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Research Trajectory Generalists and The Direction of Scientific Research: Evidence from Kinect

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Abstract
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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). 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 are less explored.

In particular, the simple fact that knowledge exists doesn't guarantee the ability to access it and incorporate it in further innovation (Mokyr, 2002). Scientists need to be aware of prior knowledge, pay the associated costs of accessing it, and have the ability to exploit it. Scholars have engaged in exploring these dynamics starting with implications of cost conditions on accessing prior knowledge. For example, we now have a better understating of the impact of costs conditions imposed by intellectual property protection (Murray and Stern, 2007; Williams, 2012) or relaxed by institutions (Furman and Stern, 2006) on the rate of innovative activity. Other cost conditions and their implications on cumulative innovation are yet to be explored. Moreover, little was said on the ability of scientists to explore prior knowledge under given cost conditions. Such an extension is necessary given that heterogeneity in ability to build on prior knowledge has a direct influence on the direction of innovative activity and thus on the evolution of research trajectories (Murray and O'Mahony, 2007).

In this paper I explore a different type of cost influencing access to existing knowledge: the cost of research technology. Research technology packs prior knowledge in a tool that aids in the process of scientific research. I focus on motion-sensing devices used in scientific research to capture and analyze motion-sensing data. I move beyond exploring implications of research technology costs on the rate of innovative activity, to also investigating implications for the direction of cumulative knowledge creation. Thus the main contributions of this paper are twofold.

First, the cost of research technology influences the knowledge production process by altering the pace of scientific research (Stephan, 2012). However, scholars of scientific and technological change face a challenge in isolating the marginal impact of a reduction in research technology costs on the rate of knowledge production. This is due to the fact that changes in the cost of research technology and founding conditions which lead to such reductions in costs are highly correlated. This selection effect could be manifested for example in situations where funding is selectively injected for high-quality research technologies which are expected to have a significant and positive impact on the rate of scientific research. In such cases, the marginal effect of the observed impact on the rate of innovative activity cannot be empirically distinguished from the selection effect. Thus I ask: *What is the marginal impact of research technology costs on the rate of scientific inventive activity?* I find evidence of up to 47% disproportionate increase in academic publications directly attributable to a reduction in cost of motion-sensing research technology.

Second, I focus on factors affecting scientists' ability to build on prior knowledge. Although reductions in cost of accessing existing knowledge were found to positively influence the rate of follow-on innovation, we don't have a good understanding of the differential impact of cost conditions on research trajectories. This is important because the sources and associated implications of the observed heterogeneous outcomes of cost conditions on the rate of inventive activity are informative in moving the analysis towards an understanding of the factors affecting the direction of scientific research. It is a salient step towards a deeper perspective on the cumulative dynamics of knowledge production, since it moves from exploring factors affecting the flow of knowledge and ideas to factors influencing the ability to integrate prior knowledge in furthering knowledge creation (Murray and O'Mahony, 2007). In particular, I ask: *Who are the scientists who are able to exploit opportunities brought about reductions in cost of research technology? How do they do it?* I find that research trajectory generalists, as opposed to research trajectory specialists, "scientists with broader if shallower expertise" (Jones, 2010), have a higher propensity to draw from research opportunities brought by reductions in cost of motion-sensing research technology. Collaboration emerges as an influential mechanism. First, collaboration is correlated with generalists' ability of maintaining broad knowledge across research trajectories. This facilitates identification of knowledge creation opportunities across knowledge areas. Second, it is through collaboration that research trajectory generalists coordinate between research trajectory specialists who have the depth of knowledge required to move the innovative process further.

Taken together, these results suggest not only a significant impact of research technology costs on the rate of innovative activity, but also, and perhaps more importantly, they speak to salient division of labor dynamics influencing the evolution of research trajectories. Thus the findings are informative from several perspectives. First, they draw attention to the influential role of research technology cost conditions on the process of knowledge creation. Second, they get one step closer to quantifying these cost implications. Third, they uncover the central role played by research trajectory generalists in the cumulative process of knowledge creation. This latter finding is particularly noteworthy when acknowledging that specialization on progressively narrower niches is on the rise (Jones, 2009). Last, the results augment prior scholarly findings with regards to the increasingly salient role of collaboration as mechanism for knowledge production (Jones, 2009; Agrawal et al., 2013) since research trajectory generalists perform through team work, not in isolation.

All these dynamics have broad welfare implications (Agion et al., 2008; Acemoglu, 2012; Azoulay et al., 2012). However, the degree to which they are informative in crafting incentive mechanisms as policy levers is contingent on the extent to which they uncover causal relationships. Identification is difficult because many unobservable are correlated with both observed research behavior and research outcomes over time, following changes in research technology costs. In order for my analysis to provide more compelling insights on the consequences of research technology cost conditions on the rate and direction of scientific innovation, I need an instrument that is correlated with reductions in cost of research technology, but not correlated with scientists' characteristics and research behavior.

The launch of Microsoft Kinect provides such an instrument. On November 4, 2010 Microsoft launched Kinect for Xbox 360, a motion-sensing video gaming device. Unexpectedly, within days of Kinect's launch the open source community released a driver which made possible the use of Kinect as motion-sensing research device in academia. Given Kinect's technological sophistication and low selling price, the consequence was an unforeseen reduction in the cost of engaging with motion-sensing technology in scientific research. The event marked the start of what Microsoft coined as 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 Kinect's <u>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)

Given the unexpected nature of these events, the launch of Kinect provides an instrument correlated with reductions in cost of motion-sensing research technology, but exogenous to scientists' ex-ante research behavior. In other words, the launch of Kinect offers a natural experiment from which I can draw more causal inferences regarding the relationship between research technology costs and associated observed follow-on research developments.

In my empirical analysis I focus on academic publications in electrical engineering, computer science and electronics from 2005 until 2012 as listed in the IEEE bibliographical database. I make use of two features of the IEEE database to empirically test for implications on the rate and direction of scientific research triggered by the launch of Kinect. First, the ability to search the full text of each publication allows me to identify papers which cite motion-sensing research topics and technologies. This approach is in line with other studies of cumulative innovation which trace cumulativeness through measures of citations to prior art. But rather than following references trails, I focus on cites of key terms which refer to motion-sensing research topics and technologies. This method allows for a comprehensive yet granular identification of academic publications referencing motion-sensing. Second, I exploit the fact that each publication included in the IEEE bibliographical database is assigned a limited set of keywords drawn from a multi-hierarchical keyword taxonomy developed and maintained by IEEE. This controlled vocabulary aids in uncovering scientists' involvement with various research areas, and, as such, their level of specialization.

The remainder of the paper is structured as follows. Section 2 details on the concepts of research trajectory generalists and specialists. Section 3 and Section 4 present the setting, data and empirical framework. I present and discuss results in Section 5 and conclude in Section 6.

2. Research trajectory generalists and research trajectory 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 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). Furthermore, there is also evidence of increasing specialization in academia explained by the growth in knowledge stock and the continuous forward movement of the knowledge frontier (Jones, 2009, 2010, 2011).

