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# Does greater diversification increase individual productivity? The moderating effect of attention allocation

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**Abstract**

Despite the consensus on the “double-edged sword” effect of diversification (of knowledge and collaborators) on individual performance, little is known about the contingencies that affect the relationship between diversification and individual productivity. Drawing on the attention-based view, we theorize the moderating role of attention allocation to advance our understanding of the curvilinear relationship between diversification (of knowledge and collaborators) and individual productivity. Relevant hypotheses are tested using a longitudinal sample of more than 25,000 individual scholars. Our analysis reveals that although a moderate level of knowledge diversification is optimal for research productivity when the level of cognitive attention is low, a high level of knowledge diversification is more beneficial for research productivity when the level of cognitive attention is high. Furthermore, we show that a moderate level of collaborator diversification, coupled with a high level of collaborative attention, is optimal for research productivity. Our study provides important implications for highly skilled and creative individuals.

***Keywords:*** attention; cognition; collaboration; diversification; research productivity

## 1. Introduction

Over the past few decades, the advent of information and communication technology has reduced information asymmetry and communication problems and enhanced global connectivity (Chai and Menon, 2019; Crescenzi et al., 2016; Wagner and Leydesdorff, 2005). On this basis, it became common practice for many individual academic researchers to diversify their scientific knowledge (i.e. knowledge diversification) and collaborators (i.e. collaborator diversification) while engaging in research production (Franzoni and Rossi-Lamastra, 2017; Leahey et al. 2017; Nagle and Teodoridis, 2019). Yet, it is still challenging for individual researchers to decide how to diversify their portfolio of research disciplines and their network of coauthors. In this respect, researchers are burdened by screening, processing, and acting upon such overabundance of knowledge and collaborators, as they need to decide how to allocate their attention across different knowledge (i.e. cognitive attention) and collaborators (i.e. collaborative attention) (Simon, 1947).

Prior studies suggest that overdependence on a wider set of knowledge and collaborators hinders highly skilled individuals, who work with a high level of ambiguity and uncertainty, from allocating a proper level of attention (Belkhouja and Yoon, 2018; Dahlander et al., 2016; Hoegl and Proserpio, 2004; Laursen and Salter, 2014). Consistent with these studies, cultivation of diversification (i.e., broadening exposure to a variety of knowledge and collaborators) has an opportunity cost, as it takes attention away from other knowledge and collaborators that are familiar and closer to the focal individual (Dahlander et al., 2016). Despite the scarcity of attention (Oscasio, 1997, 2011) and its importance in effectively managing such a dilemma (Chai and Menon, 2019; Iyer and Katona, 2015; Van Knippenberg et al., 2015), we have limited understanding of the act of attention allocation as a mechanism through which individuals mitigate knowledge and collaboration overload (Rhee and Leonardi, 2018; Fiske and Taylor, 2013).

Motivated by these issues, this paper theorizes and examines the moderating effects of attention allocation on the relationship between diversification and individual research productivity. The notion of attention encompasses "noticing, encoding, interpreting and focusing of time and effort" (Ocasio, 1997, p. 189). Through the act of attention allocation, individuals focus on some information and tie in their memory while ignoring others (Ocasio, 1997, p. 189), which can be manifested in two ways (Rhee and Leonardi, 2018). First, focused (meaning high-level) attention involves more deliberate processing of information from a particular body of knowledge or tie than others (Kahneman, 1973, p. 112), enabling selective information processing (Rhee and Leonardi, 2018). Second, divided (meaning low-level) attention occurs when a person doles out symmetrical attentional resources across all available information and collaborators (Kahneman, 1973, p. 136).

The moderating effects of attention allocation on the diversification-individual research productivity relationship are tested in the context of academic research production, which enables us to isolate the impact of diversification on individual research productivity for the following reasons. First, academic researchers or scholars are generally given more freedom to pursue research topics that they find appealing, whereas researchers employed in the industry tend to be more focused on supporting their employer's business agenda and have less freedom to work on disparate topics (Bush, 1945). Second, researchers who work in academia are more likely to diversify their research and collaborators, on average, than their colleagues employed in the private sector (Nagle and Teodoridis, 2019). Subsequently, using a longitudinal sample of more than 25,000 academic researchers who have published articles in business and management journals, our analysis shows that, a moderate level of knowledge diversification is optimal for research productivity when cognitive attention is low (i.e., divided). In contrast, the higher the knowledge diversification, the greater the research productivity will be when cognitive attention is high (i.e., focused). Moreover, we show that a moderate level of collaborator diversification, coupled with a high level of (i.e., focused) collaborative attention, is an optimal strategy for research productivity.

Our contributions are twofold. First, we contribute to a growing body of micro-foundations research on individuals, in particular (Bogers et al., 2018; Felin and Foss, 2005; Gavetti, 2005; Teece, 2007; Foss, 2011), by developing a theoretical framework based on the attention-based view (Ocasio, 1997, 2011). Specifically, our framework focuses on theorizing contingencies that attention allocation can create with respect to the well-known curvilinear relationship between diversification and individual performance (Belkhouja and Yoon, 2018; Dahlander et al., 2016; Mannucci and Yong, 2018). Given the dilemma between diversification and attention, our exploration of the moderating effects of attention allocation is theoretically valuable (Ocasio, 1997). This, in turn, enables us to develop a more nuanced understanding of the relationship between diversification and the performance outcomes of highly skilled individuals.

