Jack of All Trades and Master of Knowledge: The Role of Diversification in New Distant Knowledge Integration

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Abstract

Organization-level knowledge diversification facilitates exploration – integration of external new knowledge –, yet knowledge accumulation poses a challenge because there is a trade-off between individual-level breadth and depth of knowledge. This leads to a need to coordinate larger teams in order to gather enough diverse expertise and capitalize on its benefits, a complex and costly process. As an alternative, we consider and show evidence of the role of individual-level diversification as a mechanism through which skilled researchers engage in successful exploration by utilizing the benefits of their breadth of knowledge and by mitigating the perceived disadvantages of their shallower depth of knowledge through diverse collaboration networks. Our results suggest that organizations seeking to innovate at the frontier should consider the benefits of hiring diverse researchers.

JEL Codes: O31, O32, O33

Keywords: innovation, exploration, recombination, diversification, specialization, collaboration, process of knowledge creation

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I. Introduction

The role of innovation in creating value and competitive advantage for organizations has long been of interest to the fields of strategy, management, and economics (e.g., Schumpeter, 1934; Nelson and Winter, 1977). In particular, the ability to "explore", namely, to recognize and integrate new external knowledge, that is outside one's domains of expertise, has continually been shown to allow organizations to thrive (Tushman and Anderson, 1986; Cohen and Levinthal, 1989; Christensen, 1992; Fleming, 2001; Chatterji and Fabrizio, 2014). For example, Charles Babbage famously utilized advances in silk-weaving, which created patterns in silk fabric using cards with holes, to invent computational machines powered by punch cards, which laid the groundwork for modern computers.

Despite this fact, the precise individual characteristics that allow innovators and by extension, their organizations, to be amongst the first to successfully explore by integrating new external knowledge – knowledge that is outside their existing domains of expertise – have gone underexamined. By and large, scholars have revealed that ability is a precursor to successful exploration, both at the individual and the organization level (e.g., Henderson, 1993; Gavetti and Levinthal, 2000; Fleming, 2001; King and Tucci, 2002; Greve, 2007; Ahuja *et al.*, 2008). However, while at the organization level various mechanisms through which ability[1] leads to successful exploration were analyzed, including aspiration levels (Cybert and March, 1963; Greve, 2003; Dothan and Lavie, 2016), connections to basic science (Fleming and Sorenson, 2004) and the role of motivation (Eggers and Kaul, 2018), less is known about mechanisms through which the successful exploration of skilled individuals[2] manifests.

Understanding this is important because individuals' ability to explore directly contributes to successful organizational-level exploration. Furthermore, knowledge-based organizations are increasingly relying on scientists, engineers, and researchers to drive value creation and competitive advantage (Agrawal *et al.*, 2017; Barth *et al.*, 2017). After all, combining broadly across the knowledge frontier has been shown to lead to the most significant discoveries (e.g., Weitzman, 1998; Katila and

[1] There are also numerous studies focused on uncovering factors that contribute to building an ability to successfully explore, such as complementary assets (Tripsas, 1997; Rothaermel, 2001; Taylor and Helfat, 2009) and competition pressures (Bayus and Agarwal, 2007; Eggers, 2014; Wu, Wan and Levinthal, 2014).

[2] We use the phrase "skilled individuals" throughout the paper to denote individuals who have the proper skill-set, and therefore level of ability necessary for exploration.

Ahuja, 2002; Schilling and Green, 2011; Boudreau *et al.*, 2011; Uzzi *et al.*, 2013; Chai, 2017; Lifshitz-Assaf, 2017).

In this paper, we contribute to this literature by drawing attention to the individuals' level of knowledge diversification as a mechanism through which successful exploration of skilled individuals manifests. Knowledge accumulation – the increase in knowledge stock – places a burden on individuals looking to explore as individual capacity to store knowledge remains relatively unchanged. In particular, Jones (2009, 2010) argues that the knowledge burden effect generates a need to specialize on increasingly narrower niches of knowledge. This suggests that individual-level breadth of knowledge is likely to come at the expense of knowledge depth. Thus, an alternative response is to compromise on knowledge depth in order to cultivate knowledge breadth (Jones 2009, 2010; Schilling and Green, 2011). This implies that, conditional on ability, individuals' breadth and depth of knowledge – their level of knowledge diversification[3] – become increasingly relevant when evaluating exploration – attempts to integrate new knowledge that is outside one's domains of expertise.

While we focus on the individual level, it is important to note that, ultimately, our goal is to inform on organization-level decisions that lead to successful exploration. Knowledge diversification at the organization level has long been recognized as a requirement for successful exploration (Cohen and Levinthal, 1990; Katila and Ahuja, 2002). However, given the increase in knowledge accumulation, achieving knowledge diversification across individuals in an organization is becoming increasingly costly, and is therefore a strategic decision that needs to be carefully evaluated. In particular, the fact that individual-level breadth of knowledge is likely to come at the expense of knowledge depth implies that the ability of an individual to single-handedly capitalize on the benefits of external knowledge combinations to generate impactful discoveries is reduced. An alternative for organizations is to coordinate larger scale collaborations between individuals with different levels of knowledge breadth and hence, depth (Wuchty *et al.*, 2007; Jones, 2009, 2010; Agrawal *et al.*, 2016) in order to capitalize on the benefits of cumulative diversification for integrating new external knowledge. However, the increasingly narrower niches of specialization at the individual level suggest an increasing complexity in

[3] Our focus is on individual-level diversification while holding experience constant. In other words, we focus on comparing the role of skilled individuals that have the same amount of expertise either spread across multiple domains (diversified individuals) or concentrated in a narrower set of domains (specialized individuals). It follows that a diversified individual with the same amount of total expertise spread across multiple domains would, by definition, have less expertise in each domain when compared to a specialist in that domain.

organization-level hiring decisions relative to the optimal combinations of knowledge specializations, such as choices of types of specializations to hire and concerns of coordination costs in large teams of collaborators (Bikard *et al.*, 2015). In this paper, we theorize and provide evidence of the benefits of diversified individuals in integrating new knowledge that is outside their domains of expertise, despite these individuals' perceived disadvantage in knowledge depth; the diverse set of collaborators of such individuals are a key antecedent to their success. Therefore, our study aims to inform managers looking to refine their hiring practices particularly in firms that rely on cutting-edge research to produce value, such as those in the biotech, information technology (IT), and chemical fields.

To evaluate the role of individual-level diversification in integrating new external knowledge, we focus on researchers' propensity to engage with new knowledge as captured by new technology developments outside their current domains of knowledge. First, we focus on technology developments as embodiments of new knowledge in line with Mokyr's (2002) arguments that technology facilitates access to knowledge that is otherwise inaccessible because it did not exist or because it was costly to access. Second, we focus on researchers to be able to measure innovative output in a tangible way - academic papers. Although this paper trail of innovation primarily tracks the inventive output of individuals working in research-oriented organizations, existing work shows that, within a given field, industrial and academic researchers behave similarly in the context of knowledge creation (Sauermann and Stephan, 2013). In addition, the use of publications, rather than an alternative measure such as patents, is appropriate for addressing the proposed question since we focus on analyzing the role of individual levels of diversification in knowledge creation that occurs at all stages of innovation, not only at the later, patentable stages.

Identifying a relationship between individual levels of knowledge diversification and the propensity to engage with new technology developments is difficult because, when observing successful exploration, it is unclear if individual's level of diversification facilitates that successful engagement or if the individual strategically chose to focus on certain domains of knowledge that were promising in facilitating the engagement or if both the level of diversification and the successful engagement are driven by individual's degree of ability. Ideally, we would like to observe individuals exhibiting similar ability, but varying levels of diversity being exposed to a new and exogenous technology development that is outside their domains of knowledge, and then estimate if individuals with higher levels of diversity exhibit a higher propensity to successfully integrate the new technology.

We attempt to get close to this setting by following a two-step empirical strategy. First, we exploit the unexpected use of Microsoft Kinect in research as a new technology development in motion-sensing research. Kinect, an add-on for Xbox 360, was launched in November 2010 in the video game market but was unexpectedly embraced by the research community as a motion-sensing research technology in fields ranging from artificial intelligence, robotics, and virtual reality to paleontology, education, health care, music, cinematography, market research, and advertising.[4] We follow the interpretation of the events in Teodoridis (2018), which argues that the role of Kinect as a motion-sensing research technology was not anticipated by the research community. Second, we observe the impact of this technology on a sample of researchers where we hold ability constant but allow for varying levels of knowledge diversity. We do so by employing Coarsened Exact Matching (Iacus *et al.*, 2011a, 2011b) which allows us to compare individuals who, before the arrival of Kinect, exhibit varying levels of diversity, as observed through the breadth of their publication portfolio before Kinect's launch, but comparable levels of ability as measured by their publication age, numbers of publications, number of citations and number of coauthors (e.g., Waldinger, 2012; Azoulay *et al.*, 2013; Conti *et al.*, 2013).

To capture the role individual-level diversity plays in the propensity to engage with the new Kinect technology, we estimate the propensity of our ability-matched, diversity-varying sample of researchers to publish academic papers referencing the Kinect in the period after the launch. We utilize the publication behavior of researchers in the four years before the Kinect's launch (2007-2010) to construct our sample of ability-matched diversity-varying individuals, and their publication behavior in the four years after the launch (2011-2014) to observe the role diversification plays in the propensity to successfully engage with this new, unexpected, technology development.

We find that individuals without prior direct experience with motion-sensing – individuals for who Kinect represents a new technology development outside their domains of expertise –, but who are in the top quartile of knowledge diversification, are 3.1 times more likely to engage with Kinect in their research than individuals of similar ability and without motion-sensing experience, but who are in the

[4] See, for example, kinecthacks.com and blogs.msdn.microsoft.com/kinectforwindows for a compilation of various applications of Kinect outside the gaming industry. A Factiva search on Kinect articles returns close to 20,000 hits for the period 2011–2014.

bottom quartile of knowledge diversification. The effect is even more pronounced when focusing on highly cited output, with diversified researchers being 3.8 times more likely to produce papers in the top 10th percentile of academic papers ranked by number of citations. Importantly, the propensity to write highly cited output is not accompanied by an increase in output at the left tail of the impact distribution (less-cited output). Reassuringly, we find that diversity does not play a significant role when the new knowledge is local, namely within the group of individuals with prior expertise in motion-sensing. We interpret these results as providing strong support to our arguments that diversification at the individual level plays an important role in the propensity to explore – integrate new knowledge that is outside the individual's domains of knowledge. Finally, we show that diversified researchers have a more diverse network of collaborators than more specialized researchers. We interpret this finding as evidence of the antecedents facilitating the benefits of individual-level diversification, and a feasible mechanism for the primary effect.

Our findings contribute to the strategy literature by identifying the role of an important individual-level characteristic in successful exploration: these "jacks of all trades, masters of knowledge" are more effective at integrating new knowledge that is outside their domains of prior knowledge than their more specialized colleagues. In doing so, we offer a deeper understanding of individual characteristics that may contribute to firm success, an approach that has been proposed as a central avenue for pushing the boundaries of strategic management research (Felin and Foss, 2005; Gavetti, 2005; Teece, 2007; Foss, 2011). We also help shine a light on the role of the individual in absorptive capacity (Cohen and Levinthal, 1990), which we argue to be particularly important given the increased tendency of firms to rely on knowledge workers to drive value creation and competitive advantage (Fabrizio, 2009; Perkmann *et al.*, 2013). For example, in our dataset, a scientist at Intel whose research before Kinect had covered diverse topics such as personal activity sensors (similar to the FitBit), privacy concerns related to public WiFi, self-awareness of physical exercise, and human–robot interaction quickly engaged with this new and distant knowledge (relative to his research domains up to that point) to help create a system allowing a robot to play physical board games, an important research contribution in artificial intelligence. We further contribute to the academic literature on the economics of science and innovation by offering insights into the role of diversified individuals in knowledge creation and into how academics and other researchers pursue their careers. Young researchers, especially in academia, are frequently encouraged to be highly specialized and to focus on a very narrow field (Stephan, 2012), even though distant novel combinations of knowledge are shown to generally lead to the most impactful results (e.g., Weitzman, 1998; Katila and Ahuja, 2002; Schilling and Green, 2011; Boudreau *et al.*, 2011; Uzzi *et al.*, 2013; Chai, 2017; Lifshitz-Assaf, 2017).

Overall, our results suggest that practitioners in knowledge-based organizations would benefit from considering the potential benefits of diversified researchers. Specifically, organizations seeking to integrate distant knowledge into their knowledge creation efforts should consider hiring such diversified individuals to help increase their ability to explore the knowledge frontier more broadly. Finally, our results suggest that decision-makers in all fields where research integrating distant knowledge is important should reduce the emphasis they place on individual specialization at the expense of diversification.