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. 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). However, this also implies that coordination of scientific innovation across knowledge areas grows in complexity as specialization increases. First, it is increasingly costly to search for ideas which require spanning across knowledge areas. Second, it is getting increasingly difficult to coordinate efficient teams of research trajectory specialists that work on topics spanning knowledge areas (Jones, 2010). This search problem is indicative of a potential demand for research trajectory generalists, as opposed to research trajectory specialists, "scientists with broader if shallower expertise" (Jones, 2010) who have enough broad knowledge to lower coordination costs between specialists. Stated differently, research trajectory generalists act as glue between research trajectory specialists, a role which seems to increase in importance as the research specialization niches become increasingly narrow.

Research trajectory generalists have sufficient broad knowledge to recognize opportunities for knowledge creation which require spanning across knowledge areas, and to identify and coordinate connections between necessary research trajectory specialists. In turn, research trajectory specialists have the depth of knowledge required to push the knowledge creation process further. In organizational settings generalists were already identified as playing a salient role in coordinating complex problem solving (Garicano, 2000) which require specialist expertise. Furthermore, this role was found to grow in importance in environments that necessitates a multifaceted set of specialists (Ferreira and Sah, 2009). I draw from these insights and consider the role of research trajectory generalists in the context of the scientific innovative landscape. For expositional simplicity in what follows I refer to the groups of research trajectory generalists and specialists, as generalists and specialists respectively.

3. Kinect

I focus on the events triggered by the launch of Microsoft Kinect on November 4, 2010. Microsoft positioned its technology as a revolutionary device for the gaming industry: an add-on for Xbox 360 which allows users to interact with video games without the need of a controller, through motion-sensing. But nobody, including Microsoft, anticipated the wide-reaching impact Kinect would have on scholarly research in electrical engineering, computer science and electronics.

3.1. Brief description of Kinect as gaming technology

Kinect was launched 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 through 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, facial, gesture and voice recognition. The sensor is superior to any other 3D cameras in the accuracy of capturing movement and in the recognition capabilities of multiple simultaneous subjects.

Microsoft announced Project Natal, the development endeavor which was to create Kinect, in June 2009. Between 2009 and November 2010 when Kinect was released, Microsoft made sure to instill excitement among gamers by presenting video game demos at various events. Important however, nowhere during this period was Microsoft or any other party engaged in promoting, linking or in any way suggesting the use of Kinect technology outside its intended purpose of gaming device. Here is how the events unfolded.

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 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 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. The bounty, originally in amount of US$1,000, was placed in search for 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 benefiting from capturing and interpreting motion-sensing data.

Only hours after AdaFruit made the search for an open source driver public, Microsoft voice its disapproval on CNET news 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, following Microsoft's announcement within the same day, AdaFruit tripled the bounty to US$3,000. Six days later, on November 10, 2010, a Spanish technology enthusiast, Héctor Martín Cantero released the open source driver and won the bounty. From this point on the gates for creative development opened. Microsoft reacted within a couple of days following the release of the open source driver. First the company went public 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).

Another couple of days later, as the Kinect unexpected effect continued to pick up, Microsoft dropped all concerns and announced its intention to allow and support the unanticipated developments. The benefit for academic research was recognized and Microsoft was on board.

The significant impact for motion-sensing research technology derived from Kinect was not foreseen. The unexpected nature of this incident and the fact that it was triggered by AdaFruit's open source contest hours after Kinect's official launch as gaming device are strengthen by a former core Kinect team member confession:

> *"I actually have a secret to share on this topic. When my internal efforts for a [Kinect] driver stalled, I decided to approach AdaFruit to put on the Open Kinect contest. For obvious reasons, I couldn't run the contest myself. […] Without a doubt, the contest had a significant impact in raising awareness about the potential for Kinect beyond Xbox gaming both inside and outside the company. Best $3,000 I ever spent.”* (Lee, 2011).

Johnny Lee is a former Microsoft employee who now works for Google.

3.3. Kinect in academia

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

Kinect as motion-sensing research technology attracted interest from scientists who both were and weren't previously involved with motion-sensing technology in their research. For example, computer science scholars involved in computer learning algorithms targeted at detecting human emotions were using motion-sensing technologies to map facial expressions. These scientists were attracted by Kinect's more granular facial expression recognition capabilities. Similarly, scholars focused on robotics were interested in the depth motion-sensing capabilities of Kinect which aid in better development of robots that can more accurately navigate a complex landscape. Kinect also raised interest among scholars who were not using motion-sensing research technology prior to Kinect's launch. For example, scholars involved in the development of technologies for impaired individuals 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 a room.

The use and impact of Kinect as motion-sensing research technology were not anticipated. As such, the setting provides a natural experiment to draw more causal (albeit not without limitations) inferences with regards to the impact of reductions in cost of research technology on observed follow-on research developments. Stated differently, the unanticipated Kinect Effect provides an instrument that is correlated with reductions in 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 recognize opportunities uncovered by the reduction in costs.

4. Data and empirical framework

4.1. Data collection

I focus on academic publication data from scholars 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. This represents six years of data before the launch of Kinect and two years of data after the launch of Kinect. 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 Kinect's launch is not as long, however I argue that this is 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 more than 3-million full-text documents from some of the world's most highly cited publications in electrical engineering, computer science and electronics." I collect data on 1,446,866 publications in electrical engineering, computer science and electronics spanning the period of interest from 2005 to 2012. This represents the full set of journal publications, early access publications and conference proceedings available though IEEE *Xplore*.

4.2. Variables of interest

In order to analyze Kinect's impact on the dynamics of motion-sensing research topics, I need to first identify the set of publications on topics which reference motion-sensing. I need this data in order to estimate the impact of reductions in cost of accessing prior knowledge (here in the form of motion-sensing research technology) on the subsequent rate of scholarly publication. Second, I need to identify the generalists and the specialists. This data is required to estimate the propensity of generalists to recognize opportunities opened by the reduction in cost of motion-sensing research technology and to coordinate between specialists. To do so, 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.

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 which were carefully identified 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 or technologies I search for broad terms describing motion-sensing as well as more targeted terms referencing motion-sensing technologies. These terms are carefully selected through conversations with experts and cross-referenced against IEEE's taxonomy which includes a total of 51 main research areas (Table 2). I don't restrict mapping the boundaries of research topics to the list of 51 research areas for two reasons. 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 reduction in costs of research technology is an influencing factor for the evolution 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 which are outside the traditional "Computers and Information Processing" research area but are referencing motion-sensing.

4.2.2. Generalists and specialists

I define generalists as scientists who have an above sample average diversification level of research portfolio topics as identified through an inspection of the set of keywords assigned by IEEE from their taxonomy to scientists' publications. Specialists are defined as the reminder set 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 topics. Furthermore, the fact that the research areas defined under the IEEE taxonomy are at a broader level doesn't negatively impact my estimations as it down-plays generalists' breath of research portfolio topics.

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. There are less than 7% of publications without keywords which I drop from my dataset. The reminder 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 topics at the individual level which adjusts for the fact that the probability for 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 Kinect's launch. I refer to the period before 2011 since the focus is on estimating the propensity of generalists to recognize opportunities such as the one brought by the launch of Kinect. As such, the relevant individual level characteristics are the ones observed before the arrival of Kinect. Next, I convent the count in percentages and calculate the Euclidian length in the multidimensional space of 51 research areas. Note that the length, by construction, is less or equal to one, and never zero. The length is shortest when the percentages per research area are equally spread, or when the level of diversification of research portfolio topics is highest. Thus, for mathematical convenience, I construct the diversification measure to be equal to one minus the calculated Euclidian length. The higher the value, the higher the diversity of research portfolio topics at the individual level *i*:

$$DiversificationOfResearchTopics_j = 1 - \sqrt{\sum_k CategoryPercentage_{jk}^2}$$

Generalists are thus defined as those scholars with a value of diversification of research portfolio topics above the sample mean. Specialists are those scholars with such values below the sample mean.

