my sample is 0.0712 (std. dev. 0.308). The 89,428 specialists in my sample have a mean number of Kinect publications equal to 0.0159 (std. dev. 0.173). This suggests that generalists have a higher propensity than specialists to publishing a paper citing the word "Kinect". I formally estimate this using a logit model. I represent person i's engagement with Kinect as:

$$PubReferencingKinect_i = I(\alpha Generalist_i + \theta X_i + \epsilon_i > 0).$$

The main coefficient of interest captures the propensity of generalists, identified as such based on their publication behavior before the launch of Kinect, to reference Kinect in their academic publications after its launch. The dependent variable is an indicator variable equal to 1 for author i who publishes at least one paper referencing Kinect during either 2011 or 2012, and 0 otherwise. $Generalist_i$ is a dummy equal to 1 if the level of diversification of research portfolio areas of individual i is in the top 5%, and 0 otherwise. The vector X_i is a vector of controls.

I interpret a positive estimated value of the coefficient of interest α as implying that a higher level of diversification of research portfolio areas in the period before Kinect predicts a higher propensity to respond to opportunities opened by the reduction in cost of motion-sensing research technology. I interpret these estimation results under the assumption that the Kinect Effect is exogenous to the observed individual levels of diversification of research portfolio areas in the before period. Stated differently, Kinect provides a plausible natural experiment that helps address concerns of selection into treatment.

I present the cross-section probability model estimation results in Table 4 and report results of a baseline model without controls in Columns 1 and 2. Column 1 reports the odds ratio of the logit estimation, and Column 2 reports the estimation coefficient. The coefficient of the term $Generalist_i$ is positive and statistically significant, indicating a higher propensity for generalists than specialists to publish a paper referencing the word "Kinect" after the launch.

Since one might worry that the propensity to publish a paper referencing the new Kinect technology is correlated with a researcher's prior inventive activity, I add to the baseline

[7] The results remain robust to considering the full period before Kinect's launch, 2005 to 2010, inclusive.

model controls for the stock of publications and main domain of expertise in the two-year period prior to Kinect's launch. I calculate the stock as a count of publications in the period 2009 to 2010. It is important to note that by construction the diversification measure accounts for researchers' publication stock in the period 2005 to 2008.

Furthermore, I control for an additional source of heterogeneity correlated with the propensity to publish referencing the word "Kinect," namely the level of prior direct engagement with motion-sensing research topics. I add to the main estimating equation two terms that capture the variation from being a researcher who has published both at least one paper referencing motion-sensing keywords prior to Kinect and at least one paper referencing the word "Kinect" during 2011-2012. I do so to ensure that the salient role of generalists in recognizing opportunities is not entirely explained by direct prior involvement with motion-sensing. I identify 1,157 generalists with direct prior involvement with motion-sensing, out of total of 2,950 generalists. Other scientists with direct prior involvement with motion-sensing include 7,228 specialists out of a total of 89,428 specialists. Formally, I estimate:

$$PubReferencingKinect_{i1} = \alpha_0 + \alpha_1 Generalist_{i0} + \alpha_2(Generalist_{i0} \times MotionSensingScientist_{i0}) + \alpha_3 MotionSensingScientist_{i0} + X_i + \epsilon_i.$$

$MotionSensingScientist_{i0}$ is a dummy equal to 1 if researcher i has published at least one paper referencing motion-sensing keywords before the launch of Kinect, and 0 otherwise. Thus, the coefficient α_3 captures the propensity of researchers with direct prior involvement with motion-sensing before the launch of Kinect to publish at least one paper citing the word "Kinect" after the launch. The interaction term $Generalist_{i0} \times MotionSensingScientist_{i0}$ captures the variation from being a generalist as well as a researcher with direct prior motion-sensing involvement before Kinect.

I include estimation results in Table 4 (Columns 3 and 4). Perhaps not surprisingly, direct prior involvement with motion-sensing topics before the launch of Kinect is associated with an increased likelihood to publish a paper referencing Kinect after the launch. Interestingly, however, the result on generalists persists. Furthermore, direct prior involvement with motion-sensing has less of an effect on generalists than on specialists in the propensity to publish a paper citing the word "Kinect" after the launch. I interpret this as suggesting that generalists are three times more likely than specialists to respond to opportunities opened by the reduction in cost of motion-sensing research technology.