II. Theory and hypotheses development

Our goal is to evaluate the role of individual-level diversification in successful exploration. We define exploration as the process of integrating new external[5] knowledge – that is outside of the individual's domains of knowledge – into successful knowledge creation. Integrating new distant knowledge is not necessarily superior to integrating new local knowledge (Kaplan and Vakili, 2015) and both approaches were found to benefit organizations. In this paper, we choose to focus on the process of integrating distant pieces of knowledge, which the literature considers important for leading to novel and impactful innovations. This has been shown to be the case in economics (e.g., Nelson and Winter, 1973; Weitzman, 1998), strategic management (Katila and Ahuja, 2002; Schilling and Green, 2011; Uzzi *et al.*, 2013), and open and user innovation (Laursen and Salter, 2006; Jeppesen and Lakhani, 2010; Boudreau *et al.*, 2011; Afuah and Tucci, 2012; Altman, Nagle, and Tushman, 2014; Boudreau et al, 2016; Lifshitz-Assaf, 2017).

[5] We use the terms "external knowledge" and "distant knowledge" interchangeably. Search distance is frequently thought of in the realm of product development and new firm-level innovations (Shane, 2000; Katila and Ahuja, 2002; Gupta, Smith, and Shalley, 2006). As Adner and Levinthal (2008) point out, "The distance of search is usually measured as the extent of departure from established routines and behavioral patterns." However, in the realm of knowledge creation and research, we can think of "established routines and behavioral patterns" as the areas in which an individual has performed research before. So, when a researcher with prior experience performing research exclusively in the field of microeconomics publishes a paper that builds on some new piece of knowledge in the field of microeconomics, they were exploiting their existing experience and utilizing local knowledge. However, when the same researcher publishes a paper that builds on some new piece of knowledge in the field of biology, and they have never used knowledge from the field of biology, they are exploring new domains of knowledge by performing a distant search and using distant knowledge.

Novel and impactful innovations are important for organizations because they can be a source of competitive advantage (Cohen and Levinthal, 1990; Murmann, 2003). Keeping in mind that knowledge production is a recombinant process (Schumpeter, 1943; Fleming, 2001), this implies that there is a competitive process in which organizations search for distant knowledge pieces and for the best combinations of such pieces with other (potentially local) knowledge pieces, and try to be the first to use them. In examining this process, scholars have investigated numerous factors that allow organizations to successfully engage in such a recombination process. One of the fundamental findings of this literature is that ability is a precursor to successful exploration, both at the individual and the organization level (e.g., Henderson, 1993; Gavetti and Levinthal, 2000; Fleming, 2001; King and Tucci, 2002; Greve, 2007; Ahuja *et al.*, 2008). However, while there is fairly extensive evidence on several mechanisms through which skilled organizations can achieve successful exploration (Greve, 2003; Fleming and Sorenson, 2004; Dothan and Lavie, 2016; Eggers and Kaul, 2018), less is known about individual-level mechanisms of successful exploration.

We contribute to this literature by drawing attention to individual-level knowledge diversification. At the organization-level, knowledge diversification was found to lead to an increased propensity of organizations to integrate new distant knowledge (Cohen and Levinthal, 1990; Katila and Ahuja, 2002). We argue that achieving organization-level knowledge diversification is an increasingly complex endeavor and one that places the role of the individual front and center in exploration attempts. The reason for this is the continuous increase in knowledge stock which creates both opportunities and challenges for recombining distant pieces of knowledge. In particular, as the burden of knowledge accumulation increases, researchers and scientists are forced to specialize in narrower domains of knowledge (Jones, 2009). This implies that individuals become increasingly likely to focus their knowledge output (producing research) and their knowledge input (consuming research) in the field they are specialized in and are therefore unlikely to be aware of and identify distant knowledge given their narrow focus in their own field (Toh, 2014). This is important because it suggests that in order to achieve organization-level diversification, organizations should ensure access to a wider pool of specialists who can collaborate to combine their narrow-specialized knowledge (Jones, 2009, 2010; Agrawal *et al*., 2016). However, this is a costly process. First, it is unclear which specializations should be kept on hand in order to achieve a combined level of diversification that is conducive to successful exploration. Second, large teams suffer from coordination costs that increase exponentially with the number of specialist collaborators (Bikard *et al.*, 2015; Teodoridis, 2018).

An alternative to individual-level specialization is an individual who chooses to respond to the burden of knowledge accumulation by embracing a wider breath of knowledge albeit at the expense of some knowledge depth (Jones, 2010). Thus, unlike their specialized colleagues, individuals who choose this diversification path benefit from a higher variety in their knowledge breadth and hence are more likely to become aware of new knowledge beyond domains they have produced research in previously. Furthermore, these individuals would be more likely to recognize fruitful combinations of knowledge pieces that include the new external knowledge. The literature on exploration argues that combining distant pieces of knowledge will also lead to more breakthroughs (Schilling and Green, 2011; Uzzi *et al.*., 2013). However, in order to achieve breakthroughs, it is important to understand which knowledge pieces to recombine. This can be difficult for specialized individuals (Toh, 2014; Chai, 2017) who rely on knowledge pieces that cover a rather narrow knowledge distance and who do not have experience working with a wider breadth of knowledge domains. Diversified individuals benefit from experience in working across different knowledge domains and hence have a higher propensity to understand what knowledge is necessary for potentially impactful recombinations. Because of this type of experience, diverse individuals are also more likely to know what knowledge combinations would lead to less impactful recombinations.

However, the shallower knowledge depth of these individuals can present a challenge in their ability to single-handedly and successful bring to fruition the identified recombination opportunities. We argue that these individuals can successfully execute on the identified recombination opportunities because they engage in diverse collaboration. It is this collaboration that allows diversified individuals to capitalize on the benefits of their knowledge breadth, and also to sustain and grow their breadth of knowledge. Indeed, individuals who have broader networks that bridge diverse groups were found to be more likely to have novel ideas that are higher quality and more innovative (Cross *et al.*, 2002; Burt, 2004). Furthermore, such individuals were found to have a higher propensity to identify unique recombination opportunities by having access to a network of collaborators characterized by diverse knowledge (Tortoriello *et al.*, 2014) and be more likely to engage in collaboration with individuals with a variety of expertise when such opportunities arise (Teodoridis, 2018).

More formally, our arguments can be summarized in three hypotheses:

H1: Individuals who have a higher degree of knowledge diversification have a higher propensity to integrate new knowledge from outside their domains of expertise than those who have a lower degree of knowledge diversification.

H2: Individuals who have a higher degree of knowledge diversification are more likely to integrate new knowledge from outside their domains of expertise in a manner that produces more high-impact output than low-impact output.

H3: All else equal, individuals with a higher degree of knowledge diversification have networks of collaborators that are more diverse than that of individuals with a lower degree of knowledge diversification, and they similarly utilize more diverse sets of co-authors to integrate new external knowledge.

Overall, our argument is that individuals who chose to respond to the burden of knowledge by embracing a wider breadth of knowledge at the expense of some depth offer a unique benefit for organizations in facilitating successful exploration – identification of new distant knowledge and of opportunities for recombinations that lead to breakthroughs. These individuals are not characterized by superior ability, but rather by a choice to invest in breadth of knowledge and more diverse collaboration, albeit at the expense of some individual-level knowledge depth. Specialists are individuals who chose the alternative strategy, that of investing in knowledge depth, and hence reduce breadth and, by extension, reduced diversity of collaborators. This is important because traditionally it is assumed that these "jack-of-all-trades" are spread too thin across domains to have enough depth to make substantial contributions to science. Our arguments highlight a process through which these individuals play a critical role in the production of knowledge by helping to successfully integrate new distant knowledge into innovation.

III. Data and empirical strategy

To test our hypotheses, we follow a three-step strategy. First, we focus on individual researchers and their innovative output as captured in academic publications. We do so not only to align with our theoretical argument at the individual researcher level but also to gain access to a reliable and measurable paper trail of innovation. Second, we focus on new technology developments as embodiments of new knowledge in line with Mokyr's (2002) arguments that technology facilitates access to knowledge that was previously inaccessible because it either did not exist or was costly to access.

Third, we recognize that, in observational data, a correlation between individual levels of knowledge diversification and the propensity to engage with new external technological developments can be driven by unobserved factors. Specifically, if we are to observe diversified individuals having a higher propensity to engage with such a technology it is unclear if these individuals' level of diversification facilitates that successful engagement, or if the individuals strategically chose to focus on certain domains of knowledge that were promising in facilitating the engagement, or other unobserved factors, such as ability, drove both the level of diversification and the successful engagement. Ideally, we would like to observe individuals of equal ability and other relevant characteristics but varying levels of diversity being exposed to a new and exogenous technology development that is outside their domains of knowledge, and then estimate if individuals with higher levels of diversity exhibit a higher propensity to successfully integrate the new technology in knowledge creation.

We attempt to get close to this ideal setting through a two-step empirical strategy. First, we exploit the unexpected use of Microsoft Kinect in research as a new technology development in motion-sensing research. Second, we observe the impact of this technology on a sample of researchers where we hold ability constant but allow for varying levels of knowledge diversity. We focus on ability as the main factor that might confound the effect of diversity in line with findings in prior literature that show that ability is a precursor for successful exploration and in line with our theory focused on evaluating the role of individual level diversity in successful exploration as a mechanism through which individual-level ability to explore manifests. At the same time, we acknowledge and discuss the possibility of other relevant unobserved factors that limit causal interpretations of our findings.

III.1. Kinect

Microsoft Kinect was launched on November 4, 2010 as an add-on to the Xbox 360 video game system. It allowed users to interact with the games through body gestures rather than using a hand-held controller, similar to the competing devices from Nintendo, the Wii Remote, and from Sony, the PlayStation Move. While both the Wii Remote and the PlayStation Move operated via gesture-recognition strategies, the Kinect was a significant leap forward, as it moved the gesture recognition from a single tracking point to full-body 3D motion capture, along with facial, gesture, and voice recognition. Therefore, Kinect is a significant advance in the knowledge frontier as a physical embodiment of new knowledge in motion-sensing, in line with Mokyr's (2002) arguments on the role of technology in capturing and providing access to the knowledge embedded in its algorithms.

Furthermore, the role of Kinect as motion-sensing research technology was not anticipated by the research community. Although Kinect was launched with great anticipation, at no time before the launch did Microsoft or any other party promote, link, or suggest using the Kinect technology outside its intended purpose as a gaming device. The starting point of the unexpected adoption of Kinect in research can be traced back to the bounty offered by AdaFruit Industries on the very day of Kinect's launch. AdaFruit, an electronics hobbyist company influential in the open hardware community, offered a bounty in search of someone who could develop and distribute an open source driver for Kinect. The driver would make it possible for researchers and enthusiasts to access the Kinect motion-sensing algorithms and use them to integrate with any project of their choice.

Hours after AdaFruit made the search for an open source driver public, Microsoft voiced its disapproval on CNET, saying that it "*does not condone the modification of its products* . . . *With Kinect, Microsoft built in numerous hardware and software safeguards designed to reduce the chances of product tampering. Microsoft will continue to make advances in these types of safeguards and work closely with law enforcement and product safety groups to keep Kinect tamper-resistant*" (Terdiman, 2010). AdaFruit did not withdraw the contest but rather tripled its bounty. Six days later, on November 10, 2010, a Spanish technology enthusiast, Hector Martin Cantero, released an open source driver and won the bounty (BBC News, 2010). As the unexpected Kinect effect in research began to rapidly unfold, Microsoft recognized the benefit of Kinect for research and, essentially, approved of its use for such purposes although this was not the original intention.[6]

III.2. Data collection

We collect data on academic publications of researchers in computer science, electrical engineering and electronics, as available through IEEE Xplore, the bibliographical database maintained by the Institute of Electrical and Electronics Engineers (IEEE). We collect data on every academic publication, early-

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[6] Researchers engaged with Kinect in a broad set of projects, like detecting human emotions, with applications ranging from security to market research, improving the ability of robots to navigate complex landscapes and sudden changes in scenery, helping individuals with impaired abilities, such as allowing the blind to hear an accurate and timely description of their surrounding environment as they attempt to walk within a room, and improving medical procedures, such as the ability to track cameras traveling within a patient during surgery, or simulating custom joint prosthetics.

access publication, and conference proceeding during a 14-year period from 2001 to 2014 (inclusive), resulting in 2,492,451 publications.

We estimate the propensity of diversified researchers to engage with Kinect based on an eight-year subset of this data, from 2007 to 2014 (1,776,125 publications). This represents four years of data before and four years after the launch of Kinect. The estimation period is substantial considering that the publication cycle is fairly short in computer science, electrical engineering and electronics, and conference proceedings are often the primary outlet for disseminating knowledge in these fields. We use the remainder of the data (2001–2006) to better estimate researchers' experience in academic research measured as number of years of active publication since 2001 (researchers' age)[7]; we use the measure as part our strategy to hold ability constant in our final estimation sample.