4.3. Estimation strategy

The estimation strategy is comprised of two main steps.

First I estimate the marginal impact of a reduction in the cost of accessing prior knowledge on the rate of inventive activity. Specifically, I estimate the impact of a reduction in cost of motion-sensing research technology on the propensity to publish academic papers which reference motion-sensing topics. I do so using a difference-in-differences estimation.

Second I investigate the type of scientist who has the ability to recognize opportunities to build on existing knowledge, and thus influence the direction of scientific research through his impact on the evolution of research trajectories. In particular, I estimate the propensity of generalists to draw on opportunities brought about the reduction in cost of motion-sensing research technology. Specifically, I estimate the propensity of scientists with above sample average values of diversification of research portfolio topics to engage with Kinect. I do so using a cross-section probability model.

4.3.1 Difference-in-differences estimation

I compare the number of motion-sensing publications ("treated") with the number of publications on other research topics in electrical engineering, computer science and electronics ("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. This approach helps distinguish between the increase in motion-sensing publications directly attributable to the reduction in cost of motion-sensing research technology triggered by the launch of Kinect and changes in publication volume over time, while controlling for differences in publication trends between treated and control research topics. Formally, I estimate:

$$LogPubCount_{jt} =$$

$$\beta\left(MotionSensingPub_j \times AfterKinectLaunch_t\right) + ResearchTopic_j + \gamma_t + \varepsilon_{jt}$$

$LogPubCount_{jt}$ 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 *i* are listed as published in 2011 or 2012 and 0 otherwise. This applies to publications from both 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 motion-sensing papers published after the reduction in cost of motion-sensing research technology triggered by the launch of Kinect, and equals 0 for all others. I interpret a positive estimated value of this coefficient as implying that the average number of motion-sensing publications increased disproportionately more relative to publications on other topics of electrical engineering, computer science and electronics, and this increase was triggered by the reduction in cost of motion-sensing research technology facilitated by the launch of Kinect.

4.3.2 Cross-section probability model

I am interested in estimating the propensity of generalists to recognize opportunities brought about the reduction in cost of motion-sensing research technology triggered by the launch of Kinect. As such, engagement with Kinect in research is most informative. This is observed as publication output which references the work "Kinect". For person *i* their engagement with Kinect can be represented as:

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

The main coefficient of interest, α captures the propensity of generalists, indentified as such based on their publication behavior before the launch of Kinect, to engage with Kinect. The vector $\mathrm{X_i}$ includes controls for main domain of expertise, publication stock before the launch of Kinect and collaboration levels before the launch of Kinect. I assume ε_i has a type-2 extreme value distribution, implying a logit specification. Thus, I estimate:

$$\mathrm{PubReferencingKinect_{i1}} = \alpha_0 + \alpha\mathrm{Generalist_{i0}} + \mathrm{X_i} + \varepsilon_\mathrm{i}$$

The dependent variable is an indicator variable equal 1 for author i who published at least one paper referencing Kinect during either 2011 or 2012 and 0 otherwise. $\mathrm{Generalist_{i0}}$ is a dummy equal 1 if the level of diversification of research portfolio topics of individual *i* is above the sample mean prior to Kinect's launch and 0 otherwise.

I interpret a positive estimated value of the coefficient of interest α as implying that a higher level of diversification of research portfolio topics in the period before Kinect predicts a higher propensity to recognize opportunities brought about 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 topics in the before period. Stated differently, Kinect provides a plausible natural experiment which helps address concerns of selection into treatment.

5. Results

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 all other research topics listed in Table 1, two years before and two years after the launch of Kinect. I focus only on data from two years before the launch of Kinect to make possible a realistic comparison of means. I find evidence of a disproportionate increase in the mean growth rate of publications referencing motion-sensing, as represented in Figure 1.

However, there may be a concern that systematic differences between publications which reference and those which don't reference motion-sensing drive the observed difference in normalized mean growth rates. As such, I turn to the difference-in-differences estimation and present results in Table 4. I identify treated and control publications through a search on terms as described in Section 3.2.1. In the first column I consider control research topics which are similar in volume with motion-sensing before the launch of Kinect. In the second column I include all research topics from Table 1 as controls.

The main result of interest is the estimated coefficient of the interaction term *MotionSensingPubxAfterKinectLaunch* which is positive and statistically significant for both estimations.

This implies that the difference in the number of publications referencing motion-sensing vs. other research topics is greater after the reduction in cost of motion-sensing technology triggered by the launch of Kinect, than before.

To ensure that this result is not driven by underlying trends, I next examine the timing of this effect by estimating and plotting the interaction coefficients between year dummies and the indicator variable $MotionSensingPub_j$ equal to 1 if research topic *j* is motion-sensing and 0 otherwise.

$$logPubCount_{jt} = \sum_{s=0}^{t} \beta_s(\gamma_s \times MotionSensingPub_s) + Field_j + \gamma_t + \varepsilon_{jt}$$

I include all data for this estimation to facilitate a better evaluation of pre-Kinect trends. I refer to research-topics which are close in volume before the launch of Kinect as controls. The results are displayed in Figure 2[1]. Each point represents the coefficient value of the covariate *Year x MotionSensingPub* which describes the relative difference in yearly publication counts between papers referencing motion-sensing and papers referencing other topics of research. The bars surrounding each point represents 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 which were referencing motion-sensing and those which weren't was small and stable until the end of 2010, the time of Kinect's launch. Thereafter, the difference increased, as evidenced by the higher coefficients.

5.2. Generalists have a higher propensity to benefit from reductions in cost of research technology

Having established that the reduction in cost of motion-sensing research technology triggered by the launch of Kinect led to an increase in the number of publications referencing motion-sensing, I turn to investigating the scientists who were able to exploit opportunities opened by Kinect. Since

[1] Estimation coefficients are included in Appendix Table 1.

Kinect was the technology to lower the cost of engagement with motion-sensing and, consequently, triggered the set of opportunities for research referencing motion-sensing topics, I focus on tracking scientists who published at least one paper referencing Kinect during 2011 or 2012 as a proxy for an ability to recognize and draw on opportunities brought by reductions in cost of accessing prior knowledge.

I identify 2,459 scholars who published at least one paper referencing Kinect during 2011 or 2012. These scientists are heterogeneous with regards to their main domain of expertise before the launch of Kinect. Individual main domain of expertise is identified based on the set keywords assigned by IEEE to each scientist's set of publications. It represents the research area (out of 51) with the highest count of keywords assigned to scientist's publication portfolio between 2005 and 2010. Table 3 lists the number of scholars per domain of expertise who published at least one Kinect paper during 2011-2012. About 63% of these scientists did not publish papers referencing motion-sensing before the launch of Kinect.