Next, I repeat the estimation, taking into account the quality of publications referencing the word "Kinect." Specifically, I modify the dependent variable $PubReferencingKinect_{i1}$ to be equal to 1 for researchers publishing at least one paper referencing the word "Kinect" in top journals or conference proceedings in electrical engineering, computer science, and electronics. I consider the top 10 journals and conferences in computer science and electrical and electronics engineering based on cumulative citation counts as listed in Microsoft Academic Search. The mean number of top Kinect publications for generalists is 0.0139 (std. dev. 0.141) and for specialists is 0.0043 (std. dev. 0.087). I present estimation results in Table 4 (Column 5 and Column 6). The coefficient of the term $Generalist_i$ remains positive and statistically significant. I interpret this as evidence that generalists have a higher propensity than specialists to publish quality research using Kinect after the launch.

All results remain robust to alternative definitions of generalist that consider diversification of research portfolio areas in the top 10% and in the top 25%. The coefficient of the term $Generalist_i$ remains positive and statistically significant in estimations considering all Kinect publications (Table 5, Column 1 to Column 4) as well as in estimations focused on Kinect publications from top journals and conference proceedings (Table 5, Column 5 to Column 8).

Taken together, the results suggest that generalists play an important role in responding to opportunities opened by the reduction in cost of motion-sensing technology. Stated differently, generalists play a significant role in the organization of knowledge creation through their propensity to respond to opportunities opened by a reduction in cost of knowledge access.

In what follows, I investigate how this role influences the type of knowledge created following the reduction in cost. This speaks directly to the organization of knowledge creation as a factor influencing the direction of inventive activity.

5.3 Collaboration

Researchers' collaboration and level of diversification of research portfolio areas are codetermined. Indeed, generalists collaborate more than specialists and, related, publish a higher number of papers than specialists (Table 6).[8] 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 6, Columns 1 and 3). Related, generalists publish more than specialists (Table 6, Column 5) and the difference in magnitude can be attributed to the higher level of collaboration: When considering a number of publications weighted by the number of co-authors per publication the difference in count is reduced while the difference in percentages persists (Table 6, Column 7).

Thus, while it is unclear if diversity of individual research portfolio areas is the result of increased collaboration or vice versa, collaboration emerges as an influential factor for generalists' role in spanning knowledge areas.

[8]The mean number of publications after the launch of Kinect is influenced by the lag in adding 2012 publications to the IEEE bibliographical database.

In what follows, I test how the level and composition of collaboration changes following the reduction in cost of access to knowledge. First, I test for changes in team size on papers referencing motion-sensing keywords after the launch of Kinect. Second, I explore the formal model predictions described in Section 2.3. In particular, I investigate changes in the composition of teams publishing papers referencing motion-sensing keywords. I do so in several steps. I start by testing for changes in the collaboration level of generalists, motion-sensing specialists, and non-motion-sensing specialists, relative to one another. I do not focus directly on papers referencing motion-sensing since by definition non-motion-sensing specialists are not involved in motion-sensing projects before Kinect. Thus, this approach avoids meaningless comparisons with zero in the period before Kinect's launch while at the same time being informative about changes in collaboration separately for generalists, motion-sensing specialists, and non-motion-sensing specialists. Last, I investigate how the composition of teams varies with changes in team size on projects referencing motion-sensing by explicitly 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.

5.3.1 Changes in Collaboration Levels of Generalists and Specialists Following the Reduction in Cost of Motion-Sensing Research Technology

I start by comparing the average research team size on papers referencing motion-sensing keywords with the average team size on other papers before and after the launch of Kinect (Figure 4). Before the launch of Kinect, the average team size on papers referencing motion-sensing keywords is 3.583 (std. dev. 1.88) and the average team size on other papers is 3.395 (std. dev. 1.97). After the launch of Kinect, the average team size on papers referencing motion-sensing increases to 3.764 (std. dev. 1.86) while the average team size on other papers rises to 3.503 (std. dev. 1.97). To ensure that systematic differences between papers referencing motion-sensing keywords and other papers is not driving the disproportionate increase in team size on papers referencing motion-sensing keywords, I turn to a difference-in-differences estimation. This approach distinguishes between the increase in team size on papers referencing motion-sensing keywords directly attributable to the reduction in cost of motion-sensing technology from the underlying differences both between collaboration trends on papers referencing other keywords and in team size in electrical engineering, computer science, and electronics over time. Formally, I test:

$$TeamSize_{jt} = \beta(MotionSensingPub_j \times AfterKinectLaunch_t) + MotionSensingPub_j + ResearchArea_j + \gamma_t + \epsilon_{jt}.$$

$TeamSize_{jt}$ is a measure of team size for each academic paper j published in year t. $MotionSensingPub_j$ is an indicator variable equal to 1 if publication j is motion-sensing, and 0 otherwise. $AfterKinectLaunch_t$ is an indicator variable equal to 1 if paper j is published in 2011 or 2012, and 0 otherwise. This applies to publications from both treated and control groups. $PubResearchArea_j$ represents the main research area (out of 51) where paper j contributes. 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 between $MotionSensingPub_j$ and $AfterKinectLaunch_t$. Table 7 shows evidence of a disproportionate increase in team size on papers referencing motion-sensing keywords relative to other publications in electrical engineering, computer science, and electronics research areas after the launch of Kinect.