Next, we construct our dataset at the individual level, while taking advantage of the IEEE-curated unique author identifiers. IEEE identifies 1,391,313 unique names authoring over the period 2001–2014. We restrict our analysis to researchers who publish at least one paper in the four-year period before Kinect's launch (2007–2010), which reduces the sample to 342,872 researchers. We focus on this subset for two main reasons. First, we want to ensure that our estimations account for researchers' pre-Kinect productivity, which is important for our strategy of controlling for ability. Second, we need to observe researchers for a period before Kinect's launch to determine their degree of diversification across research areas, which is our primary variable of interest.

Within this group, we further reduce the number of authors in our dataset by eliminating outlier author IDs that have more than 50 or fewer than three publications in the four-year period before Kinect's launch. We eliminate researchers with fewer than three publications to ensure that our results on diversification are not driven by comparisons with unproductive individuals who would, mechanically, appear as researchers with a low degree of diversification. This is an important early step towards obtaining our final sample that aims to control for researchers' ability. Note that the group of researchers with fewer than three publications includes occasional authors, such as industry partners and researchers from other domains outside computer science, electrical engineering and electronics. There

[7] In an ideal scenario, we would know how many years it has been since a researcher finished their degree and became research active. However, data limitations prevent this. Therefore, we capture age via how long a researcher has been active during the complete period of time we observe in our data (i.e., starting in 2001). Although this is not perfect, it does help control for whether or not someone just started doing research at the beginning of our sample window (research age = 1), or if they have been research-active for 10+ years (research age = 10), or anything in between.

are 156,688 researchers with fewer than three publications in the four-year period before Kinect's launch. We also eliminate researchers with more than 50 publications in the four-year period to ensure that our results are not driven by outliers on the higher end of the productivity spectrum.[8] We limit the maximum number of publications to 50 to align with the anecdotal view of realistic productivity in the fields of computer science, electrical engineering and electronics. There are 3,200 researchers with over 50 publications in the four-year period before Kinect's launch, less than 1 percent of the sample. The resulting sample includes 182,984 researchers. Our results remain robust to considering lower or higher cut-off values, including using the full sample.[9]

III.3. Sample construction and empirical strategy

We are interested in identifying how individual levels of knowledge diversification influence the propensity to engage with the new Kinect technology in a sample of researchers with comparable degrees of ability at the time of the Kinect's arrival. We infer individual-level diversification from researchers' breadth of academic publications across knowledge areas. We measure engagement with Kinect by tracking researchers' publications that reference this technology after its arrival. We restrict to comparable degrees of individual-level pre-Kinect ability through a combination of estimation controls and a matching procedure.

We start by using 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 nearly 9,000 words. The first feature of the IEEE Xplore database helps us identify publications that refer to Kinect. We search the full text and metadata of all publications included in the IEEE using the keyword "Kinect."[10] Next, we label authors of at least one such identified Kinect publication as a Kinect author i.e. a researcher who successfully engaged with the new technology. All other researchers in our dataset are labeled non-Kinect authors. We also use the search feature of the IEEE database to identify researchers with

[8] In addition, this helps address concerns related to potentially inaccurate name disambiguation in the IEEE database that might incorrectly assign individuals with the same name to the same author identifier. Such an error is not uncommon in bibliographical databases and generally occurs when the names are very common. We carefully review the set of authors that might fall into this category and observe that the list indeed is composed of common names.

[9] All additional robustness results not included in the manuscript, mentioned here and thereafter, are not shown due to space constraints but are available from the authors upon request.

[10] In our robustness tests, we also use a more restrictive definition of Kinect publications whereby we search only in the metadata for the keyword "Kinect." The results remain consistent.

knowledge in motion-sensing, the knowledge domain to which Kinect belongs. This is needed to distinguish between researchers for whom the Kinect represents local knowledge and those for whom it represents knowledge outside their domains, a distinction that is key to our theoretical arguments. To do so, we repeat our search in the full text and metadata of all publications in our dataset using a set of keywords that describe motion-sensing research topics. We follow the same set of keywords in Teodoridis (2018). The keywords were carefully selected through conversations with experts and cross-referenced with IEEE's taxonomy. We focus on the four-year period before Kinect's launch (2007–2010) since we seek to identify researchers who had or did not have local domain knowledge at the time the new knowledge embodied in the Kinect device became available. We label authors with at least one such identified motion-sensing publication as a motion-sensing author, and all other as non-motion-sensing authors i.e. researchers for whom Kinect is new knowledge that is outside their prior domains of knowledge.

The second feature of the IEEE Xplore database helps us calculate an index of diversification at the individual researcher level. The IEEE taxonomy groups publications under 51 main research areas (Appendix Table A1). We focus exclusively on the IEEE set of research areas because the taxonomy provides a stable and thus tractable classification of scholars' research portfolio areas. Furthermore, our estimates are conservative using this approach since the research areas defined under the IEEE taxonomy are at the highest level in the taxonomy. To calculate the individual-level diversity index, we begin by collecting all IEEE-assigned keywords per author for the four-year period before Kinect's launch (2007–2010).[11] We only use the period before Kinect's launch since the focus is on estimating the role of individual-level diversification in the propensity to engage with new knowledge brought by the launch of Kinect. As such, the relevant individual-level characteristics are the ones observed before the arrival of Kinect. Next, we refer to the IEEE's taxonomy to identify the main research area (out of the 51 IEEE-identified areas) for each keyword. We proceed by constructing a list of main research areas per author and the corresponding keywords used in his/her publications. With these data, we construct a measure of diversification of research 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, we

[11] The IEEE taxonomy remains unchanged over this period.

measure the frequency of occurrence of each research area at the author level for publications between 2007 and 2010. Specifically, we count the total number of keywords assigned to each of the 51 IEEE top categories across all authors' papers published between 2007 and 2010. Next, we convert the count to percentages and calculate the Euclidian distance in the multidimensional space of the 51 research areas.[12] We focus on percentages rather than counts of publications because our goal is to capture variation in knowledge breadth while controlling for within variation in knowledge depth. Note that, by construction, the measure is less than or equal to 1 and is never 0. The measure is lowest 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, we construct the diversification measure to be equal to 1 minus the calculated Euclidian length. The higher the value, the higher the diversity of research areas at the individual level:

$$DiverseIndex_i = 1 - \sqrt{\sum_{k=1}^{51} CategoryPercentage_{ik}^2} \qquad (1)$$

where i is the individual researcher and $CategoryPercentage_{ik}^2$ represents the squared percentage of keywords of researcher i in each category k of the 51 high-level categories of the IEEE taxonomy.

Last, we restrict our estimations to a set of researchers who exhibit similar levels of ability before the launch of Kinect. To construct our sample, we employ the Coarsened Exact Matching (CEM) method (Iacus *et al.*, 2011a, 2011b) which pairs individuals based on specified characteristics. In our case, the goal is to pair individuals who did and did not successfully engaged with Kinect after its launch based on their observed ability in the period before the launch. This approach allows us to compare individuals of equal ability and to observe if the individuals who successfully engaged with Kinect i.e., published papers that mention Kinect, are the ones characterized by higher levels of diversity before Kinect. In our CEM procedure, we capture the ability level of individuals before Kinect through a total of nine attributes: four covariates representing the total number of publications weighted by citations[13] for each researcher, per year, for the four years before Kinect's launch (e.g., one covariate for each year from 2007–2010); four covariates representing the total number of co-authors for each

[12] 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 index alone.

[13] Specifically, we sum up citations and counts of publications, such that each publication is counted as one plus its total number of citations. Robustness checks confirm that the results hold when matching on citations and publications separately, rather than in a combined measure.

researcher, per year, for the four years before Kinect's launch (2007–2010); and the research age of each individual calculated as the number of years since the first observed publication in our large dataset going back to 2001. We also include the total number of publications weighted by citations over the entire four-year period before Kinect's launch (2007–2010), the total number of co-authors over the same period, and age squared as controls in all of our estimations to capture any remaining variation from pre-Kinect time trends and non-linear effects of age that are not captured by our CEM procedure. Furthermore, we consider a CEM procedure with weights to make use of as much of our data as possible; CEM with weights considers a richer set of matched individuals based on both exact matches of paired individuals as well as pairs where the match is constructed with weights when an exact match does not exist.[14] Our results remain robust to considering only the subset of exact matches, albeit with some loss of statistical power and hence ability to more robustly interpret coefficients due to the smaller number of observations.

Taken together, we believe these sample construction steps help us generate a dataset that comes close to the ideal setting where individuals of equal ability, but varying levels of diversity, are exposed to a new technology development. At the same time, we recognize that ability is a complex attribute to accurately capture. Although we proxy for ability using individuals' observed research output in line with prior research (e.g., Waldinger, 2012; Azoulay *et al*., 2013; Conti *et al.*, 2013) and well-known norms in research evaluation procedures such as tenure decisions, we recognize that additional attributes, such as place of graduation, history of employment, grants and other awards would have been enriching. Unfortunately, we do not have data on such additional attributes, but we believe that the citation-weighted publication portfolio is a telling proxy of individuals' ability to conduct research, one that also implicitly captures the benefits of training, intellectual capacity, and other factors that might be correlated with ability, and one that we exploit in multiple ways in our sample construction in order to incorporate as much of its richness as possible.

[14] Considering that, in research, the norms (and other factors) are such that they incentivize specialization, it is reasonable to assume that the diversified researchers who survive are, in average, more productive than their specialized colleagues. In other words, the fact that not all diversified individuals can be exact matched with specialized individuals characterized by the same level of ability, as per our definition, can be a result of the current incentive structure in science which favors specialized individuals. Thus, by employing weighted matching, we aim to make the most of the otherwise truncated observational data the nature offers i.e. less able diversified individuals, unlike their less able specialized colleagues, have a higher probability of being eliminated from science given the current set of norms and incentives.

Specifically, and first, our measure of diversity has a built-in mechanism to avoid the trap of mechanically confounding an increase in volume of publication with an increase in diversity. For example, with our measure, a researcher with a publication portfolio of 10 papers in 10 different research areas will have the same calculated index of diversification as another researcher with 20 publications, two in each of the 10 research areas. Furthermore, this approach ensures that we remain true to our theoretical focus on knowledge breadth vs depth; our focus is on researchers who have the same amount of experience and that experience is either 1) spread across multiple domains (wider breadth, shallower depth) or 2) concentrated in one domain or a narrow set of domains (narrower breadth, deeper depth). Second, and because this approach is not fault-proof for controlling for individuals' volume of publication (i.e., in our example, to reach this particular level of diversification, a researcher needs a minimum of 10 papers) we turn to the CEM procedure to ensure that the effect we measure for our diversified authors is not driven by their potentially higher average volume of publications. In addition, in our CEM procedure, we account for the impact of these publications, as measured through the number of citations received. Third, we extend our matching procedure to account for the research age of the individuals in our sample and for their number of coauthors. We match on age because the ability to produce good research has been shown to increase with experience in research (e.g., Azoulay *et al*., 2013). We match on the number of coauthors because individuals can increase their number of publications by engaging in collaboration with more individuals. Fourth, we include additional covariates in our regression estimates that control for the total number of citation-weighted publications in the period before Kinect, thus capturing any remaining variation due to e.g., time trends and for a non-linear effect of age.

Furthermore, our CEM approach is more conservative than regression estimates that include the covariates used in the matching procedure as controls alone. The reason for this stems from the CEM process that excludes from the matched sample those individuals for who a suitable exact or weighted match could not be located. This is important because it ensures that our sample includes a counterfactual for each exploring researcher included in the sample. Absent this approach, an estimation using regressions with controls alone could provide results driven by outliers in the group of exploring researchers for whom a comparable non-exploring researcher does not exist. However, such non-CEM regressions would ensure that our analysis captures all successful exploring researchers, even if the ability to draw more causal conclusions is weakened.[15] Therefore, we utilize this non-CEM approach as a robustness check and the results are consistent.

Our main estimating equation is a cross-sectional probability model with CEM weights:

$$KinectAuthor_i = I(\alpha DiverseIndex_i + \beta DiverseIndex_i * MotionSensingAuthor_i + \theta X_i + \varepsilon_i) > 0 \quad (2)$$

where i is the individual researcher and X_i is a vector of control variables that includes the indicator variable $MotionSensingAuthor_i$ equal 1 for researchers who published at least one motion-sensing paper before Kinect's launch, between 2007 and 2010, and 0 otherwise. The dependent variable is an indicator variable equal to 1 for author i who publishes at least one paper referencing Kinect during the four-year period after Kinect's launch (2011–2014), and 0 otherwise. The coefficient of interest α captures the propensity of ability-matched diversified researchers, identified as such based on their publication behavior before the launch of Kinect, to refer to Kinect in their academic publications after the launch. We interpret a positive estimated value of this coefficient as indicating that a higher level of diversification of research portfolio areas in the period before Kinect predicts a higher propensity to engage with the new knowledge brought about by the arrival of Kinect. The coefficient β captures how the effect of diversification manifests for researchers with prior local knowledge, namely for researchers with prior experience in motion-sensing, the knowledge domain of Kinect.