Next, I turn to investigating the propensity of generalists to author at least one academic paper referencing Kinect. I present the cross-section probability model estimation results in Table 5. I report both odds ratios and logit coefficients for three models: 1) a baseline without controls, 2) model controlling for main domain of expertise and publication stock from the period before Kinect, 3) model with an additional control for the level of collaboration before the launch of Kinect. The main result of interest is the coefficient of the term *Generalist* which is positive and statistically significant across all estimations. This is consistent with the hypothesis that generalists have a higher propensity to recognize opportunities brought about reductions in cost of research technology.

To further strengthen this finding, I exploit an additional source of heterogeneity, namely the level of prior engagement with motion-sensing research topics. I add to the main estimating equation two terms which capture the variation from being a scientist who both engaged with motion-sensing topics prior to Kinect and published at least one Kinect paper during 2011-2012. I do so to ensure that the salient role of generalists in recognizing opportunities is not entirely driven by direct prior involvement with motion-sensing, but rather is indicative of an ability to span across knowledge areas. Formally, I estimate:

$$
\begin{aligned}
PubReferencingKinect_{i1} \\
&= \alpha_0 + \alpha_1 Generalist_{i0} + \alpha_2 (Generalist_{i0} \times MotionSensingScientist_{i0}) \\
&+ \alpha_3 MotionSensingScientist_{i0} + X_i + \varepsilon_i
\end{aligned}
$$

$MotionSensingScientist_{i0}$ is a dummy equal 1 if scholar *i* has published at least one paper referencing motion-sensing topics before the launch of Kinect and 0 otherwise. The estimation results are included in Table 6. The main result of interest, the coefficient of the term *Generalist*, remains positive and statistically significant across all estimations. This is indicative of the fact that the result on generalists is not fully explained by a prior involvement with motion-sensing topics. It strengthens the assertion regarding the influential role of generalists for the direction of scientific research through generalists' ability to recognize and draw from opportunities brought about reductions in cost of motion-sensing research technology.

5.3. Collaboration as mechanism

5.3.1 Collaboration as generalists' mechanism that facilitates lower the cost of search across knowledge areas

The cross-section estimation results discussed thus far control for the level of collaboration prior to Kinect's launch. The approach acknowledges that collaboration and authors' levels of diversification of research portfolio topics are codetermined. Indeed, generalists collaborate more than specialists and, related, they also publish more intensively than the specialists. Before the launch of Kinect, the average collaboration levels of generalists was 1.67 times the collaboration levels of specialists, while the publication rates of generalists was 2.54 times that of specialists. The mean collaboration levels and publication rates are calculated from a balanced individual level panel dataset comprised of collaboration and publication rates per year per author two years before the launch of Kinect and account for years during which authors didn't publish.

Thus, while it is unclear if diversity of individual research portfolio topics is the result of increased collaboration, or the other way around, these descriptives are indicative of collaboration as a mechanism that facilitates lower costs of search across knowledge areas as well as, related, lower costs of coordinating collaboration on research projects. In other words, through collaboration generalists manifest their ability to exploit opportunities of knowledge creation that require spanning across knowledge areas. It follows that these dynamics are of interest in understanding the evolution of research trajectories as influenced by reductions in costs of accessing prior knowledge. I detail on this point in what follows.

5.3.2 Collaboration as generalists' mechanism that facilitates coordination with specialists

Scholars have found that knowledge accumulation leads to an increased need for collaborative work in order to combine the progressively narrow niches of specialization (Jones, 2009; Agrawal et al., 2013). This finding suggests two influencing aspects of the generalist-specialist dynamic in the context of cumulative knowledge creation. First, cost of collaboration becomes central in knowledge creation as the knowledge frontier moves forward. Specifically, increases in team size are hindered by co-authorship coordination costs above a certain threshold (Bikard, et al., 2013). Second, collaboration emerges as contingent on the easiness of accessing prior knowledge. In other words, changes in collaboration levels are influenced by the cost of accessing prior knowledge. For example, Kinect lowered the cost of accessing prior knowledge by packing it in a tool, thus reducing the pressure of knowledge accumulation on collaboration levels.

Taken together, it becomes unclear how the forward movement of the motion-sensing frontier, triggered by the launch of Kinect, affects collaboration levels and patterns between generalists and specialists. On the one hand the forward movement of the frontier should lead to an increased need for collaboration, albeit restricted by coordination costs. On the other hand the reduction in cost of accessing prior knowledge should lead to a decreased need for collaboration, as Kinect lowers the pressure of knowledge accumulation on collaboration. I conjecture that the labor division dynamics between generalists and specialists are informative in unpacking the effect of these apparent opposite forces. I investigate this in what follows.

First, I distinguish between motion-sensing and non motion-sensing specialists, specialists who were and weren't, respectively, involved in research related to motion-sensing topics before the launch of Kinect. Prior to Kinect, motion-sensing knowledge was available through motion-sensing specialists. With the arrival of Kinect, part of motion-sensing prior knowledge was made available through the Kinect device. This lowered the cost of accessing prior motion-sensing knowledge, and thus the need to collaborate with motion-sensing scholars for projects utilizing motion-sensing as research technology. From this perspective I expect a decrease in the level of motion-sensing specialists listed as co-authors on academic projects referencing motion-sensing topics after the launch of Kinect.

Following the same line of thought, such a decrease should free co-authorship capacity on papers referencing motion-sensing topics after the launch of Kinect. This could result in additional non motion-sensing specialists added to the team, however, this change is limited by collaboration coordination costs. The cross-section estimation results included in this paper suggest generalists, scientists with lower coordination costs, as salient in incorporating specialists in collaborative teams exploiting opportunities brought by the reduction in cost of accessing prior motion-sensing knowledge.

In other words, generalists have the ability to realize the opportunity for knowledge creation brought by the launch of Kinect due to their lower coordination costs which aid in facilitating research co-authorship teams of non motion-sensing specialists. From this perspective, I expect an increase in the level of non motion-sensing specialists listed as co-authors on academic projects referencing motion-sensing topics after the launch of Kinect. This effect should be stronger for co-authorship teams which include a generalist.

In what follows I test these hypotheses. First, I investigate general changes in publication levels referencing motion-sensing. Next I review changes in collaboration levels of specialists and generalists involved in projects referencing motion-sensing topics. Last I test changes in co-authorship team composition. I find strong evidence of collaboration as a mechanisms through which generalists realize their ability to span across knowledge areas, coordinate between specialists and influence the evolution of research trajectories by incorporating motion-sensing knowledge.

Table 7 compares mean values of publication for generalists and specialists before and after the launch of Kinect. Specialists increase their level of publication in motion-sensing after the launch of Kinect, and they do so disproportionately more than generalists who exhibit rather similar motion-sensing publication levels before and after the launch of Kinect[2]. I test if this differential impact is driven by systematic differences between specialists and generalists. I do so in a difference-in-differences estimation which measures the disproportionate increase in motion-sensing publications for specialists after the launch of Kinect, relative to generalists' levels of publication. At the author-year level, I estimate:

$$LogPubCount_{it} = \beta(Specialist_i \times AfterKinectLaunch_t) + \delta_i + \gamma_t + \varepsilon_{it}$$

[2] The apparent decrease in motion-sensing publications authored by generalists can be attributed to the lag in adding 2012 publication to the IEEE bibliographical database, at the time of data collection in late December 2012.