To ensure that underlying time trends are not driving this result, I also examine the timing of this effect by estimating and plotting the interaction coefficients between year dummies and $MotionSensingPub_j$, which is equal to 1 if publication j is referencing motion-sensing keywords and 0 otherwise:

$$TeamSize_{jt} =$$
$$\sum_{s=0}^{t} \beta_s(\gamma_s \times MotionSensingPub_j) + MotionSensingPub_j + ResearchArea_j + \gamma_t + \epsilon_{jt}.$$

I display results in Figure 5. Each point represents the coefficient value of the covariate ($Year \times MotionSensingPub$), which describes the relative difference in yearly team size between papers referencing motion-sensing keywords and other papers. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 2005. The graph shows that the difference in team size between papers that reference motion-sensing keywords and those that do not is small and fairly stable until 2010, the time of Kinect's launch. Thereafter, the difference increases, as evidenced by the higher coefficients.

5.3.2 Changes in Collaboration Composition between Generalists and Specialists Following the Reduction in Cost of Motion-Sensing Research Technology

Next, I turn to investigating changes in the composition of teams working on projects referencing motion-sensing keywords by first testing for changes in collaboration levels of generalists, motion-sensing specialists, and non-motion-sensing specialists, followed by changes in team composition. For this set of estimations, I focus on publication data between 2009 and 2012, since I use the publication data between 2005 and 2008 to define a researchers type as either generalist or specialist.

I initially test for changes in the collaboration levels of specialists and generalists after the launch of Kinect. I focus on two measures of collaboration: 1) the average number of co-authors per period (extensive collaboration level) and 2) the average number of unique co-authors per period (intensive collaboration level). Table 6 (Columns 1 to 4) compares mean values of collaboration levels for generalists and specialists before and after the launch of Kinect. While both generalists and specialists exhibit an increase in collaboration levels, specialists disproportionately increase their collaboration levels after the launch of Kinect relative to generalists; this difference is driven by non-motion-sensing specialists increase in collaboration. I test if indeed non-motion-sensing specialists are driving this disproportionate increase through a difference-in-differences estimation:

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

$LogCollaborationLevel_{it}$ is equal to the logged value of the level of collaboration of author i in year t (plus 1, to account for years with no publications). The estimation results included in Table 8 attest to a disproportionate increase in specialists' collaboration levels relative to generalists' after the launch of Kinect (Columns 1 and 3), a result driven by changes in the collaboration levels of non-motion-sensing specialists (Columns 2 and 4).

Table 9 takes this estimation result one important step further by focusing on changes in collaboration levels between specialists and generalists. Two noteworthy insights emerge from this estimation. First, the collaboration between generalists and specialists increases relative to collaboration between generalists and between specialists after the launch of Kinect (Columns 1 and 3). Second, this increase is driven by an increase in collaboration between generalists and non-motion-sensing specialists relative to all other collaborating scientists (Columns 2 and 4).

Next, I explicitly test how these changes in collaboration levels are reflected in changes to team composition on publications referencing motion-sensing keywords after the launch of Kinect. In a difference-in-differences estimation at the publication level, 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 co-authorship 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:

$$TeamCompositionDummy_{jt} =$$
$$\beta(MotionSensingPub_j \times AfterKinectLaunch_t) + MotionSensingPub_j + \gamma_t + \epsilon_{jt}.$$

$TeamCompositionDummy_{jt}$ is a dummy variable equal to 1 if the co-authorship team on publication j includes at least one scientist of the mentioned type, 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. The main result of interest is the estimated coefficient of the interaction term ($MotionSensingPub \times AfterKinectLaunch$).

Table 10 indicates an increase in the occurrence of non-motion-sensing specialists on co-authored 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). Taken together, the results suggest a relative increase in the occurrence of collaborating generalists and non-motion-sensing specialists on publications referencing motion-sensing keywords after the launch of Kinect, relative to the occurrence of other collaborating scientists.

Next, I specifically test for an increase in collaborating generalists and non-motion-sensing specialists on publications referencing motion-sensing keywords relative to other collaborating scientists. I present results in Table 11. Column 1 shows a positive and statistically significant increase in the frequency of teams comprised of generalists and non-motion-sensing specialists on publications referencing motion-sensing keywords after the launch of Kinect relative to other collaborating scientists. Moreover, there is a disproportionate decrease in the frequency of teams comprised of generalists and motion-sensing specialists (Column 2) and non-motion-sensing specialists and motion-sensing specialists (Column 3) publishing papers referencing motion-sensing keywords after the launch of Kinect, relative to all other publications in electrical engineering, computer science, and electronics.