Additionally, in all of our estimations, we include a variable capturing the affiliation of researchers, either in the public or private sector. We collect this information based on the affiliation listed in the IEEE profile of researchers in the period before Kinect's launch. We locate and confirm the affiliation of 83,983 individuals in our sample out of 101,593 in total. We include a dummy variable in all of our estimations to account for the remaining 17,610 cases where we could not verify researchers' affiliation. We further distinguish between researchers with an industry affiliation, a total of 18,669 individuals, and academic researchers, a total of 65,314 individuals. We do so to confirm that our results are not a phenomenon that occurs only in an academic environment but is representative of research behavior in both industrial and academic settings (Sauermann and Stephan, 2013). Further, we test an interaction of an author's affiliation (academic or industry) with their diversity and find that there is no differing

[15] Given that, in research, the norms and other factors incentivize specialization, it is reasonable to assume that the diversified researchers who survive are, in average, more productive than their specialized colleagues.

impact of diversity depending on affiliation. The impact of diversity is the same for both academic and industry researchers.

Our approach is not without limitations and causal interpretations should be made with care. Specifically, and in addition to the already mentioned limitations, it is possible that other attributes that are relevant for researchers' propensity to explore remain unobserved in our empirical strategy. We believe our empirical strategy captures the most central attributes, namely those that proxy for individuals' ability, thus allowing us to get closer to drawing causal implications but not without limitations. Furthermore, it is important to note that the boundaries of our attempts to get closer to causal estimates end with our evaluation of the role of diversified individuals in exploration. We do not deny the role of certain unobservable attributes, such as curiosity or a taste for diversification or for exploration that might explain why certain individuals become diversified in the first place. In fact, we acknowledge that individuals choose to pursue certain levels of diversification or specialization. The implication is that our findings should not be used to argue for becoming a generalist. Rather, our study suggests that conditional on expressing a preference for the path of a specialist or that of a generalist, there are benefits to diversification; diversification is a choice of equally able individuals. Our goal is to show that these individuals play at least one important role in knowledge creation, that of enabling successful exploration.

III.4. Descriptive statistics

We conduct all of our main estimations on the matched sample but present descriptive statistics for the full sample as well. From the full sample of 182,984 researchers, we identify 4,705 who published at least one Kinect paper during the period 2011–2014. The remaining 178,279 researchers represent the full sample of non-Kinect authors. Table 1, Panel 1 shows that Kinect authors are generally more productive than non-Kinect authors during the four-year period before Kinect's launch (2011–2014). Specifically, Kinect authors publish more papers, receive more citations, and have more co-authors than non-Kinect authors do. Furthermore, Kinect authors also exhibit a higher level of diversification and are on average one year older than non-Kinect authors.

While these differences are most likely attributable to the larger variance in the non-Kinect author sample, they nonetheless motivate the use of the CEM methodology to ensure that our group of Kinect authors and our group of non-Kinect authors are comparable in ability as measured by productivity, number of co-authors, and age in the period before Kinect's launch. Table 2 shows the CEM balance on all covariates included in the matching. Table 1, Panel 2 shows the same descriptive statistics as Panel 1 but for the matched sample. The matching reduces the number of Kinect authors to 2,994 and the number of non-Kinect authors to 101,593. In this sample, both groups of authors have similar levels of productivity in the period before Kinect's launch. However, as preliminary support for our arguments, the difference in diversification persists.

******* Tables 1 and 2 about here *******

In our estimations, we present results using three measures of diversification. First, we show results using a continuous measure of diversification equal to our diversification index calculated using equation (1). Second, we create a dummy measure of diversification equal to 1 if the focal researcher has an index of diversification in the top half of the distribution of the diversification index of all authors, namely above 0.646, and 0 otherwise. Third, we create a set of quartile dummies of diversification where the omitted category is the bottom 25th percentile of the diversification distribution (bottom quartile). Specifically, the omitted category is composed of researchers with a diversification index below 0.596. The quartile of diversification in the bottom 25th to 50th percentiles of the distribution (second quartile) is composed of researchers with a diversification index above 0.596 but below 0.646. The quartile of diversification in the top 50th to 75th percentiles of the distribution (third quartile) is composed of researchers with a diversification index above 0.646 but below 0.687. Finally, the quartile of diversification above the top 75th percentile (top quartile) is composed of researchers with a diversification index above 0.687.

IV. Results

The results shown in Table 3 are consistent with H1, that among individuals for whom Kinect represents new knowledge that is outside of their prior domains of knowledge i.e. non-motion-sensing researchers, those with a higher degree of diversification have a higher propensity to engage with Kinect in research. Specifically, estimates of a logit model using our three measures of diversification show that the propensity to write Kinect papers increases with increased diversification (the coefficient of our diversification measures is positive and statistically significant in all models), and that the effect holds only for researchers who were not involved in motion-sensing prior to the launch of Kinect (the coefficient of our diversification measures interacted with an indicator variable capturing involvement in motion-sensing in the period before Kinect is not statistically significant, meaning the effect is close to a statistically estimated zero). We include baseline effects without interaction terms in columns 1, 3 and 5, and estimations including interaction terms in columns 2, 4 and 6. Columns 1 and 2 show estimates using our continuous measure of diversification based on researchers' publication portfolios in the four years before Kinect's launch (2007–2010), as described in equation (1). In columns 3 and 4, we replace the continuous measure of diversification with a dummy variable equal to 1 if the researcher ranks above the median level of the diversification distribution. In columns 5 and 6, we further break down this covariate to capture the effect on quartiles across the diversification distribution. The results indicate that researchers above the median level of the diversification distribution are 2.1 times more likely to write a paper using Kinect than researchers with a diversification level below the median. Furthermore, the effect increases linearly with the magnitude of the diversification index. Researchers in the second quartile are 1.5 times more likely to engage with Kinect than researchers in the bottom quartile, while researchers in the third quartile are 2.1 times more likely to do so. Researchers in the top quartile are 3.1 times more likely to include Kinect in their research than researchers in the bottom quartile. In all cases, the effect of diversity is positive only when integrating new distant knowledge. When the knowledge is local, namely for researchers with prior knowledge in motion-sensing (the knowledge domain of Kinect) diversification does not offer an advantage over specialization. This is reassuring as our theory is about the benefits of diversification in integrating new knowledge that is outside the individual's prior knowledge domains; when the knowledge is local, it is expected that generalists will not have an advantage over specialized individuals who are also familiar with that local knowledge space, which allows them to also successfully integrate the new knowledge (Shane, 2000).

Although we do not directly theorize about the direction and magnitude of these interaction terms, it is important to acknowledge the Ai and Norton (2003) critique, that the sign and magnitude of marginal effect of these terms are not necessarily the same as the sign and the magnitude of the interaction coefficients. We take several steps to demonstrate that the critique does not influence the conclusion we can draw from these estimations. First, we do not rely on interpreting marginal effects but rather interpret odds ratios, a regression output that is free from the Ai and Norton (2003) critique (e.g., Buis, 2010). Second, the Ai and Norton (2003) concern does not hold in the case of nonlinear models with binary interaction terms (Green, 2010; Kolasinski and Siegel, 2010; Puhani, 2012), like the ones in the models presented in columns 4 and 6. Third, we repeat the estimation separately, using split samples, for the groups of researchers with and without prior experience in motion-sensing (Appendix Table A2). We observe that in all models the coefficient of the diversification measures is positive and statistically significant for the subsample of non-motion-sensing researchers, while the effect diminishes in magnitude and statistical significance in the subsample of motion-sensing researchers. Fourth, our results remain robust to using a linear probability model (Appendix Table A3). Angrist and Pischke (2009) show that there is little qualitative difference between a linear probability model and a logit specification, with the advantage that the Ai and Norton (2003) critique does not apply to linear estimation models. Taken together, we argue that these steps are reassuring in our interpretation of the odds ratios of the interaction terms in our main logit specification as supporting evidence for our main effect estimations.

******* Tables 3 about here *******

Our Table 3 results persist when employing our alternative method of identifying Kinect papers, based exclusively on metadata searches (Appendix Table A4). This definition of Kinect papers is more conservative than our main specification since it excludes those academic publications that mention Kinect only in the body of the text, but not in keywords, abstract, or title. Not only do our results hold, but the magnitude persists, further strengthening the argument that, within the group of non-motion-sensing researchers, the more diversified researchers are the ones more likely to engage with Kinect in their research.

Furthermore, since we estimate our models on a cross-sectional dataset where the four publication years after Kinect are aggregated, we also want to ensure our results are not driven by any particular year, especially a year far after the Kinect launch event. As such, we repeat our main estimation on subsets of the data, one for each of the four years after Kinect's launch. Here, the dependent variable is 1 if, in a given year, the author published a Kinect paper for the first time (i.e., they had not published a Kinect paper in a previous year). We include these results in Appendix Table A5 and observe that the effect of diversification on the propensity to engage with Kinect begins immediately in 2011, the first year after Kinect's launch, and persists in following years. We present these results using the continuous measure of diversification since this approach is most conservative. Our results remain robust when considering the dummy and quartile covariates.

Next, we turn to testing our second hypothesis by restricting the dependent variable to equal 1 only for those Kinect authors who published at least one Kinect paper ranking in the top 10 percent of papers in IEEE Xplore by citation count. We identify such highly cited papers relative to the entire population of publications, not only relative to work referencing Kinect.[16] In other words, to ensure that we capture the propensity to produce high-impact research, we identify those Kinect publications that enter the ranks of the top 10 percent most-cited papers of all papers published in computer science, electrical engineering and electronics between 2011 and 2014, our four years of interest after Kinect's launch.[17] To confirm robustness to the definition of "highly cited," we also consider a top 5 percent threshold, and the results remain substantively similar.

We present results of this one-tailed test of H2 in Table 4 to allow for a more accurate interpretation of the magnitude of the coefficient and then utilize a two-tailed estimation to complete the H2 testing. As before, in columns 1 and 2 we show estimates of a logit model using the continuous measure of diversification based on researchers' publication portfolios in the four years before Kinect's launch (2007–2010). In columns 3 and 4, we replace the continuous measure of diversification with a dummy variable equal to 1 if the researcher ranks above the median of the diversification distribution, and in columns 5 and 6 we further break down this covariate to capture the effect on quartiles across the diversification distribution. All models show results that support H2, that researchers with a higher degree of knowledge diversification are more likely to produce high-impact research using new distant knowledge than those with a lower degree of diversification. As before, the sign and magnitude of the interaction terms is reassuring in that it suggests that the effect of diversification is diminished when the knowledge is local. Specifically, non-motion-sensing researchers above the median of the diversification distribution are 2.5 times more likely to produce highly impactful papers using Kinect than non-motion-sensing researchers with a diversification level below the median. Furthermore, the effect increases linearly with the magnitude of the diversification index. Non-motion-sensing researchers in the second quartile are 1.3 times more likely to produce impactful papers using Kinect than non-motion-sensing researchers in the bottom quartile, while non-motion-sensing researchers in the third quartile are 2 times

[16] We confirm that Kinect papers are no more or less likely to be highly cited than papers on other topics.

[17] As discussed above, the publication cycle in these fields is fairly short. Therefore, citations accrue more quickly than in other fields such as management and economics. Hence, a four-year post-period captures a significant portion of citations.

more likely to do so. Moreover, the result for the second quartile is not statistically significant, whereas the result for the third quartile is statistically significant, with a much tighter confidence interval that does not overlap with the lower quartile estimate. Non-motion-sensing researchers in the top quartile of the diversification distribution are 3.8 times more likely to include Kinect in their research than non-motion-sensing researchers in the bottom quartile of the diversification distribution. As before, the results persist when turning to our split sample estimation (Appendix Table A6) and to our linear probability estimation (Appendix Table A7). Furthermore, the results are robust to considering our more restrictive definition of Kinect publications, and per-year estimation models.

******* Tables 4 about here *******

In testing H2, a remaining concern is that the increased propensity to produce highly cited papers might be an artifact of simply producing more output. To address this issue, Tables 5 and 6 extend our analysis to consider the change in publication propensity at the right tail of the citation distribution relative to changes in the left tail. More specifically, in Table 5 we replace our dependent variable with an indicator variable equal to 1 if the focal researcher published more Kinect papers ranked in the top rather than in the bottom 10^{th} percentile of the citation distribution. In Table 6, we consider an alternative dependent indicator variable, equal to 1 if the focal researcher published more cited papers than non-cited papers. Given the skewed nature of citations, especially in the fields of computer science, electrical engineering and electronics most papers in our sample have zero citations. In all cases, we continue to find support for our hypothesized effects of diversification (H2). As before, the results persist when turning to our split sample estimation (Appendix Tables A8 and A9) and our linear probability estimation (Appendix Tables A10 and A11).