$LogPubCount_{it}$ is equal to the logged value of motion-sensing publication counts (plus one, to account for years with no publications). $Specialist_i$ is a dummy equal 1 for authors who are not generalists and 0 for generalists. The main effects $Specialist_i$ and $AfterKinectLaunch_t$ drop out of the estimating equation since I include year and individual fixed effects. The main result of interest is the estimated coefficient of the interaction term *SpecialistxAfterKinectLaunch*, included in Table 8, Column 1. Column 2 distinguishes between motion-sensing specialists and non motion-sensing specialists, identified as such based on specialists' involvement with motion-sensing prior to Kinect's launch. As expected, specialists disproportionately increase their publication level of papers referencing motion-sensing topics relative to generalists, and this result is driven by non motion-sensing specialists.

Next I test for similar changes in collaboration levels of specialists and generalists involved in projects referencing motion-sensing topics. First, Table 9 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 (as hypothesized), specialists disproportionately increase their collaboration level after the launch of Kinect relative to generalists. I test if this disproportionate increase is driven by non motion-sensing specialists through a difference in-differences estimation:

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

where $LogCollaborationLevel_{it}$ is equal to the logged value of publication weighted collaboration levels (plus one, to account for years with no publications). The estimation results included in Table 10 attest to a disproportionate increase in specialist collaboration levels relative to generalists' on papers referencing motion-sensing topics, after the launch of Kinect (Column 1). The result is driven by collaboration level changes of non motion-sensing specialists (Column 2).

Table 12 takes this estimation result one important step further by focusing on changes in collaboration levels between specialists and generalists. There are two noteworthy insights that emerge from this estimation. First, the increase in collaboration levels of non motion-sensing specialists is driven by increases in collaboration with generalists. Second, there is a decrease in the level of collaboration of motion-sensing specialists with generalists relative to others, as hypothesized.

Last, I explicitly test if these changes in collaboration and publication levels are indicative of salient labor division dynamics of research trajectory evolution triggered by reductions in costs of accessing prior knowledge, here in the form of motion-sensing research technology. In a difference in-differences estimation at the publication level 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.

$$TeamCompositionDummy_{jt} =$$

$$\beta\left(MotionSensingPub_j \times AfterKinectLaunch_t\right) + MotionSensingPub_j + \gamma_t + \varepsilon_{jt}$$

where $TeamCompositionDummy_{jt}$ is a dummy variable equal 1 if the co-authorship team on publication *j* includes at least one scientist of the identified type and 0 otherwise. $MotionSensingPub_j$ is a dummy equal 1 if publication *j* is a paper referencing motion-sensing research topics and 0 otherwise. The main result of interest is the estimated coefficient of the interaction term *MotionSensingPubxAfterKinectLaunch*, included in Table 12. Column 1 shows a positive and statistically significant increase in teams comprised of generalists and non-motion sensing specialists on publications referencing motion-sensing research topics after the launch of Kinect, as hypothesized. Also as predicted, there is a disproportionate decrease in generalists (Column 2) and non motion-sensing specialists (Column 3) collaborating with motion-sensing specialists on papers referencing motion-sensing topics after the launch of Kinect, relative to all other publications in electrical engineering, computer science and electronics.

Taken together these results indicate to collaboration as mechanism through which generalists span across knowledge areas and coordinate between specialists, thus shaping the evolution of research trajectories. Generalists play a central role in realizing opportunities for knowledge creation opened by reductions in cost of accessing prior knowledge.

6. Discussion

The focus of this paper is to examine implications of reductions in costs of accessing prior knowledge on cumulative innovation by exploiting the launch of Kinect as an instrument resulting in a sudden reduction in motion-sensing technology costs. I move beyond results of a positive impact on the rate of innovative activity, to shedding some light on factors influencing scientists' ability to build on knowledge.

First, and in line with prior findings, I confirm that costs of accessing prior knowledge have a significant impact on follow-on innovation. I contribute by focusing on a different type of cost, that of accessing research technology. Research technology packs prior knowledge in a tool which aids in the process of scientific research. I find evidence of up to 47% increase in academic publications directly attributable to a reduction in cost of motion-sensing research technology.

Second, I uncover evidence of the role of generalists in the process of knowledge creation. Through their ability to span across knowledge areas, generalists coordinate knowledge creation opportunities between specialists. This role is especially important given the increased tendency for specialization on narrower niches which results in a progressively accentuated need for collaboration in order to move the knowledge frontier further forward.

Third, I connect implications of knowledge cost conditions on the rate of scientific research to insights of labor division dynamics relative to knowledge creation under increased pressure of knowledge accumulation. I provide evidence of generalists' influential role in exploiting opportunities brought by reductions in costs of accessing prior knowledge. The findings are suggestive to a need for incentives accounting for this group of scholars as it is through generalists that cost opportunities are realized.

These results are not without limitations. While the launch of Kinect offers a plausible natural experiment to draw more causal inferences regarding labor division dynamics of cumulative knowledge creation, the general limitations of a natural experiment apply. Furthermore, Kinect represents one instance of reduction in cost of accessing prior knowledge in the form of research technology. Studying it is subject to the idiosyncrasies of electrical engineering, computer science and electronics research dynamics.

Nevertheless, this paper brings to our attention noteworthy labor division dynamics worthy of further investigation. I have studied the role of generalists in the context of academic research, however similar insights can be extended to R&D departments elsewhere given the common scope of knowledge creation.

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

	Research Topic	List of key terms
1	Motion Sensing	"motion sensing" OR "motion tracking" OR "motions tracking" OR "motion recognition" OR "motion sensor" OR "motion capture" OR "3D tracking" OR "3-dimentional tracking" OR "3D imaging" OR "3-dimentional imaging" OR "depth camera" OR "depth cameras" OR "ranging camera" OR "ranging cameras" OR "flash lidar" OR "time of flight camera" OR "time-of-flight camera" OR "time of flight cameras" OR "time-of-flight cameras" OR "RGB-D camera" OR "RGB-D cameras" OR "3D camera" OR "3D cameras" OR "Kinect"
2	Speech and Voice Recognition	speech recognition" OR "voice recognition" OR "speech processing" OR "linguistics" OR "natural language communication" OR "natural voice communication" OR "speech signal" OR "voice technology" OR "voice-controlled interface" OR "speech interface" OR "voice interface" OR "speech coding" OR "spoken language technology" OR "spoken language technologies" OR "speech technology" OR "voice technology" OR "HMM" OR "hidden Markov model" OR "VQ" OR "vector quantization" OR "ANN" OR "artificial neural network" OR "SVM" OR "support vector machine" OR "VQ/I IMM"
3	Green Energy	"green energy" OR "greenhouse gas" OR "greenhouse gases" OR "renewable energy" OR "environmentally friendly" OR "green technologies" OR "biofuel" OR "biofuels" OR "bio-fuel" OR "bio-fuels" OR "global warming" OR "fossil fuel" OR "climate change" OR "climate changes" OR "green technology" OR "renewable technology" OR "renewable technologies" OR "wind energy" OR "solar energy" OR "tidal energy" OR "geothermal energy" OR "solar power"
4	Aerospace and Electronic Systems	"aerospace" OR "air traffic control" OR "air safety" OR "Earth Observing System" OR "orbit satellite" OR "orbit satellites" OR "moon" OR "space station" OR "space stations" OR "space exploration" OR "space technology" OR "aircraft" OR "propeller" OR