Taken together, these results suggest, consistent with Propositions 1a and 2a above, collaboration as a mechanism through which generalists span knowledge areas and coordinate among specialists, connecting non-motion-sensing specialists to the research opportunities opened by the reduction in cost of motion-sensing technology. More broadly, generalists play a particularly salient role in realizing opportunities for knowledge creation opened by the reduction in cost of access to motion-sensing knowledge.

6 Discussion and Conclusion

I examine implications of reductions in the cost of access to knowledge on cumulative innovation by exploiting the launch of Kinect as an exogenous event resulting in a sudden reduction in motion-sensing technology costs. I move beyond results of a positive impact on the rate of inventive activity to shedding some light on the organization of knowledge creation under these conditions as a factor influencing the direction of inventive activity.

First and in line with prior findings, I confirm that costs of access to knowledge have a significant impact on follow-on innovation. I find evidence of up to a 57% disproportionate increase in academic publications referencing motion-sensing relative to other publication areas in computer science, electrical engineering, and electronics following the reduction in cost of motion-sensing research technology. I remain agnostic on whether this increase reflects absolute growth or a shift away from other research topics. Second, I identify generalists as having a higher propensity than specialists to publish papers that reference Kinect. Third, I find evidence of an increase in team size on publications referencing motion-sensing keywords after the launch of Kinect driven by collaborations between generalists and non-motion-sensing specialists. This is consistent with the mechanism emphasized in the formal model in Section 2.3, where the reduction in cost is democratizing and generalists respond to opportunities for knowledge creation by increasing their likelihood of collaborating with non-motion-sensing specialists. Thus, generalists seem to play a central role in responding to research opportunities opened by the reduction in cost of motion-sensing technology as well as in connecting non-motion-sensing specialists to these opportunities.

These findings suggest a significant impact of research technology costs on scientific research through an influence not only on the rate but also on the direction of inventive activity. The role of generalists is suggestive of changes in the organization of inventive activity relative to the division of labor in knowledge creation, as knowledge accumulation leads to specialization in progressively narrower niches (Jones, 2009). These insights also can inform firm-level decisions with regards to the mix of employee skills required to spur creativity, particularly following technological advancements that reduce the cost of access to knowledge. More generally, the findings enrich our understanding of factors affecting knowledge creation and how individual creativity manifests itself given the freedom to access knowledge and experiment.

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 conditions of access to knowledge on the rate and direction of inventive activity, the general limitations of a natural experiment apply. Furthermore, Kinect represents one instance of a reduction in cost of access to knowledge, subject to the idiosyncrasies of electrical engineering, computer science, and electronics research. For example, the optimal balance between generalists and specialists might be contingent on various factors, such as the frequency of technological advancements that result in reductions in the cost of access to knowledge. In research domains where such changes are frequent, the proportion of generalists relative to specialists might be larger than in settings that undergo less frequent occurrences of reductions in the cost of access to knowledge. The hypothesis rests on the assumption that generalists exists because they are at an advantage around the time of cost reduction, while specialists are at an advantage in between such events. Further details and implications are the subject of future research. For example, the geographic distribution of generalists and specialists might influence heterogeneity in regional innovation strength.

Similarly, future research should extend the analysis to consider implications for the direction of inventive activity at the research field level. In particular, it would be informative to investigate to what extent reductions in the cost of access to knowledge impact the direction of inventive activity through an increase in the breadth of research trajectories or the displacement of existing research trajectories. At the individual level, such an analysis would inform the extent to which changes in the cost of access to knowledge influence entry and exit into research domains or scientific careers altogether.