******* Tables 5 and 6 about here *******

Having established the role of diversification in integrating new distant knowledge, we turn to shedding some light on the process through which skilled researchers activate this diversification mechanism for exploration. Specifically, we test if diversified individuals are more likely to have a diverse network of collaborators and utilize similarly diverse collaborators to integrate new distant knowledge (H3). First, we focus on the pre-Kinect period and test if diversified individuals do indeed have a diverse network of coauthors. To provide more direct evidence, we turn to our main sample before the CEM procedure and repeat our main estimation where we replace the dependent variable with measures of collaboration diversity. We construct two such measures: 1) a measure of collaboration frequency where instead of counting distinct collaborators we count the total number of coauthors (allowing for counting the same person more than once if the focal author collaborated with them more than once) on each publication over the same time period (2007-2010), and 2) a measure of the pooled diversity of all collaborators of the focal author calculated by applying equation (1) to the total number of keywords assigned to each of the 51 IEEE top categories across all papers written by these collaborators between 2007 and 2010. As in all our estimations, we control for the number of collaborators, the productivity and age during the 2007-2010 period.

It is important to clarify why we control for the number of collaborators rather than considering it as an attribute of the network of collaborators of diverse individuals. After all, Table 1 shows that Kinect authors, on average, have a higher number of collaborators. The primary reason for this is that our theory specifically points to the diversity of the network of collaborators, not to the absolute size of the network in terms of numbers of collaborators. This is an important distinction, because, similar to our considerations in constructing the individual-level index of diversification, the larger the size of one's collaboration network, the higher the probability of diversity within that network. Thus, to ensure that we capture the role of the hypothesized diversity of the collaborator network, we need to control for size of the network.

We present these estimations in Table 7. We employ a negative binomial model for our estimations of collaboration frequency, and an OLS model for our estimation of the pooled diversity of collaborators. We chose to estimate a negative binomial model rather than a Poisson model because of concerns of overdispersion in the dependent variable. As before, column 1 shows results using our continuous measure of diversification. In column 2, we replace the continuous measure of diversification with a dummy variable equal to 1 if the researcher ranks above the median of the diversification distribution, and in column 3 we further break down this covariate to capture the effect on quartiles across the diversification distribution. The results indicate that higher degrees of diversity of collaborators are correlated with a higher degree of diversification of the focal researcher, in line with our hypothesis 3. Specifically, we find that researchers with a diversification above the median collaborate 5.5% more frequently than researchers with a diversification below the median.

Furthermore, and consistently, columns 4 to 6 shows that more diversified researchers have collaborators with a pooled diversification higher than that of less diversified individuals.

******* Table 7 about here *******

Next, we want to test if diverse individuals also use diverse networks of co-authors when working to integrate new distant knowledge. However, this is very difficult to test directly. A direct test would repeat the above estimation on the subsample of Kinect authors where the measures of collaboration are updated to reflect collaboration on the Kinect papers in the post period (2011-2014). However, if we are correct in our assertion that diverse individuals engage in diverse collaboration to generate Kinect publications, the collaborators of these diverse individuals will also appear as if they ramp up their collaboration effort. In other words, in our measures of collaboration we cannot isolate diverse individuals' strategy from that of other researchers if the strategy of diverse individuals is to work with these other researchers, which may result in double-counting. Unlike in the tests of H1 and H2 where there is an appropriate comparison group, less diverse authors on Kinect papers are not an appropriate comparison group for diverse authors on Kinect papers when it comes to evaluating collaboration on Kinect papers, because these researchers constitute precisely the pooled diverse network of collaborators we hypothesize about.

To address this issue, we construct a new dataset at the paper level (rather than author level) that characterizes the set of coauthors for each Kinect paper. While this approach is not suited to capture individual level patterns of collaboration, it does allow us to directly observe the type of collaborators that diverse individuals utilize when engaging in working with the new knowledge. Our dataset is comprised of 4,478 Kinect papers published between 2011 and 2014. Out of these, 2,469 papers (set A) have at least one author with diversity above the median and without local knowledge i.e., diverse non-motion-sensing researcher. The remaining 2,009 papers (set B) either have an author with local knowledge (i.e. motion-sensing researcher) but no author that is diverse without local knowledge, i.e., our individuals of interest in Set A (1,004 papers) or have only specialized individuals without local knowledge who work with individuals who are new to the IEEE set of publications (i.e., had no IEEE publications prior to 2011; 1,005 papers). It is important to note that these new individuals can either be newly minted researchers in computer science, electrical engineering and electronics, or established researchers from other domains of science who, only after Kinect, publish in computer science, electrical engineering and electronics i.e., researchers from other domains of knowledge for whom we do not have the data to evaluate their expertise and diversity, but who show signs of diversification by engaging in publication in a new domain of knowledge.

We start by comparing the set of Kinect papers authored by diverse non-motion-sensing individuals who engage in integrating new distant knowledge (set A) with the set of Kinect papers without such an author type (set B). We find that the average pooled diversification of authors is higher in set A than in set B (0.737 vs. 0.689) and the difference is strongly statistically significant with a p-value of 0.000. These differences are consistent with our hypothesis (H3) that individuals with a higher degree of diversification utilize more diverse sets of collaborators than more specialized individuals when integrating new distant knowledge.

To gain a deeper insight into the process through which these diverse individuals integrate distant knowledge, we next break set A into two subsets, with (948 papers, set A.1) and without (1,521 papers, set A.2) collaborators that have local knowledge. It is interesting in itself, that while nearly 40% of diverse non-motion-sensing individuals choose to collaborate with a motion-sensing researcher, over 60% choose to not collaborate with someone with expertise in the field of the new knowledge. Further, we find that when working with motion-sensing researchers (set A.1), diverse researchers rely less on other non-motion-sensing researchers or on new researchers that had no publications in IEEE in the pre-period. More specifically, we find that the average number of other authors who are specialists in a field other than motion-sensing is slightly lower in set A.1 than in set A.2 (1.614 vs. 1.765) but the difference is strongly statistically significant with a p-value of 0.000. Also, we find that the average number of new authors is lower in set A.1 than in set A.2 (0.808 vs. 1.045) and the difference is strongly statistically significant with a p-value of 0.000. As mentioned above, the set of new authors can either be new minted researchers in computer science, electrical engineering and electronics, or established researchers from other domains of science who, only after Kinect, publish in computer science, electrical engineering and electronics. Although, in our data, we cannot directly distinguish between the two types, we infer that new authors who publish other IEEE papers after 2011 are more likely newly minted researchers in computer science, electrical engineering and electronics, and those who publish only the Kinect paper are most likely researchers from other domains of science. Based on this criterion, we observe that diverse non-motion-sensing researchers collaborate less with researchers from other domains (who are new as per the above definition) when they have motion-sensing collaborators. More specifically, we find that the average number of such new authors is lower in set A.1 than in set A.2 (0.384 vs. 0.573) and the difference is strongly statistically significant with a p-value of 0.000. This indicates that not only are diverse non-motion-sensing researchers working with a more diverse team based on publications within IEEE, but they are also working with individuals whose experience lies in fields outside of IEEE and hence have an even broader set of expertise. The difference in average number of collaborators who are new researchers in computer science, electrical engineering and electronics (e.g. doctoral students, post-docs, etc.) is similarly lower (0.424 in set A.1 and 0.473 in set A.2), but the confidence intervals overlap and the difference is weakly statistically significant with a p-value of 0.114. These differences provide more nuance to the type of expertise coauthors of diverse non-motion-sensing individuals possess. They also capture additional nuance that we cannot capture with our measure of pooled diversification since we do not observe a pre-Kinect set of publications for these new-to-IEEE authors, which would be necessary to calculate their diversity index.

Taken together, these tests show that individuals with a higher degree of knowledge diversification have networks of collaborators that are more diverse than that of individuals with a lower degree of knowledge diversification. Further, they suggest that when new distant knowledge becomes available, these diverse individuals build upon their prior experience and engage in more diverse collaboration teams that either 1) exploit the expertise of individuals with local knowledge combined with that of individuals from other domains or 2) rely even more heavily on individuals who bring outside expertise.

V. Discussion and Conclusion

We examine the role of individual knowledge diversification in integrating new distant knowledge - that is outside of the individual's domains of knowledge. Our study is motivated by the central, yet understudied, role of the individual in influencing the innovation performance of organizations. We focus on exploration, an endeavor that was shown to contribute to the competitive advantage of organizations (Cohen and Levinthal, 1990; Barth *et al.*, 2017) and find evidence consistent with our hypotheses that diversified individuals have a higher propensity to engage with new distant knowledge and do so in a manner that produces highly impactful output. Furthermore, we show that the more diversified collaborator networks of these individuals play an important role in their successful exploration endeavors.

To shed light on the role of individual-level diversification as a mechanism through which skilled individuals engage in successful exploration, our empirical strategy attempts to get close to an ideal setting where equally skilled individuals with varying levels of diversity are exposed to the arrival of a new knowledge that is outside their domains of expertise. To do so, we construct a sample where we evaluate the propensity of ability-matched diversity-varying researchers in computer science, electrical engineering and electronics to publish academic papers referencing Kinect, a technology that arrived unexpectedly in motion-sensing research. We focus on the Kinect technology developments as embodiments of new knowledge in line with Mokyr's (2002) arguments that technology facilitates access to knowledge that is otherwise inaccessible because it did not exist or because it was costly to access.

While our empirical strategy offers certain benefits that allow us to get closer to causal interpretations of the findings, the approach is not without limitations. First, there might be theoretically-relevant, empirically-unobserved attributes that we cannot capture in our analysis. By following prior research and norms in academic evaluations to proxy for researchers' ability using their observed research output, number of collaborators and research age we believe we have captured the most relevant factors. Second, our analysis is conditional on observed selection into different levels of diversification, and thus is not informing on the antecedents of diversification such as different levels of curiosity or taste for diversification. Third, we study researchers engaging with a particular type of new knowledge in a particular area of science – computer science, electrical engineering and electronics. It is possible that at least some of the observed magnitudes reflect idiosyncratic aspects of this setting. Our hope is that our study provides enough compelling evidence to shine a light on the role of individual-level diversification and to start a conversation that encourages scholars to gain access to more comprehensive or granular data in order to refine and extend our findings.

Our study contributes to the literature examining how organizations can best use their limited resources to integrate new external knowledge in impactful and productive ways, which is often referred to as absorptive capacity (Cohen and Levinthal, 1989, 1990). While there are many studies on the topic (e.g., Lane *et al.*, 2001; Lenox and King, 2004; Pacheco-de-Almeida and Zemsky, 2007; Eggers and Kaplan, 2009; Escribano *et al.*, 2009), most focus on firm-level characteristics, despite Cohen and Levinthal's (1990) argument that the concept of absorptive capacity occurs not only at the organization level but also at the individual level. After all, individuals are at the root of the knowledge creation process, and it has been posited that diverse knowledge in an individual allows for learning and problem solving that leads to innovation (Simon, 1985). Further, our results provide a deeper understanding of what individual characteristics allow for more successful exploration through distant search, the benefits of which are long-term and lasting (March, 1991) and allow organizations to succeed during rapid technological shifts (Tushman and Anderson, 1986; Christensen, 1992; Cohen and Levinthal, 1994; Christensen *et al.*, 1998).

More broadly, the study offers insights into the career paths of researchers and scientists. Although institutional norms in both firms and research organizations frequently demonstrate preferences for specialization, our results show that individuals with high levels of knowledge diversity play an important role in pushing the knowledge frontier forward in critical ways. Furthermore, this role might grow in importance with increased knowledge accumulation and divisions into even narrower knowledge areas. In aggregate, our study contributes to calls for more individual-level perspectives to better understand the micro-foundations of strategy (Felin and Foss, 2005; Gavetti, 2005; Teece, 2007; Foss, 2011) by drawing attention to the possibility that rather than being a "jack of all trades and master of none," individuals with high levels of knowledge diversity might play an important role as a "jack of all trades and master of knowledge."