		"electronic warfare" OR "electronic countermeasure" OR "electronic countermeasures" OR "radar countermeasure" OR "radar countermeasures" OR "military satellite" OR "military satellites" OR "weapon" OR "weapons" OR "gun" OR "guns" OR "missile" OR "missiles" OR "airborne radar" OR "bistatic radar" OR "doppler radar" OR "ground penetrating radar" OR "laser radar" OR "meteorological radar" OR "millimeter wave radar" OR "multistatic radar" OR "MIMO radar" OR "passive radar" OR "radar countermeasure" OR "radar countermeasures" OR "radar detection" OR "radar imaging" OR "radar measurements" OR "radar polarimetry" OR "radar remote sensing" OR "radar tracking" OR "radar clutter" OR "spaceborne radar" OR "spread spectrum radar" OR "synthetic aperture radar" OR "synthetic aperture radar" OR "sonar"
5	Antennas and Propagation	"antennas" OR "antenna" OR "Butler matrix" OR "phased arrays" OR "planar arrays" OR "diffraction" OR "propagation" OR "electromagnetic reflection" OR " optical reflection" OR "optical surface wave" OR "optical surface waves" OR "optical waveguide" OR "optical waveguides" OR "radio propagation" OR "radiowave propagation" OR "radio astronomy"
6	Broadcast Technology	"broadcast" OR "broadcasting" OR "Digital Radio Mondiale" OR "digital audio player" OR "digital audio players" OR "frequency modulation" OR "radio network" OR "radio networks"
7	Packaging and Manufacturing Technology	"capacitor" OR "capacitors" OR "varactor" OR "varactors" OR "coil" OR "coils" OR "diode" OR "diodes" OR "electrode" OR "electrodes" OR "anode" OR "anodes" OR "cathode" OR "cathodes" OR "microelectrode" OR "microelectrodes" OR "fuse" OR "fuses" OR "active inductor" OR "active inductors" OR "thick film inductor" OR "thick film inductors" OR "thin film inductor" OR "thin film inductors" OR "resistor" OR "resistors" OR "memristor" OR "memristors" OR "varisor" OR "varistors" OR "optical switch" OR "optical

		switches" OR "transducer" OR "transducers" OR "damascene integration" OR "micromachining" OR "radiation hardening" OR "flip chip" OR "high-K gate dielectrics" OR "quasi-doping" OR "semiconductor device doping" OR "semiconductor epitaxial layer" OR "semiconductor epitaxial layers" OR "semiconductor growth" OR "silicidation" OR "wafer bonding" OR "electronic packaging" OR "electronics packaging" OR "chip scale packaging" OR "environmentally friendly manufacturing technique" OR "environmentally friendly manufacturing techniques" OR "surface-mount technology" OR "multichip module" OR "multichip modules" OR "integrated circuit packaging" OR "semiconductor device packaging"
8	Dielectrics and Electrical Insulation	"dielectric" OR "dielectrics" OR "capacitor" OR "capacitors" OR "ferroelectric" OR "piezoelectric" OR "pyroelectric" OR "dielectrophoresis" OR "electrohydrodynamics" OR "electrokinetics" OR "electrostriction" OR "electric breakdown" OR "avalanche breakdown" OR "corona" OR "arc discharge" OR "arc discharges" OR "electrostatic discharge" OR "flashover" OR "glow discharge" OR "glow discharges" OR "partial discharges" OR "partial discharge" OR "surface discharge" OR "surface discharges" OR "cable insulation" OR "gas insulation" OR "sulfur hexafluoride" OR "insulator" OR "insulators" OR "trees - insulation" OR "isolation technology" OR "oil insulation" OR "oil filled cable" OR "oil filled cables" OR "plastic insulation"
9	Electromagnetic Compatibility and Interference	"electromagnetic" OR "reverberation chamber" OR "spark gap" OR "spark gaps" OR "mutual coupling" OR "optical coupling" OR "Eddy currents" OR "inductive power transmission" OR "Gamma ray" OR "Gamma rays" OR "Line-of-sight propagation" OR "cable shielding" OR "magnetic shielding" OR "EMP" OR "EMTDC" OR "EMTP" OR "power system transient" OR "power system transients" OR "crosstalk" OR "diffraction" OR "echo interference" OR "radiofrequency interference" OR "specific absorption rate" OR "radiative interference" OR "electrostatic

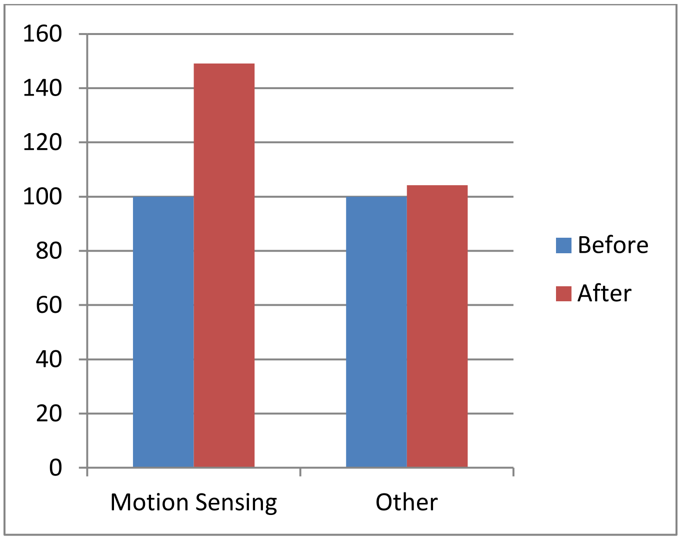
		interference" OR "interchannel interference" OR "interference cancellation" OR "interference channel" OR "interference channels" OR "interference elimination" OR "interference suppression" OR "intersymbol interference" OR "TV interference"
10	Imaging Technology	"imaging" OR "angiocardiography" OR "angiography" OR "cardiography" OR "echocardiography" OR "electrocardiography" OR "DICOM" OR "encephalography" OR "mammography" OR "ground penetrating radar" OR "holography" OR "image converter" OR "image converters" OR "active pixel sensor" OR "active pixel sensors" OR "CCD image sensor" OR "CCD image sensors" OR "CMOS image sensor" OR "CMOS image sensors" OR "charge-coupled image sensor" OR "charge-coupled image sensors" OR "infrared image sensor" OR "infrared image sensors" OR "magnetic resonance" OR "diffusion tensor" OR "magneto electrical resistivity" OR "atomic force microscopy" OR "electron microscopy" OR "photoelectron microscopy" OR "scanning electron microscopy" OR "transmission electron microscopy" OR "scanning probe microscopy" OR "Talbot effect" OR "thermoreflectance" OR "radiography" OR "tomography" OR "ultrasound"
11	Microwave Technology	"microwave" OR "beam steering" OR "maser" OR "masers" OR "gyrotron" OR "gyrotrons" OR "K-band" OR "L-band" OR "Rectenna" OR "Rectennas" OR "millimeter wave" OR "MIMIC" OR "MIMICs" OR "submillimeter wave"
12	Oceanic Engineering and Marine Technology	"marine" OR "underwater" OR "rebreathing" OR "ocean" OR "oceanographic"
13	Resonance Theory and Technology	"ferroresonance" OR "magnetic resonance" OR "nuclear magnetic resonance" OR "paramagnetic resonance" OR "resonance light scattering" OR "stochastic resonance"