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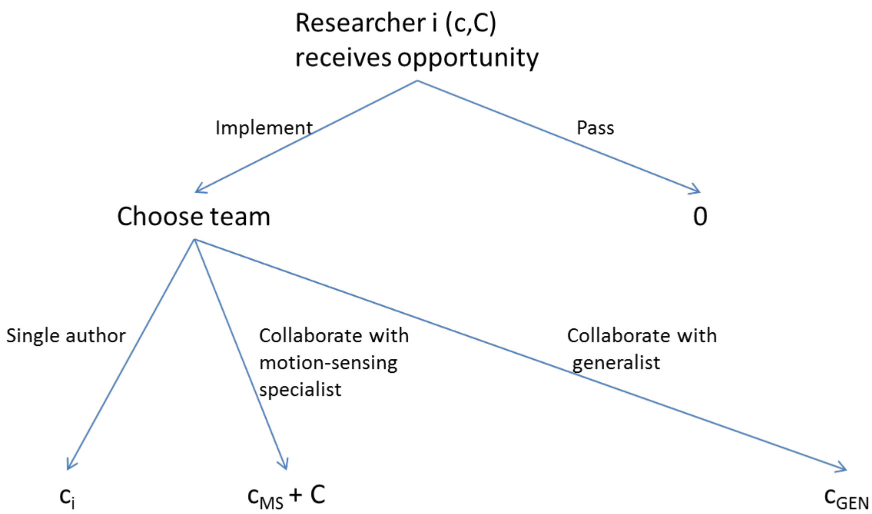
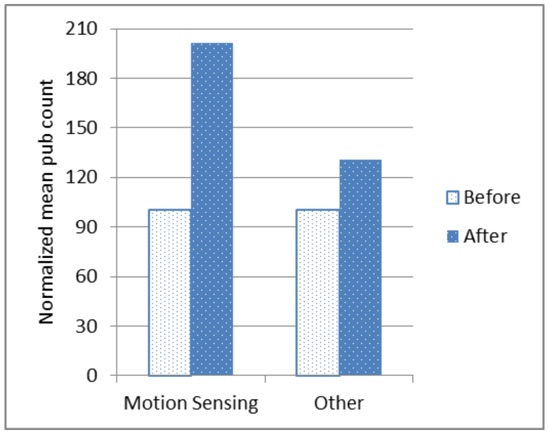
Figure 1: **Decision tree for researcher i**



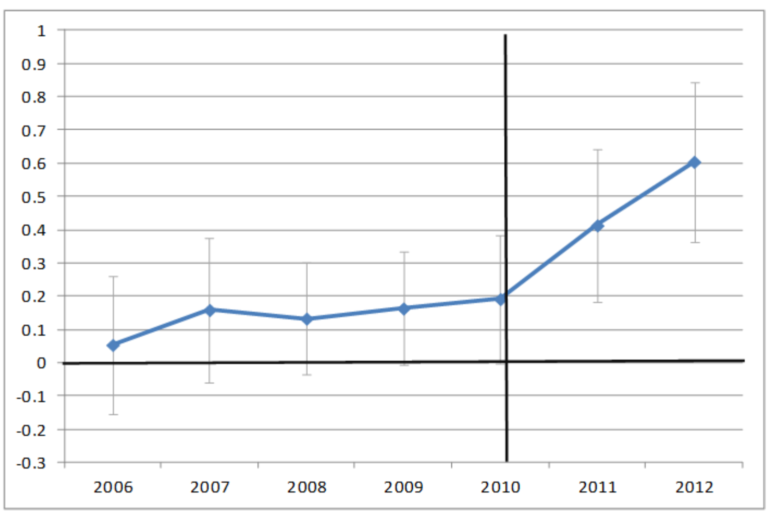
Note: The payoffs display the cost of engagement with motion-sensing under each option. The cost ci represents the individual cost of researcher i to engage with motion-sensing in research and is equal to $c_{MS} for motion-sensing specialists$, c_{OTH} for non-motion-sensing specialists and c_{GEN} for generalists. In the period before the reduction in cost of motion-sensing research technology, the individual costs of engagement with motion-sensing are given by $c_{MS}(0)$, $c_{OTH}(0)$, $c_{GEN}(0)$. In the period after the reduction in cost of motion-sensing research technology, the individual costs of engagement with motion-sensing are given by $c_{MS}(1)$, $c_{OTH}(1)$, $c_{GEN}(1)$.

Figure 2: **Disproportionate increase in normalized mean growth rate of publications referencing motion-sensing relative to publications referencing other research topics after Kinect**



Note: Motion-sensing compared to research topics close in volume to motion-sensing before Kinect's launch. 2005 to 2012 publication data.

Figure 3: **Estimated difference between count of publications referencing motion-sensing keywords and count of other publications per year**



Note: 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 $MotionSensingPub \times Year$ and thus describes the relative difference in publication rates between papers referencing motion-sensing keywords and other papers that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 2005.