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Table 1. Descriptive statistics

	Panel 1 Unmatched sample					Panel 2 Matched sample (CEM)				
Variable	**Observations**	**Min**	**Max**	**Mean**	**St. Dev**	**Observations**	**Min**	**Max**	**Mean**	**St. Dev**
Diversification measure										
All authors	182,984	0	0.804	0.645	0.074	104,587	0	0.793	0.646	0.072
Kinect authors	4,705	0	0.798	0.688	0.058	2,994	0	0.790	0.674	0.060
Non-Kinect authors	178,279	0	0.804	0.644	0.074	101,593	0	0.793	0.645	0.073
Number of publications 2007–2010										
All authors	182,984	3	50	8.493	7.587	104,587	3	50	7.318	4.926
Kinect authors	4,705	3	50	13.091	10.934	2,994	3	50	7.398	4.953
Non-Kinect authors	178,279	3	50	8.371	7.441	101,593	3	44	7.316	4.925
Number of co-authors 2007–2010										
All authors	182,984	3	1073	41.356	48.709	104,587	3	511	29.855	22.253
Kinect authors	4,705	4	662	58.956	60.652	2,994	4	509	29.742	22.324
Non-Kinect authors	178,279	3	1073	40.892	48.268	101,593	3	511	29.859	22.251
Number of citations 2007–2010										
All authors	182,984	0	1612	17.952	39.462	104,587	0	198	11.992	16.876
Kinect authors	4,705	0	900	33.735	57.518	2,994	0	179	12.082	16.691
Non-Kinect authors	178,279	0	1612	17.536	38.785	101,593	0	198	11.989	16.881
Number of citations-weighted pubs										
All authors	182,984	3	1662	26.445	43.813	104,587	3	217	19.310	19.186
Kinect authors	4,705	3	932	46.826	63.566	2,994	3	217	19.480	19.127
Non-Kinect authors	178,279	3	1662	25.907	43.039	101,593	3	206	19.187	19.187
Author age 2001–2010										
All authors	182,984	1	10	6.572	2.808	104,587	1	10	6.973	2.699
Kinect authors	4,705	1	10	7.621	2.556	2,994	1	10	7.005	2.709
Non-Kinect authors	178,279	1	10	6.545	2.809	101,593	1	10	6.972	2.699

Table 2. Coarsened Exact Matching balance

CEM balance	Full Sample			Matched Sample (CEM)		
	Kinect authors	Non-Kinect authors	t-stat	Kinect authors	Non-Kinect authors	t-stat
Citation-weighted publication count 2007	15.324	8.015	23.48	6.137	6.131	0.03
Citation-weighted publication count 2008	15.035	8.305	23.13	5.802	5.773	0.17
Citation-weighted publication count 2009	8.694	5.038	26.02	3.788	3.732	0.64
Citation-weighted publication count 2010	7.773	4.549	28.91	3.753	3.669	1.09
Co-author count 2007	13.726	9.537	14.73	6.369	6.490	0.72
Co-author count 2008	14.336	10.319	16.50	7.193	7.328	0.78
Co-author count 2009	14.638	9.999	22.12	7.478	7.458	0.14
Co-author count 2010	16.255	11.036	23.62	8.702	8.583	0.73
Total citation-weighted publication count 2007–2010	46.826	25.907	32.42	19.480	19.305	0.49
Total co-author count 2007–2010	58.956	40.892	25.15	29.742	29.859	0.28
Author age	7.621	6.545	25.99	7.005	6.972	0.64
Observations	4,705	178,279		2,994	101,593	

Table 3. Diversification and the propensity to write Kinect papers

DV = 1 if author published at least one Kinect paper and 0 otherwise; Matched sample						
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**1.060/0.059 (0.004)**	**1.071/0.068 (0.004)**	**1.922/0.653 (0.047)**	**2.091/0.738 (0.050)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**1.511/0.413 (0.078)**	**1.514/0.415 (0.084)**
Diversification before Kinect in 50th to 75th percentiles					**2.105/0.744 (0.074)**	**2.134/0.758 (0.080)**
Diversification before Kinect in 75th to 100th percentiles					**2.777/1.021 (0.072)**	**3.146/1.146 (0.076)**
Motion-sensing author	5.967/1.786 (0.065)	281.26/5.639 (0.763)	6.208/1.826 (0.065)	9.586/2.260 (0.118)	6.006/1.793 (0.065)	10.376/2.339 (0.204)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.945/-0.056 (0.011)		0.584/-0.538 (0.140)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						0.840/-0.174 (0.251)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.731/-0.313 (0.239)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.451/-0.797 (0.224)
Total citation-weighted publications before (2007–2010)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)
Total co-authors before (2007–2010)	0.993/-0.007 (0.002)	0.993/-0.007 (0.002)	0.995/-0.005 (0.002)	0.995/-0.005 (0.002)	0.994/-0.006 (0.002)	0.994/-0.006 (0.002)
Author age	0.956/-0.045 (0.066)	0.940/-0.062 (0.065)	0.961/-0.040 (0.066)	0.957/-0.044 (0.065)	0.956/-0.045 (0.066)	0.946/-0.056 (0.066)
Author age sq	1.002/0.002 (0.004)	1.003/0.003 (0.003)	1.002/0.002 (0.004)	1.002/0.002 (0.004)	1.002/0.002 (0.004)	1.003/0.003 (0.004)
Unable to obtain affiliation (flag)	0.275/-1.293 (0.090)	0.273/-1.299 (0.090)	0.270/-1.312 (0.089)	0.269/-1.314 (0.089)	0.272/-1.303 (0.090)	0.270/-1.309 (0.089)
University affiliation (flag)	1.093/0.089 (0.055)	1.094/0.089 (0.055)	1.101/0.097 (0.055)	1.101/0.096 (0.055)	1.093/0.089 (0.055)	1.094/0.090 (0.055)
LL	-12,488.84	-12,467.13	-12,527.51	-12,516.69	-12,494.90	-12,474.94
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table 4. Diversification and the propensity to write top-cited Kinect papers

DV = 1 if author published at least one Kinect paper in the top 10th percentile of the citation distribution of all papers published between 2011 and 2014, and 0 otherwise; Matched sample						
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**1.066/0.064 (0.012)**	**1.077/0.074 (0.014)**	**2.320/0.841 (0.130)**	**2.480/0.909 (0.142)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**1.257/0.229 (0.227)**	**1.330/0.285 (0.249)**
Diversification before Kinect in 50th to 75th percentiles					**2.091/0.738 (0.204)**	**2.025/0.706 (0.230)**
Diversification before Kinect in 75th to 100th percentiles					**3.166/1.152 (0.196)**	**3.768/1.326 (0.213)**
Motion-sensing author	6.077/1.805 (0.131)	166.64/5.116 (1.502)	6.290/1.839 (0.128)	8.528/2.143 (0.299)	5.985/1.789 (0.131)	11.222/2.418 (0.468)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.953/-0.048 (0.022)		0.696/-0.362 (0.329)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						0.629/-0.464 (0.605)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.848/-0.164 (0.525)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.404/-0.907 (0.497)
Total citation-weighted publications before (2007–2010)	1.013/0.013 (0.003)	1.013/0.013 (0.003)	1.012/0.012 (0.003)	1.012/0.012 (0.003)	1.013/0.013 (0.003)	1.013/0.013 (0.002)
Total co-authors before (2007–2010)	0.987/-0.013 (0.004)	0.988/-0.013 (0.004)	0.989/-0.011 (0.003)	0.989/-0.011 (0.003)	0.987/-0.013 (0.003)	0.987/-0.013 (0.003)
Author age	0.774/-0.257 (0.164)	0.761/-0.272 (0.164)	0.768/-0.265 (0.164)	0.766/-0.266 (0.164)	0.764/-0.269 (0.165)	0.752/-0.286 (0.165)
Author age sq	1.012/0.012 (0.009)	1.013/0.013 (0.009)	1.013/0.012 (0.009)	1.013/0.013 (0.009)	1.013/0.013 (0.009)	1.014/0.013 (0.009)
Unable to obtain affiliation (flag)	0.227/-1.484 (0.249)	0.225/-1.492 (0.249)	0.225/-1.492 (0.249)	0.224/-1.496 (0.249)	0.226/-1.489 (0.250)	0.222/-1.503 (0.250)
University affiliation (flag)	1.005/0.005 (0.133)	1.004/0.004 (0.133)	1.012/0.012 (0.133)	1.010/0.010 (0.133)	1.001/0.001 (0.133)	0.999/-0.001 (0.132)
LL	-2,348.54	-2,346.21	-2,347.46	-2,346.81	-2,341.52	-2,336.93
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table 5. Diversification and propensity to write more top than bottom cited Kinect papers

DV = 1 if author published more Kinect papers in the top than the bottom 10th percentile of the citation distribution of all papers published between 2011 and 2014, and 0 otherwise; Matched sample

	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**1.077/0.075 (0.014)**	**1.082/0.079 (0.016)**	**2.458/0.899 (0.163)**	**2.600/0.955 (0.177)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**0.966/-0.034 (0.286)**	**0.962/-0.039 (0.309)**
Diversification before Kinect in 50th to 75th percentiles					**1.642/0.496 (0.252)**	**1.644/0.497 (0.274)**
Diversification before Kinect in 75th to 100th percentiles					**3.135/1.142 (0.234)**	**3.441/1.236 (0.248)**
Motion-sensing author	4.779/1.564 (0.171)	25.426/3.236 (2.236)	5.030/1.615 (0.168)	6.835/1.922 (0.403)	4.683/1.544 (0.172)	7.471/2.011 (0.631)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.976/-0.024 (0.032)		0.698/-0.360 (0.439)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						0.874/-0.134 (0.819)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.798/-0.226 (0.724)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.535/-0.625 (0.665)
Total citation-weighted publications before (2007–2010)	1.013/0.013 (0.003)	1.013/0.013 (0.003)	1.012/0.012 (0.003)	1.012/0.012 (0.003)	1.013/0.013 (0.003)	1.014/0.013 (0.003)
Total co-authors before (2007–2010)	0.985/-0.016 (0.004)	0.985/-0.015 (0.004)	0.987/-0.013 (0.004)	0.987/-0.013 (0.004)	0.985/-0.016 (0.004)	0.985/-0.015 (0.004)
Author age	0.712/-0.340 (0.230)	0.707/-0.347 (0.230)	0.712/-0.341 (0.230)	0.710/-0.343 (0.230)	0.706/-0.348 (0.231)	0.699/-0.357 (0.230)
Author age sq	1.018/0.018 (0.012)	1.018/0.018 (0.012)	1.018/0.018 (0.012)	1.018/0.018 (0.012)	1.018/0.018 (0.012)	1.019/0.019 (0.012)
Unable to obtain affiliation (flag)	0.278/-1.280 (0.282)	0.277/-1.284 (0.282)	0.275/-1.293 (0.282)	0.273/-1.297 (0.282)	0.275/-1.293 (0.282)	0.272/-1.301 (0.282)
University affiliation (flag)	0.866/-0.144 (0.163)	0.866/-0.144 (0.162)	0.875/-0.134 (0.162)	0.873/-0.135 (0.162)	0.861/-0.149 (0.163)	0.859/-0.151 (0.162)
LL	-1,549.68	-1,549.39	-1,551.67	-1,551.33	-1,543.88	-1,542.85
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table 6. Diversification and propensity to write more cited Kinect papers than Kinect papers without citations

DV = 1 if author published more cited Kinect papers than Kinect paper with zero citations, and 0 otherwise; Matched sample	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**1.071/0.069 (0.009)**	**1.081/0.078 (0.010)**	**2.209/0.793 (0.097)**	**2.360/0.859 (0.106)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**1.445/0.368 (0.171)**	**1.411/0.344 (0.185)**
Diversification before Kinect in 50th to 75th percentiles					**2.148/0.765 (0.158)**	**2.017/0.702 (0.173)**
Diversification before Kinect in 75th to 100th percentiles					**3.306/1.196 (0.151)**	**3.696/1.307 (0.160)**
Motion-sensing author	5.546/1.713 (0.107)	140.94/4.948 (1.275)	5.799/1.758 (0.105)	8.050/2.086 (0.228)	5.517/1.708 (0.107)	7.650/2.035 (0.416)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.954/-0.047 (0.019)		0.674/-0.394 (0.255)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						1.013/0.013 (0.500)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						1.094/0.090 (0.459)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.550/-0.598 (0.439)
Total citation-weighted publications before (2007–2010)	1.007/0.007 (0.002)	1.007/0.007 (0.002)	1.006/0.006 (0.002)	1.006/0.006 (0.002)	1.007/0.007 (0.002)	1.007/0.007 (0.002)
Total co-authors before (2007–2010)	0.984/-0.016 (0.003)	0.985/-0.015 (0.003)	0.987/-0.013 (0.003)	0.987/-0.013 (0.003)	0.985/-0.015 (0.003)	0.985/-0.015 (0.003)
Author age	0.809/-0.213 (0.127)	0.797/-0.227 (0.126)	0.809/-0.212 (0.126)	0.807/-0.214 (0.126)	0.805/-0.217 (0.127)	0.796/-0.229 (0.127)
Author age sq	1.011/0.011 (0.007)	1.012/0.011 (0.007)	1.011/0.011 (0.007)	1.011/0.011 (0.007)	1.011/0.011 (0.007)	1.011/0.012 (0.008)
Unable to obtain affiliation (flag)	0.309/-1.178 (0.170)	0.306/-1.183 (0.170)	0.303/-1.194 (0.170)	0.302/-1.197 (0.170)	0.305/-1.187 (0.170)	0.303/-1.194 (0.170)
University affiliation (flag)	0.919/-0.084 (0.103)	0.920/-0.084 (0.102)	0.928/-0.075 (0.103)	0.927/-0.076 (0.102)	0.918/-0.085 (0.103)	0.919/-0.084 (0.103)
LL	-3,609.61	-3,606.30	-3,617.65	-3,616.40	-3,605.74	-3,599.81
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table 7. Broadness and diversity of author networks before Kinect