Table 2: List of main research areas as included in the IEEE taxonomy

	Description
1	Aerospace and electronic systems
2	Antennas and propagation
3	Broadcast technology
4	Circuits and systems
5	Communications technology
6	Components, packaging, and manufacturing technology
7	Computational and artificial intelligence
8	Computers and information processing
9	Consumer electronics
10	Control systems
11	Dielectrics and electrical insulation
12	Education
13	Electromagnetic compatibility and interference
14	Electron devices
15	Electronic design automation and methodology
16	Engineering - general
17	Engineering in medicine and biology
18	Engineering management
19	Geoscience and remote sensing
20	IEEE organizational topics
21	Imaging
22	Industrial electronics
23	Industry applications
24	Information theory
25	Instrumentation and measurement
26	Intelligent transportation systems
27	Lasers and electroopics
28	Magnetics
29	Materials, elements, and compounds
30	Mathematics
31	Microwave theory and techniques
32	Nanotechnology
33	Nuclear and plasma sciences
34	Oceanic engineering and marine technology
35	Power electronics
36	Power engineering and energy
37	Product safety engineering
38	Professional communication
39	Reliability
40	Resonance
41	Robotics and automation
42	Science - general
43	Sensors

44	Signal processing
45	Social implications of technology
46	Solid state circuits
47	Superconductivity
48	Systems engineering and theory
49	Systems, man, and cybernetics
50	Ultrasonics, ferroelectrics, and frequency control
51	Vehicular and wireless technologies

Figure 1: Disproportionate increase in normalized mean growth rate of publications referencing motion-sensing after the launch of Kinect relative to publications referencing other research topics



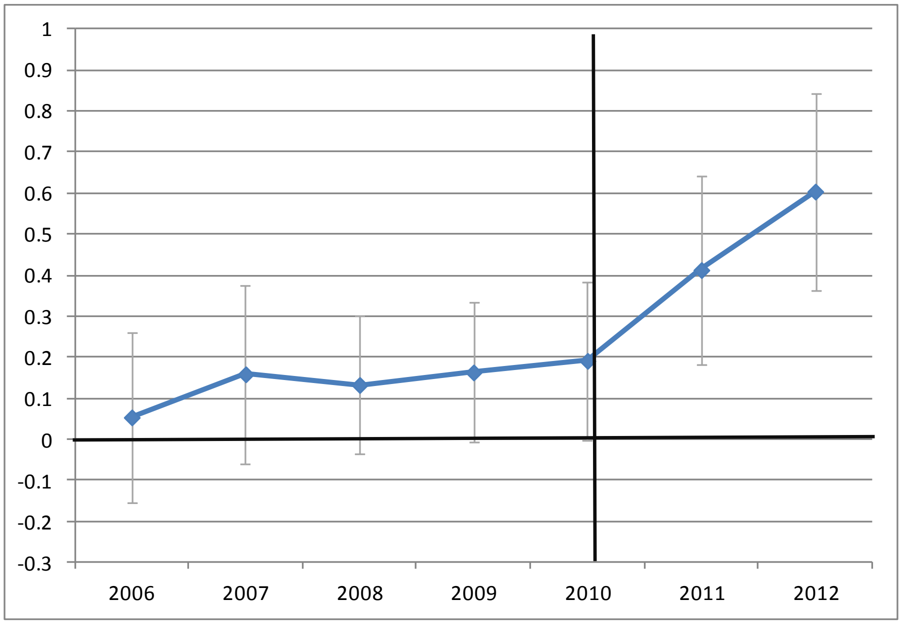
Note: Motion-sensing compared to research topics close in volume to motion-sensing before Kinect's launch

Table 3: Scientist publish disproportionately more on topics referencing motion-sensing after the launch of Kinect

Dependent variable: log of count of publications per year per research topic		
	Compared to research topics close in volume to motion-sensing before Kinect's launch	**All research topics listed in Table1**
MotionSensingPub x AfterKinectLaunch	**0.392*** (0.1105)**	**0.473*** (0.0690)**
Year fixed effects	Yes	Yes
Research topic fixed effects	Yes	Yes
R-squared	0.980	0.984
Observations	64	104

The unit of analysis is year - research topic. All models are OLS with robust standard errors, clustered by research topic.
*significant at 10%, **significant at 5%, ***significant at 1%

Figure 2: Plot of estimated coefficients on the interaction between treated publications and year dummies



Notes: I base this figure on 6 years of publication data before the launch of Kinect (2005-2010) and 2 years of publication data after the launch of Kinect (2011-2012). Each point on the graph represents the coefficient value on the covariate MotionSensingPubxYear and thus describes the relative difference in publication rates between papers referencing motion-sensing topics and papers referencing other research topics in that year. The bars surrounding each point represent the 95% confidence interval. All values are relative to the base year of 2005. I include the same results in table format in Appendix Table 1.

Table 4: Kinect authors by research area

	Research Area	Count of Kinect Authors
1	Aerospace and electronic systems	6
2	Antennas and propagation	11
3	Broadcast technology	1
4	Circuits and systems	22
5	Communications technology	183
6	Components, packaging, and manufacturing technology	0
7	Computational and artificial intelligence	45
8	Computers and information processing	730
9	Consumer electronics	1
10	Control systems	45
11	Dielectrics and electrical insulation	1
12	Education	5
13	Electromagnetic compatibility and interference	2
14	Electron devices	1
15	Electronic design automation and methodology	80
16	Engineering - general	0
17	Engineering in medicine and biology	42
18	Engineering management	26
19	Geoscience and remote sensing	1
20	IEEE organizational topics	3
21	Imaging	18
22	Industrial electronics	68
23	Industry applications	0
24	Information theory	4
25	Instrumentation and measurement	178
26	Intelligent transportation systems	3
27	Lasers and electroopics	48
28	Magnetics	4
29	Materials, elements, and compounds	63
30	Mathematics	220
31	Microwave theory and techniques	0
32	Nanotechnology	0
33	Nuclear and plasma sciences	7
34	Oceanic engineering and marine technology	0
35	Power electronics	1
36	Power engineering and energy	25
37	Product safety engineering	1
38	Professional communication	38
39	Reliability	0
40	Resonance	0
41	Robotics and automation	296
42	Science - general	185
43	Sensors	35

44	Signal processing	31
45	Social implications of technology	0
46	Solid state circuits	0
47	Superconductivity	0
48	Systems engineering and theory	6
49	Systems, man, and cybernetics	6
50	Ultrasonics, ferroelectrics, and frequency control	0
51	Vehicular and wireless technologies	17