Figure 4: **Disproportionate increase in mean team size of publications referencing motion-sensing keywords relative to other publications after the launch of Kinect**

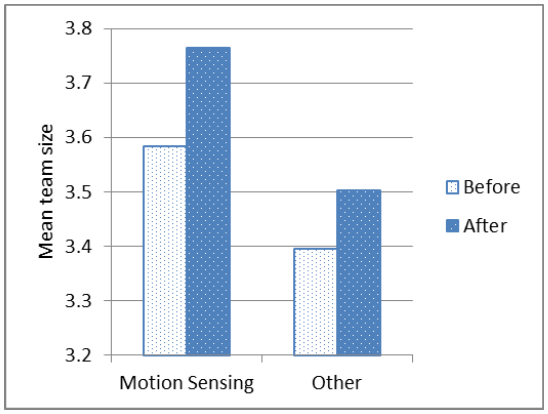
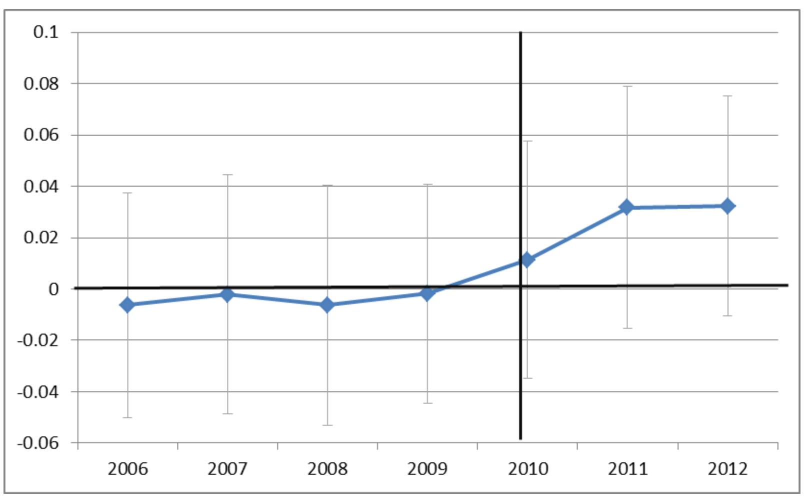


Figure 5: **Estimated difference in team size between publications referencing motion-sensing keywords and other publications per year**



Note: 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 $MotionSensingPub \times Year$ and thus describes the relative difference in team size between papers referencing motion-sensing keywords and other papers in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 2005.

Table 1: **Set of key terms used to identify publications referencing certain research topics**

	Research Topic	**Close in volume to motion-sensing**	**List of key terms**
1	Motion-sensing	N/A	motion sensing, motion tracking, motions tracking, motion recognition, motion sensor, motion capture, 3D tracking, 3-dimentional tracking, 3D imaging, 3-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
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/I IMM
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

	Research Topic	Close in volume to motion-sensing	List of key terms
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
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

	Research Topic	**Close in volume to motion-sensing**	**List of key terms**
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

Table 2: **Research areas and Kinect authors by research area**

	Research Area	**Count of Kinect Authors**	**Count of Kinect Authors with Motion-Sensing Experience**	**Percentage of Kinect Authors with Motion-Sensing Experience**
1	Aerospace and electronic systems	3	0	0%
2	Antennas and propagation	4	1	25%
3	Broadcast technology	1	0	0%
4	Circuits and systems	8	0	0%
5	Communications technology	90	33	37%
6	Components, packaging, and manufacturing technology	0	0	0%
7	Computational and artificial intelligence	7	3	43%
8	Computers and information processing	431	201	47%
9	Consumer electronics	0	0	0%
10	Control systems	13	3	23%
11	Dielectrics and electrical insulation	0	0	0%
12	Education	1	0	0%
13	Electromagnetic compatibility and interference	0	0	0%
14	Electron devices	0	0	0%
15	Electronic design automation and methodology	29	15	52%
16	Engineering - general	0	0	0%
17	Engineering in medicine and biology	6	3	50%
18	Engineering management	8	1	13%
19	Geoscience and remote sensing	1	0	0%
20	IEEE organizational topics	0	0	0%
21	Imaging	6	6	100%
22	Industrial electronics	0	0	0%
23	Industry applications	23	5	22%
24	Information theory	1	1	100%
25	Instrumentation and measurement	110	56	51%
26	Intelligent transportation systems	0	0	0%
27	Lasers and electropics	22	6	27%
28	Magnetics	3	1	33%
29	Materials, elements, and compounds	40	14	35%
30	Mathematics	120	58	48%
31	Microwave theory and techniques	0	0	0%
32	Nanotechnology	0	0	0%
33	Nuclear and plasma sciences	6	2	33%
34	Oceanic engineering and marine technology	0	0	0%
35	Organizational communication	13	3	23%
36	Power electronics	0	0	0%
37	Power engineering and energy	18	6	33%