	Sample without matching					
	DV=Collaboration frequency			DV=Combined coauthor diversification		
	Continuous	Above median	Quartiles	Continuous	Above median	Quartiles
Diversification before Kinect (2007–2010)	**1.390/0.329** **(0.014)**	**1.055/0.054** **(0.002)**		**0.281** **(0.002)**	**0.035** **(0.000)**	
Diversification before Kinect in bottom 25th to 50th percentiles			**1.004/0.004** **(0.003)**			**0.023** **(0.000)**
Diversification before Kinect in 50th to 75th percentiles			**1.026/0.026** **(0.003)**			**0.038** **(0.000)**
Diversification before Kinect in 75th to 100th percentiles			**1.082/0.079** **(0.003)**			**0.055** **(0.000)**
Motion-sensing author	1.038/0.037 (0.004)	1.038/0.038 (0.004)	1.032/0.032 (0.004)	0.005 (0.000)	0.008 (0.000)	0.006 (0.000)
Total citation-weighted publications before (2007–2010)	0.999/-0.000 (0.000)	0.999/-0.000 (0.000)	0.999/-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Total co-authors before (2007–2010)	1.015/0.014 (0.000)	1.015/0.014 (0.000)	1.015/0.014 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Author age	1.124/0.117 (0.003)	1.124/0.117 (0.003)	1.123/0.116 (0.003)	-0.001 (0.001)	-0.001 (0.000)	-0.001 (0.001)
Author age sq	0.995/-0.005 (0.000)	0.995/-0.005 (0.000)	0.995/-0.005 (0.000)	0.001 (0.000)	0.001 (0.000)	0.000 (0.000)
Unable to obtain affiliation (flag)	1.361/0.307 (0.004)	1.361/0.308 (0.004)	1.361/0.308 (0.004)	0.006 (0.000)	0.006 (0.000)	0.006 (0.000)
University affiliation (flag)	0.952/-0.050 (0.004)	0.952/-0.050 (0.004)	0.951/-0.051 (0.004)	0.002 (0.000)	0.002 (0.000)	0.002 (0.000)
LL	652,118.51	652,065.22	651,876.43			
R-squared				0.202	0.202	0.202
Observations	176,233	176,233	176,233	175,350	175,350	175,350

The data is a cross-section at the author level. The models in the first three columns are negative binomial. The models in the last three columns are OLS. All models are estimated with robust standard errors. Estimations in the negative binomial models are presented as Incidence Ratio/Coefficient (st. error).

Appendix

Table A1: IEEE Taxonomy

	Research Area	IEEE code
1	Aerospace and electronic systems	104
2	Antennas and propagation	218
3	Broadcast technology	600
4	Circuits and systems	803
5	Communications technology	916
6	Components, packaging, and manufacturing technology	926
7	Computational and artificial intelligence	937
8	Computers and information processing	992
9	Consumer electronics	1019
10	Control systems	1059
11	Dielectrics and electrical insulation	1288
12	Education	1457
13	Electromagnetic compatibility and interference	1527
14	Electron devices	1566
15	Electronic design automation and methodology	1584
16	Engineering - general	1691
17	Engineering in medicine and biology	1695
18	Engineering management	1697
19	Geoscience and remote sensing	2085
20	IEEE organizational topics	2400
21	Imaging	2543
22	Industrial electronics	2587
23	Industry applications	2625
24	Information theory	2652
25	Instrumentation and measurement	2699
26	Intelligent transportation systems	2892
27	Lasers and electrooptics	3110
28	Magnetics	3202
29	Materials, elements, and compounds	3206
30	Mathematics	3397
31	Microwave theory and techniques	3397
32	Nanotechnology	3599
33	Nuclear and plasma sciences	3731
34	Oceanic engineering and marine technology	3771
35	Organizational communication	4410
36	Power electronics	4279
37	Power engineering and energy	4283
38	Product safety engineering	4394
39	Reliability	4695
40	Resonance	4729
41	Robotics and automation	4787
42	Science - general	4856
43	Sensors	4938
44	Signal processing	4981
45	Social implications of technology	5053
46	Solid state circuits	5113
47	Superconductivity	5346
48	Systems engineering and theory	5435
49	Systems, man, and cybernetics	5438
50	Ultrasonics, ferroelectrics, and frequency control	5773
51	Vehicular and wireless technologies	5849

Table A2: Diversification and the propensity to write Kinect papers - split sample

	DV = 1 if author published at least one Kinect paper and 0 otherwise; Matched sample					
	Non-motion-sensing authors			Motion-sensing authors		
	Continuous	Above median dummy	Quartiles	Continuous	Above median dummy	Quartiles
Diversification before Kinect (2007–2010)	**1.070/0.068 (0.004)**	**2.081/0.733 (0.050)**		**1.013/0.012 (0.011)**	**1.260/0.231 (0.134)**	
Diversification before Kinect in bottom 25th to 50th percentiles			**1.511/0.413 (0.084)**			**1.269/0.238 (0.236)**
Diversification before Kinect in 50th to 75th percentiles			**2.130/0.756 (0.080)**			**1.568/0.450 (0.225)**
Diversification before Kinect in 75th to 100th percentiles			**3.139/1.144 (0.075)**			**1.437/0.363 (0.217)**
Total citation-weighted publications before (2007–2010)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)	0.999/-0.001 (0.002)	0.999/-0.001 (0.005)	0.999/-0.001 (0.005)	0.999/-0.001 (0.005)
Total co-authors before (2007–2010)	0.992/-0.008 (0.002)	0.995/-0.005 (0.002)	0.993/-0.007 (0.002)	0.996/-0.004 (0.005)	0.996/-0.004 (0.005)	0.996/-0.004 (0.005)
Author age	0.933/-0.070 (0.068)	0.953/-0.049 (0.068)	0.941/-0.061 (0.068)	0.911/-0.093 (0.181)	0.900/-0.105 (0.182)	0.903/-0.102 (0.183)
Author age sq	1.004/0.004 (0.004)	1.003/0.003 (0.004)	1.004/0.004 (0.004)	1.002/0.002 (0.010)	1.003/0.003 (0.010)	1.003/0.003 (0.010)
Unable to obtain affiliation (flag)	0.288/-1.245 (0.097)	0.282/-1.265 (0.097)	0.284/-1.260 (0.097)	0.225/-1.490 (0.220)	0.225/-1.490 (0.220)	0.226/-1.487 (0.220)
University affiliation (flag)	1.130/0.122 (0.058)	1.142/0.133 (0.058)	1.130/0.123 (0.058)	0.984/-0.016 (0.145)	0.984/-0.016 (0.146)	0.988/-0.013 (0.145)
LL	-10,437.81	-10,488.17	-10,448.16	-2,022.91	-2,021.70	-2,020.60
Observations	100,807	100,807	100,807	3,780	3,780	3,780

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table A3: Diversification and the propensity to write Kinect papers - linear probability model

	DV = 1 if author published at least one Kinect paper and 0 otherwise; Matched sample					
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**0.113** **(0.007)**	**0.114** **(0.007)**	**0.015** **(0.001)**	**0.015** **(0.001)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**0.006** **(0.001)**	**0.006** **(0.001)**
Diversification before Kinect in 50th to 75th percentiles					**0.014** **(0.001)**	**0.012** **(0.001)**
Diversification before Kinect in 75th to 100th percentiles					**0.023** **(0.002)**	**0.023** **(0.001)**
Motion-sensing author	0.111 (0.007)	0.123 (0.081)	0.112 (0.007)	0.106 (0.012)	0.111 (0.007)	0.090 (0.018)
Diversification before Kinect (2007–2010) x Motion-sensing author		-0.017 (0.121)		0.008 (0.015)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						0.024 (0.024)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.039 (0.024)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.016 (0.021)
Total citation-weighted publications before (2007–2010)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Total co-authors before (2007–2010)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Author age	-0.001 (0.001)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)
Author age sq	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Unable to obtain affiliation (flag)	-0.021 (0.002)	-0.021 (0.002)	-0.021 (0.002)	-0.021 (0.002)	-0.021 (0.002)	-0.021 (0.002)
University affiliation (flag)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
R-squared	0.164	0.164	0.164	0.164	0.164	0.164
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are OLS with robust standard errors. Estimations presented as Coefficient (st. error).

Table A4. Diversification and the propensity to write Kinect papers – Kinect paper defined using metadata keywords only

DV = 1 if author published at least one Kinect paper and 0 otherwise; Matched sample						
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**1.058/0.056 (0.006)**	**1.067/0.065 (0.006)**	**1.911/0.647 (0.073)**	**2.027/0.707 (0.078)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**1.760/0.565 (0.128)**	**1.769/0.570 (0.138)**
Diversification before Kinect in 50th to 75th percentiles					**2.404/0.877 (0.121)**	**2.288/0.828 (0.132)**
Diversification before Kinect in 75th to 100th percentiles					**2.982/1.093 (0.117)**	**3.359/1.212 (0.125)**
Motion-sensing author	5.620/1.726 (0.085)	191.2/5.253 (0.888)	5.829/1.763 (0.084)	7.895/2.066 (0.172)	5.653/1.732 (0.084)	8.332/2.120 (0.326)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.950/-0.052 (0.013)		0.692/-0.369 (0.195)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						0.854/-0.158 (0.384)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						1.007/0.007 (0.360)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.514/-0.665 (0.346)
Total citation-weighted publications before (2007–2010)	0.996/-0.004 (0.003)	0.996/-0.004 (0.003)	0.996/-0.004 (0.003)	0.996/-0.004 (0.003)	0.996/-0.004 (0.003)	0.996/-0.004 (0.003)
Total co-authors before (2007–2010)	0.994/-0.006 (0.002)	0.994/-0.006 (0.002)	0.996/-0.004 (0.002)	0.996/-0.004 (0.002)	0.995/-0.005 (0.002)	0.995/-0.005 (0.002)
Author age	0.916/-0.087 (0.099)	0.902/-0.103 (0.098)	0.919/-0.084 (0.098)	0.917/-0.087 (0.098)	0.914/-0.090 (0.099)	0.903/-0.102 (0.099)
Author age sq	1.005/0.005 (0.005)	1.006/0.006 (0.005)	1.005/0.005 (0.005)	1.005/0.005 (0.005)	1.005/0.005 (0.005)	1.006/0.006 (0.005)
Unable to obtain affiliation (flag)	0.236/-1.444 (0.152)	0.235/-1.448 (0.152)	0.232/-1.462 (0.005)	0.231/-1.463 (0.152)	0.234/-1.452 (0.152)	0.233/-1.458 (0.152)
University affiliation (flag)	1.184/0.169 (0.082)	1.185/0.170 (0.081)	1.193/0.176 (0.082)	1.192/0.176 (0.082)	1.185/0.170 (0.082)	1.188/0.172 (0.081)
LL	-5,800.23	-5,792.83	-5,811.79	-5,809.82	-5,797.22	-5,787.64
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table A5: Diversification and the propensity to write Kinect papers - year by year analysis

DV = 1 if author published at least one Kinect paper for the first time in the respective year, and 0 otherwise Matched sample				
	2011	**2012**	**2013**	**2014**
Diversification before Kinect (2007–2010)	**1.071/0.069** **(0.012)**	**1.075/0.073** **(0.009)**	**1.068/0.066** **(0.007)**	**1.067/0.065** **(0.007)**
Motion-sensing author	686.9/6.532 (1.791)	260.8/5.564 (1.061)	227.7/5.428 (1.025)	180.8/5.197 (1.188)
Diversification before Kinect (2007–2010) x Motion-sensing author	0.939/-0.063 (0.026)	0.949/-0.052 (0.016)	0.946/-0.056 (0.015)	0.946/-0.056 (0.018)
Total citation-weighted publications before (2007–2010)	0.997/-0.003 (0.004)	1.002/0.002 (0.003)	0.999/-0.001 (0.002)	0.998/-0.002 (0.003)
Total co-authors before (2007–2010)	0.994/-0.006 (0.004)	0.989/-0.011 (0.003)	0.995/-0.005 (0.002)	0.995/-0.005 (0.003)
Author age	0.741/-0.300 (0.164)	0.907/-0.098 (0.116)	0.959/-0.042 (0.101)	1.075/0.072 (0.117)
Author age sq	1.013/0.013 (0.009)	1.005/0.005 (0.006)	1.002/0.002 (0.005)	0.996/-0.004 (0.006)
Unable to obtain affiliation (flag)	0.244/-1.409 (0.256)	0.220/-1.514 (0.185)	0.277/-1.285 (0.140)	0.344/-1.067 (0.153)
University affiliation (flag)	0.956/-0.014 (0.139)	1.216/0.195 (0.097)	1.033/0.033 (0.082)	1.102/0.097 (0.095)
LL	-2,078.58	-4,335.92	-5,560.91	-4,398.73
Observations	104,587	104,248	103,437	102,377