Table 5: Generalists have a higher propensity to engage with Kinect

Dependent variable: indicator variable equal 1 for authors who published at least one Kinect paper during the two year before Kinect's launch						
	Basic (Odds Ratio)	**Basic (Coefficient)**	**Controlling for subfield of expertise and stock prior to Kinect's launch (Odds Ratio)**	**Controlling for subfield of expertise and stock prior to Kinect's launch (Coefficient)**	**Taking into account collaboration prior to Kinect's launch (Odds Ratio)**	**Taking into account collaboration prior to Kinect's launch (Coefficient)**
Generalist	**3.9188******** (0.3067)	**1.3658******** (0.0783)	**2.8044******** (0.2262)	**1.0312******** (0.0807)	**2.4346******** (0.1970)	**0.8898******** (0.0825)
Stock			1.009*** (0.0006)	0.0094*** (0.0006)	1.0084*** (0.0006)	0.0084*** (0.0006)
Collaboration					2.6130*** (0.2215)	0.9605*** (0.0848)
MainDomainOf Expertise FE			Yes	Yes	Yes	Yes
LL	-6,581.191	-6,581.191	-5,903.687	-5,903.687	-5,845.034	-5,845.034
Observations	97,429	97,429	95,531	95,531	95,531	95,531

The unit of analysis is author. All models are logit with robust standard errors, clustered by author. *significant at 10%, **significant at 5%, ***significant at 1%

Table 6: The result on generalists is not fully explained by generalists involved with motion-sensing before Kinect

Dependent variable: indicator variable equal 1 for authors who published at least one Kinect paper during the two year before Kinect's launch				
	Generalist results persists after controlling for motion sensing author prior to Kinect's launch (Odds Ratio)	**Generalist results persists after controlling for motion sensing author prior to Kinect's launch (Coefficient)**	**Generalist results persists after controlling for motion sensing generalist author prior to Kinect's launch (Odds Ratio)**	**Generalist results persists after controlling for motion sensing generalist author prior to Kinect's launch (Coefficient)**
Generalist	**1.9880***** (0.1662)	**0.6871***** (0.0836)	**2.1390***** (0.2020)	**0.7603***** (0.0944)
MotionSensingAuthor	4.0764*** (0.2793)	1.4052*** (0.0685)	5.4681*** (0.9859)	1.6989*** (0.1803)
Generalist x MotionSensingAuthor			0.7196* (0.1367)	-0.3291* (0.1900)
Stock	1.0053** (0.0005)	0.0053*** (0.0005)	1.0054** (0.0005)	0.0054*** (0.0005)
Collaboration	2.1115*** (0.1846)	0.7474*** (0.0874)	2.1009*** (0.1836)	0.7423*** (0.0874)
MainDomainOf Expertise FE	Yes	Yes	Yes	Yes
LL	-5,635.952	-5,635.952	-5,634.520	-5,634.520
Observations	95,531	95,531	95,531	95,531

The unit of analysis is author. All models are logit with robust standard errors, clustered by author. *significant at 10%, **significant at 5%, ***significant at 1%

Table 7: Specialists increase publication disproportionately more than generalists after the launch of Kinect

Mean Value Of:	**Generalist**		**Specialist**	
	Before	**After**	**Before**	**After**
Count of publications	4.207 (Std. Dev. 7.40)	3.784 (Std. Dev. 6.70)	1.657 (Std. Dev. 2.67)	1.746 (Std. Dev. 2.48)

Note: The apparent decrease in the average rate of publications for generalists is an artifact of the lag in adding 2012 publications to the IEEE bibliographical database

Table 8: Non motion-sensing specialists publish disproportionately more on topics referencing motion-sensing after Kinect's launch

Dependent variable: log of count of motion-sensing publications per author per year (plus one)		
Specialist x AfterKinectLaunch	0.1319*** (0.0032)	
MotionSensingSpecialistxAfterKinectLaunch		-0.0055 (0.0146)
NonMotionSensingSpecialistxAfterKinectLaunch		**0.1360*** (0.0033)**
Year FE	Yes	Yes
Author FE	Yes	Yes
R-squared	0.001	0.001
Observations	394,612	394,612

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

Table 9: Both generalists and specialists increase collaboration, but specialists do so disproportionately more than generalists after the launch of Kinect

Mean Value Of:	**Generalist**		**Specialist**	
	Before	**After**	**Before**	**After**
Collaboration (weighted by publications)	0.015 (Std. Dev. 0.12)	0.016 (Std. Dev. 0.13)	0.009 (Std. Dev. 0.10)	0.013 (Std. Dev. 0.12)

Table 10: Non motion-sensing specialists collaborate disproportionately more on topics referencing motion-sensing after Kinect's launch

Dependent variable: log of count of collaboration per author per year (plus one)		
	Collaboration (weighted by publications)	**Collaboration (weighted by publications)**
Specialist x AfterKinectLaunch	0.0011*** (0.0003)	
MotionSensingSpecialistxAfterKinectLaunch		0.0010 (0.0014)
NonMotionSensingSpecialistxAfterKinectLaunch		**0.0011***** **(0.0003)**
Year FE	Yes	Yes
Author FE	Yes	Yes
R-squared	0.001	0.001
Observations	394,612	394,612

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

Table 11: Non motion-sensing specialists collaborate disproportionately more with generalists on topics referencing motion-sensing after Kinect's launch

Dependent variable: log of count of collaboration per author per year (plus one)		
	Collaboration (weighted by publications)	**Collaboration (weighted by publications)**
Specialist x AfterKinectLaunch	0.0536*** (0.0031)	
MotionSensingSpecialistxAfterKinectLaunch		-0.0496*** (0.0154)
NonMotionSensingSpecialistxAfterKinectLaunch		**0.0566***** **(0.0031)**
Year fixed effects	Yes	Yes
Author fixed effects	Yes	Yes
R-squared	0.005	0.005
Observations	394,612	394,612

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

Table 12: Disproportionate increase in generalists and non motion-sensing specialists co-authoring motion-sensing papers after the launch of Kinect

Dependent variable: dummy for collaboration instances between generalists and specialists			
	Generalist and non motion sensing specialist	**Generalist and motion sensing specialist**	**Motion sensing and non motion sensing specialists**
MotionSensingPub x AfterKinectLaunch	**0.1970*** (0.0101)**	**-0.2863*** (0.0092)**	**-0.1630*** (0.0085)**
MotionSensingPub	-0.1977*** (0.0078)	0.4190*** (0.0077)	0.2694*** (0.0071)
Year fixed effects	Yes	Yes	Yes
R-squared	0.002	0.009	0.021
Observations	704,146	704,146	704,146

The unit of analysis is publication. All models are OLS with robust standard error. *significant at 10%, **significant at 5%, ***significant at 1%

APPENDIX

Appendix Table 1: Estimation coefficients displayed in Figure 2

Dependent variable: log of count of publications per year per research topic	
	Compared to research topics close in volume to motion-sensing before Kinect's launch
MotionSensingPub x 2006	0.0538* (0.0242)
MotionSensingPub x 2007	0.1588*** (0.0197)
MotionSensingPub x 2008	0.1327* (0.0673)
MotionSensingPub x 2009	0.1633 (0.1096)
MotionSensingPub x 2010	0.1915 (0.1383)
MotionSensingPub x 2011	0.4219** (0.1688)
MotionSensingPub x 2012	0.6042** (0.1765)
Year fixed effects	Yes
Research topic fixed effects	Yes
R-squared	0.980
Observations	64

The unit of analysis is year - research topic. All models are OLS with robust standard errors, clustered by research topic.
*significant at 10%, **significant at 5%, ***significant at 1%