	Research Area	Count of Kinect Authors	Count of Kinect Authors with Motion-Sensing Experience	Percentage of Kinect Authors with Motion-Sensing Experience
38	Product safety engineering	0	0	0%
39	Reliability	0	0	0%
40	Resonance	0	0	0%
41	Robotics and automation	172	116	67%
42	Science - general	101	53	52%
43	Sensors	12	7	58%
44	Signal processing	17	2	12%
45	Social implications of technology	0	0	0%
46	Solid state circuits	0	0	0%
47	Superconductivity	0	0	0%
48	Systems engineering and theory	0	0	0%
49	Systems, man, and cybernetics	2	2	100%
50	Ultrasonics, ferroelectrics, and frequency control	0	0	0%
51	Vehicular and wireless technologies	3	1	33%
	TOTAL	1,271	599	47%

Table 3: **Scientists 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) Research topics close in volume to motion-sensing before Kinect's launch	(2) All research topics listed in Table 1	(3) All other publications
MotionSensingPub x AfterKinectLaunch	**0.3924***	**0.4732***	**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

Note: The data is a panel of counts of publications between 2005 and 2012. The unit of analysis is year - research topic or year-research areas. All models are OLS with robust standard errors, clustered by research topic or research area. *significant at 10%, **significant at 5%, ***significant at 1%

Table 4: **Generalists have a higher propensity than specialists to engage with Kinect**

	Dependent variable: Indicator variable equal to 1 for authors who publish at least one Kinect paper during the two years after Kinect's launch					
	(1) All Kinect pubs (Odds Ratio)	(1) All Kinect pubs (Coefficient)	(2) All Kinect pubs (Odds Ratio)	(2) All Kinect pubs (Coefficient)	(3) Top Kinect pubs (Odds Ratio)	(3) Top Kinect pubs (Coefficient)
Generalist	**5.2776*** **	**1.6635*** **	**3.1292*** **	**1.1691*** **	**2.4556*** **	**0.9275*** **
	(0.4390)	(0.0832)	(0.4309)	(0.1339)	(0.9021)	(0.3628)
Stock			1.0103***	0.0102***	1.0044***	0.0050***
			(0.0028)	(0.0028)	(0.0011)	(0.0012)
MotionSensing Author			5.6432***	1.7305***	6.2216***	1.8779***
			(0.6101)	(0.1081)	(0.7660)	(0.1189)
Generalist x MotionSensingAuthor			0.3979***	-0.9216***	0.3955***	-0.9947***
			(0.0431)	(0.1084)	(0.1251)	(0.3130)
Main domain of expertise area fixed effects			Yes	Yes	Yes	Yes
LL	-6,493.512	-6,493.512	-5,612.410	-5,612.410	-1,921.778	-1,921.778
Observations	92,378	92,378	92,378	92,378	92,378	92,378

Note: The data is a cross-section at the author level based on the 2009-2012 publication period. I define generalist and specialist types using publication data between 2005 and 2008. The unit of analysis is author. All models are logit with robust standard errors, clustered by main domain of expertise. *significant at 10%, **significant at 5%, ***significant at 1%

Table 5: **The result on generalists remains robust to alternative definitions of generalist**

	Dependent variable: Indicator variable equal to 1 for authors who publish at least one Kinect paper during the two years after Kinect's launch							
	(1) All Kinect pubs; Generalist as top 10% (Odds Ratio)	(1) All Kinect pubs; Generalist as top 10% (Coefficient)	(2) All Kinect pubs; Generalist as top 25% (Odds Ratio)	(2) All Kinect pubs; Generalist as top 25% (Coefficient)	(3) Top Kinect pubs; Generalist as top 10% (Odds Ratio)	(3) Top Kinect pubs; Generalist as top 10% (Coefficient)	(4) Top Kinect pubs; Generalist as top 25% (Odds Ratio)	(4) Top Kinect pubs; Generalist as top 25% (Coefficient)
Generalist	**2.5247***** (0.3727)	**0.9261***** (0.1476)	**2.5186***** (0.3150)	**0.9237***** (0.1251)	**2.3091***** (0.3938)	**0.8369***** (0.1706)	**2.8583***** (0.4149)	**1.0502***** (0.1452)
Stock	1.0101*** (0.0026)	0.0101*** (0.0026)	1.0102*** (0.0031)	0.0102*** (0.0030)	1.0055** (0.0011)	0.0054** (0.0010)	1.0035** (0.0014)	0.0035** (0.0014)
MotionSensingAuthor	5.8595*** (0.6381)	1.7681*** (0.1089)	6.1429*** (0.8807)	1.8153*** (0.1434)	7.6270*** (1.0945)	2.0317*** (0.1435)	7.8713*** (1.4753)	2.0632*** (0.1874)
Generalist x MotionSensing Author	0.5161*** (0.0447)	-0.6614*** (0.0866)	0.5661*** (0.0638)	-0.5690*** (0.1128)	0.3384*** (0.0507)	-1.0836*** (0.1499)	0.4555*** (0.1096)	-0.7864*** (0.2406)
Main domain of expertise area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
LL	-5,595.042	-5,595.042	-5,569.394	-5,569.394	-1,915.897	-1,915.897	-1,903.037	-1,903.037
Observations	92,378	92,378	92,378	92,378	92,378	92,378		