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error)

Table A6. Diversification and the propensity to write top-cited Kinect papers - split sample

DV = 1 if author published at least one Kinect paper in the top 10th percentile of the citation distribution of all papers published between 2011 and 2014, and 0 otherwise; Matched sample						
	Non-motion-sensing authors			Motion-sensing authors		
	Continuous	Above median dummy	Quartiles	Continuous	Above median dummy	Quartiles
Diversification before Kinect (2007–2010)	**1.077/0.074 (0.014)**	**2.458/0.899 (0.142)**		**1.029/0.028 (0.019)**	**1.961/0.673 (0.318)**	
Diversification before Kinect in bottom 25th to 50th percentiles			**1.320/0.278 (0.249)**			**0.778/-0.250 (0.572)**
Diversification before Kinect in 50th to 75th percentiles			**2.017/0.702 (0.229)**			**1.819/0.598 (0.477)**
Diversification before Kinect in 75th to 100th percentiles			**3.738/1.319 (0.213)**			**1.583/0.459 (0.463)**
Total citation-weighted publications before (2007–2010)	1.011/0.011 (0.003)	1.011/0.011 (0.003)	1.012/0.012 (0.003)	1.018/0.018 (0.006)	1.019/0.019 (0.006)	1.020/0.019 (0.006)
Total co-authors before (2007–2010)	0.985/-0.015 (0.004)	0.987/-0.013 (0.004)	0.984/-0.016 (0.004)	0.993/-0.007 (0.007)	0.992/-0.008 (0.007)	0.993/-0.007 (0.007)
Author age	0.952/-0.049 (0.190)	0.966/-0.035 (0.190)	0.952/-0.049 (0.191)	0.391/-0.939 (0.333)	0.373/-0.986 (0.334)	0.368/-0.999 (0.334)
Author age sq	1.003/0.003 (0.010)	1.003/0.003 (0.010)	1.003/0.003 (0.010)	1.043/0.042 (0.018)	1.045/0.044 (0.018)	1.046/0.045 (0.018)
Unable to obtain affiliation (flag)	0.232/-1.460 (0.285)	0.229/-1.474 (0.285)	0.228/-1.478 (0.285)	0.204/-1.590 (0.520)	0.209/-1.565 (0.520)	0.205/-1.583 (0.525)
University affiliation (flag)	1.053/0.051 (0.153)	1.059/0.058 (0.153)	1.041/0.041 (0.153)	0.920/-0.083 (0.272)	0.934/-0.068 (0.274)	0.937/-0.063 (0.274)
LL	-1,843.55	-1,845.37	-1,835.95	-493.31	-491.22	-490.95
Observations	100,807	100,807	100,807	3,780	3,780	3,780

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table A7. Diversification and the propensity to write top-cited Kinect papers – linear probability model

DV = 1 if author published at least one Kinect paper in the top 10th percentile of the citation distribution of all papers published between 2011 and 2014, and 0 otherwise; Matched sample						
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**0.015**	**0.014**	**0.002**	**0.002**		
	(0.002)	**(0.002)**	**(0.000)**	**(0.000)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**0.000**	**0.000**
					(0.000)	**(0.000)**
Diversification before Kinect in 50th to 75th percentiles					**0.002**	**0.001**
					(0.000)	**(0.000)**
Diversification before Kinect in 75th to 100th percentiles					**0.003**	**0.003**
					(0.001)	**(0.000)**
Motion-sensing author	0.017	0.003	0.017	0.012	0.017	0.013
	(0.002)	(0.020)	(0.002)	(0.004)	(0.002)	(0.006)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.021		0.006		
		(0.030)		(0.004)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						-0.002
						(0.008)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.009
						(0.008)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.004
						(0.007)
Total citation-weighted publications before (2007–2010)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total co-authors before (2007–2010)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Author age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Author age sq	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unable to obtain affiliation (flag)	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
University affiliation (flag)	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LL	0.060	0.060	0.060	0.060	0.060	0.060
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are OLS with robust standard errors. Estimations presented as Coefficient (st. error).

Table A8. Diversification and propensity to write more top than bottom cited Kinect papers - split sample

DV = 1 if author published more Kinect papers in the top than the bottom 10th percentile of the citation distribution of all papers published between 2011 and 2014, and 0 otherwise; Matched sample						
	Non-motion-sensing authors			Motion-sensing authors		
	Continuous	Above median dummy	Quartiles	Continuous	Above median dummy	Quartiles
Diversification before Kinect (2007–2010)	**1.079/0.076 (0.016)**	**2.539/0.932 (0.176)**		**1.072/0.069 (0.030)**	**2.109/0.746 (0.419)**	
Diversification before Kinect in bottom 25th to 50th percentiles			**0.946/-0.055 (0.309)**			**0.815/-0.204 (0.773)**
Diversification before Kinect in 50th to 75th percentiles			**1.604/0.472 (0.274)**			**1.411/0.344 (0.684)**
Diversification before Kinect in 75th to 100th percentiles			**3.319/1.200 (0.247)**			**2.109/0.746 (0.650)**
Total citation-weighted publications before (2007–2010)	1.013/0.012 (0.003)	1.012/0.012 (0.003)	1.013/0.013 (0.003)	1.016/0.016 (0.008)	1.016/0.016 (0.008)	1.016/0.016 (0.008)
Total co-authors before (2007–2010)	0.984/-0.016 (0.005)	0.986/-0.014 (0.005)	0.983/-0.017 (0.005)	0.988/-0.012 (0.009)	0.991/-0.009 (0.008)	0.990/-0.010 (0.008)
Author age	0.935/-0.067 (0.266)	0.949/-0.053 (0.267)	0.935/-0.068 (0.268)	0.309/-1.198 (0.459)	0.290/-1.238 (0.461)	0.291/1.234 (0.458)
Author age sq	1.006/0.006 (0.014)	1.005/0.005 (0.014)	1.006/0.006 (0.014)	1.057/0.056 (0.024)	1.060/0.058 (0.024)	1.060/0.058 (0.024)
Unable to obtain affiliation (flag)	0.270/-1.311 (0.322)	0.266/-1.324 (0.322)	0.264/-1.333 (0.321)	0.299/-1.207 (0.178)	0.294/-1.223 (0.595)	0.299/-1.207 (0.600)
University affiliation (flag)	0.910/-0.095 (0.185)	0.916/-0.0.88 (0.185)	0.898/-0.108 (0.185)	0.794/-0.231 (0.346)	0.808/-0.213 (0.347)	0.804/-0.218 (0.350)
LL	-1,250.99	-1,252.12	-1,244.42	-290.59	-291.27	-290.55
Observations	100,807	100,807	100,807	3,780	3,780	3,780

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table A9. Diversification and propensity to write more cited Kinect papers than Kinect papers without citations - split sample

	DV = 1 if author published more cited Kinect papers than Kinect paper with zero citations, and 0 otherwise; Matched sample					
	Non-motion-sensing authors			Motion-sensing authors		
	Continuous	Above median dummy	Quartiles	Continuous	Above median dummy	Quartiles
Diversification before Kinect (2007–2010)	**1.080/0.077** **(0.010)**	**2.330/0.846** **(0.105)**		**1.037/0.036** **(0.017)**	**1.729/0.548** **(0.240)**	
Diversification before Kinect in bottom 25th to 50th percentiles			**1.404/0.340** **(0.185)**			**1.416/0.348** **(0.471)**
Diversification before Kinect in 50th to 75th percentiles			**2.004/0.695** **(0.173)**			**2.295/0.831** **(0.427)**
Diversification before Kinect in 75th to 100th percentiles			**3.650/1.295** **(0.159)**			**2.151/0.766** **(0.414)**
Total citation-weighted publications before (2007–2010)	1.006/0.006 (0.003)	1.005/0.005 (0.003)	1.006/0.006 (0.003)	1.010/0.010 (0.006)	1.010/0.010 (0.006)	1.010/0.010 (0.006)
Total co-authors before (2007–2010)	0.985/-0.016 (0.003)	0.987/-0.013 (0.003)	0.985/-0.015 (0.003)	0.985/-0.015 (0.006)	0.986/-0.014 (0.006)	0.986/-0.014 (0.006)
Author age	0.860/-0.151 (0.140)	0.877/-0131 (0.140)	0.864/-0.146 (0.141)	0.582/-0.541 (0.291)	0.564/-0.572 (0.292)	0.569/-0.564 (0.293)
Author age sq	1.008/0.008 (0.008)	1.007/0.008 (0.008)	1.008/0.008 (0.008)	1.025/0.025 (0.015)	1.027/0.026 (0.016)	1.026/0.026 (0.016)
Unable to obtain affiliation (flag)	0.303/-1.195 (0.191)	0.297/-1.214 (0.191)	0.297/-1.212 (0.191)	0.323/-1.131 (0.367)	0.323/-1.130 (0.367)	0.325/-1.123 (0.368)
University affiliation (flag)	0.921/-0.082 (0.115)	0.931/-0.072 (0.115)	0.917/-0.087 (0.115)	0.942/-0.059 (0.225)	0.951/-0.050 (0.225)	0.952/-0.904 (1.279)
LL	-2,914.12	-2,924.49	-2,908.83	-688.92	-688.03	-687.66
Observations	100,807	100,807	100,807	3,780	3,780	3,780

The data is a cross-section at the author level. All models are logit with robust standard errors. Estimations presented as Odds Ratio/Coefficient (st. error).

Table A10. Diversification and propensity to write more top than bottom cited Kinect papers – linear probability model

DV = 1 if author published more Kinect papers in the top than the bottom 10th percentile of the citation distribution of all papers published between 2011 and 2014, and 0 otherwise; Matched sample						
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**0.011** **(0.002)**	**0.010** **(0.002)**	**0.002** **(0.000)**	**0.001** **(0.000)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**-0.000** **(0.000)**	**-0.000** **(0.000)**
Diversification before Kinect in 50th to 75th percentiles					**0.001** **(0.000)**	**0.001** **(0.000)**
Diversification before Kinect in 75th to 100th percentiles					**0.002** **(0.000)**	**0.002** **(0.000)**
Motion-sensing author	0.008 (0.001)	-0.012 (0.014)	0.008 (0.001)	0.006 (0.002)	0.008 (0.001)	0.006 (0.004)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.030 (0.021)		0.003 (0.003)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						-0.001 (0.005)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.002 (0.005)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.003 (0.005)
Total citation-weighted publications before (2007–2010)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Total co-authors before (2007–2010)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Author age	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)
Author age sq	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Unable to obtain affiliation (flag)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)
University affiliation (flag)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)
LL	0.047	0.047	0.047	0.047	0.047	0.047
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are OLS with robust standard errors. Estimations presented as Coefficient (st. error).

Table A11. Diversification and propensity to write more cited Kinect papers than Kinect papers without citations – linear probability model

DV = 1 if author published more cited Kinect papers than Kinect paper with zero citations, and 0 otherwise; Matched sample						
	Continuous diversification		Above median dummy diversification		Quartiles of diversification	
Diversification before Kinect (2007–2010)	**0.027**	**0.027**	**0.004**	**0.004**		
	(0.003)	**(0.003)**	**(0.000)**	**(0.000)**		
Diversification before Kinect in bottom 25th to 50th percentiles					**0.001**	**0.001**
					(0.001)	**(0.001)**
Diversification before Kinect in 50th to 75th percentiles					**0.003**	**0.002**
					(0.001)	**(0.001)**
Diversification before Kinect in 75th to 100th percentiles					**0.006**	**0.006**
					(0.001)	**(0.001)**
Motion-sensing author	0.025	0.008	0.025	0.020	0.024	0.015
	(0.003)	(0.027)	(0.003)	(0.005)	(0.003)	(0.007)
Diversification before Kinect (2007–2010) x Motion-sensing author		0.025		0.007		
		(0.040)		(0.006)		
Diversification before Kinect in bottom 25th to 50th percentiles x Motion-sensing author						0.007
						(0.009)
Diversification before Kinect in 50th to 75th percentiles x Motion-sensing author						0.017
						(0.009)
Diversification before Kinect in 75th to 100th percentiles x Motion-sensing author						0.009
						(0.008)
Total citation-weighted publications before (2007–2010)	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Total co-authors before (2007–2010)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Author age	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Author age sq	0.000	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unable to obtain affiliation (flag)	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
University affiliation (flag)	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LL	0.077	0.077	0.077	0.077	0.077	0.077
Observations	104,587	104,587	104,587	104,587	104,587	104,587

The data is a cross-section at the author level. All models are OLS with robust standard errors. Estimations presented as Coefficient (st. error).