Note: The data is a cross-section at the author level based on the 2009-2012 publication period. I define generalist and specialist types using publication data between 2005 and 2008. The unit of analysis is author. All models are logit with robust standard errors, clustered by main domain of expertise. *significant at 10%, **significant at 5%, ***significant at 1%

Table 6: **Differences in collaboration and publication rates between generalists and specialists**

Mean Value of:	Collaboration (intensive)		Collaboration (extensive)		Publications		Publications (co-author fraction)	
	Before	After	Before	After	Before	After	Before	After
Generalist	3.302	3.415	3.772	3.810	8.957	8.268	2.004	1.775
with motion-sensing	3.413	3.552	4.012	4.064	15.605	14.607	3.360	3.050
without motion-sensing	3.259	3.361	3.709	3.767	6.630	5.994	1.530	1.318
Specialist	2.237	2.715	2.572	3.014	2.713	2.568	0.687	0.632
with motion-sensing	2.570	2.736	3.024	3.100	5.189	4.420	1.299	1.075
without motion-sensing	2.209	2.713	2.533	3.006	2.499	2.407	0.635	0.594

Table 7: **The team size on projects referencing motion-sensing increases disproportionately more relative to the team size on other publications after Kinect**

Dependent variable: number of authors per publication		
	(1) log (count of authors)	(2) count of authors
MotionSensingPub x AfterKinectLaunch	**0.0319*** **	**0.0969*** **
	(0.0084)	(0.0328)
MotionSensingPub	0.0579***	0.1512***
	(0.0052)	(0.0200)
Year fixed effects	Yes	Yes
Research area fixed effects	Yes	Yes
R-squared	0.059	0.069
Observations	1,246,235	1,246,235

Note: The data is a panel of publications between 2005 and 2012. The unit of analysis is the publication. All models are OLS with robust standard errors, clustered by research areas. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 8: **Non-motion-sensing specialists collaborate disproportionately more than generalists and motion-sensing specialists after Kinect's launch**

Dependent variable: log of count of collaboration per author per year (plus one)				
	(1) intensive		(2) extensive	
Specialist x AfterKinectLaunch	**0.1379***** (0.0185)		**0.1449***** (0.0192)	
MotionSensingSpecialist x AfterKinectLaunch		0.0138 (0.0118)		0.0065 (0.0124)
NonMotionSensingSpecialist x AfterKinectLaunch		**0.1487***** (0.0184)		**0.1569***** (0.0191)
Year fixed effects	Yes	Yes	Yes	Yes
Author fixed effects	Yes	Yes	Yes	Yes
R-squared	0.012	0.010	0.011	0.009
Observations	394,612	394,612	394,612	394,612

Note: The data 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 unit of analysis is author-year. All models are OLS with robust standard errors, clustered by main domain of expertise. *significant at 10%, **significant at 5%, ***significant at 1%

Table 9: **Non-motion-sensing specialists collaborate disproportionately more than other researchers with generalists after Kinect**

Dependent variable: log of count of collaboration per author per year (plus one)				
	(1) intensive		(2) extensive	
Specialist x AfterKinectLaunch	**0.0300***** (0.0082)		**0.0318***** (0.0089)	
MotionSensingSpecialist x AfterKinectLaunch		-0.0056 (0.0061)		-0.0063 (0.0064)
NonMotionSensingSpecialist x AfterKinectLaunch		**0.0330***** (0.0085)		**0.0350***** (0.0091)
Year fixed effects	Yes	Yes	Yes	Yes
Author fixed effects	Yes	Yes	Yes	Yes
R-squared	0.036	0.034	0.037	0.035
Observations	394,612	394,612	394,612	394,612

Note: The data 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 unit of analysis is author-year. All models are OLS with robust standard errors, clustered by main domain of expertise. *significant at 10%, **significant at 5%, ***significant at 1%.

Table 10: **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 x 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

Note: The data 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 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 10%, **significant at 5%, ***significant at 1%

Table 11: **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 specialist			
	(1) Generalist and non-motion-sensing specialist	(2) Generalist and motion-sensing specialist	(3) Motion-sensing and non-motion-sensing specialists
MotionSensingPub x AfterKinectLaunch	**0.0802*** **	**-0.0861*** **	**-0.0306***
	(0.0038)	(0.0061)	(0.01433)
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

Note: The data 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 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 10%, **significant at 5%, ***significant at 1%