Second, the emphasis on research excellence around the world (Leung, 2007; Smith et al., 2011; Rebora and Turri, 2013) has increased interest in effective management and monitoring of research performance (Chambers and Miller, 2014; Chen et al., 2019; Hoekman et al., 2010; Rafols et al., 2012; Van Leeuwen et al., 2001). Although a growing number of studies focus on explaining the drivers of the publication count (Leahey et al., 2017; Ryazanova and McNamara, 2016) and the citation count (Belkhouja and Yoon, 2018; Foster et al., 2015; Leahey et al., 2017), many higher education institutions gauge the importance of productivity considering both quantity and quality (Groot and García-Valderrama, 2006; Jauch et al., 1978; Moed, 2008). To our knowledge, no previous work examining the diversification-individual research performance relationship has combined the measures of both the *quantity* and the *quality* of research outputs. In this way, our study advances understanding of the determinants of the research productivity.

## 2. Theoretical Foundation and Hypotheses Development

### *2.1. Diversification and Research Productivity*

Two competing theories explain the effect of diversification on individual performance. First, combinatorial search literature drawing on information-processing theory suggests that the value of diversification comes from the increased range of knowledge, skills, and perspectives available to individuals (Pelled et al., 1999; Williams and O'Reilly, 1998), which can be valuable drivers of individual performance (Amabile, 1996). As such, diversification of knowledge and collaborators can enhance the problem-solving capability, creativity, innovation, and adaptability of individuals (Dahlin et al., 2005).

Second, according to the categorization theory (Pfeffer, 1983), diversification provokes unfavorable treatment of other categories (the "mine-theirs" distinction), as human beings appreciate familiar attributes. This theory postulates that the diversification-performance relationship is negative because diversification requires the coordination of several categories and induces difficulty in integrating new categories (Hannan and Freeman, 1989; Hsu, 2006; Jehn et al., 1999; Mannix and Neale, 2005; Reagans and McEvily 2003; Williams and O'Reilly, 1998).

Drawing on these two contrasting theoretical arguments, recent studies have documented a curvilinear relationship between diversification and individual performance, which is measured in terms of awards and nominations (Mannucci and Yong, 2018), the citation count (Belkhouja and Yoon, 2018), and patent quantity and quality (Dahlander et al., 2016). Building upon these contemporary studies, we subsequently argue that diversification of knowledge and collaborators has both benefits and pitfalls for individuals' research productivity.

First, knowledge diversification refers to the extent to which an individual scholar has been exposed to various knowledge domains, which is the number of disciplines covered as reflected in their past journal publication record (Belkhouja and Yoon, 2018; Nelson and Winter, 1982; Nooteboom, 2009). Exposure to different knowledge domains increases the novelty and quality of research outputs (Rodan and Galunic, 2004) to be published in journals, thereby enhancing individual research productivity. Every time authors work in a new field; they have the potential to introduce new ideas, perspectives, theories, or constructs to that field (Seibert et al., 2017). In addition, individuals who have experience in multiple domains can draw on knowledge that is no longer novel in one field but might have the potential to make significant new contributions to a different field with only minimal adaptation, thereby enhancing their research productivity. For example, Moody (2004) surmised that many sociologists publish in multiple subfields and adjacent fields of sociology because of the applicability of shared theoretical frameworks and quantitative methods across them. Furthermore, covering various disciplines can produce more stability in the expected output than working in a single discipline. For instance, individuals can reduce the risk of failure by diversifying into multiple research disciplines (Franzoni and Rossi-Lamastra, 2017).

Although reliance on a variety of knowledge is a way of improving novelty and introducing an obsolete work with minimal changes to a new discipline (Moody, 2004; Uzzi et al., 2013), diversifying knowledge can be challenging, as it entails higher coordination costs and requires more effort than specializing (Franzoni and Rossi-Lamastra, 2017). As such, scholars with an extremely high level of knowledge diversification can encounter difficulties due to the steep learning curve and integration of unfamiliar knowledge. Furthermore, diversification can compromise one's scholarly identity because research evaluators might perceive the submitted work as lacking focus in a way that could eventually depress their research productivity (Åstebro and Thompson, 2011; Leahey et al., 2017; Rafols et al., 2012). In sum, knowledge diversification can result in diminishing returns to research productivity and could even become detrimental after a certain point, as it makes absorption and integration of new knowledge more difficult (Lee et al., 2015).

Second, collaborator diversification refers to the number of different coauthors with whom an individual scholar has collaborated (Lee et al., 2015; Seibert et al., 2017). Each coauthor in a focal scholar's network is unique in the sense that he/she brings a distinct set of ideas, skills, and resources to a research project (Uzzi and Spiro 2005; Burt, 2004). Individuals can benefit from collaborator diversification by increasing the number of papers on which they work within a given period and subsequently increasing overall productivity (Beaver and Rosen, 1979; Lavie and Drori, 2012). Besides, collaborator diversification can provide significant benefits for individual scholars, as it pools more and diverse resources and expertise materializing the benefits from complementarity (Singh and Fleming, 2010). Moreover, focal scholars can take advantage of an extensive co-authorship network by receiving constructive feedback on their ongoing work, which can enhance the quality of their research and, therefore, their research productivity.

Nevertheless, as collaborator diversification increases, the effort required to coordinate various resources efficiently as well as to ensure proper communication increases significantly (Landry and Amara, 1998). Besides, having a large network of coauthors can induce the focal scholar to spend time doing or returning favors for their past and current coauthors, such as providing friendly reviews or formal reviews for journals. This implies that scholars who are interested in boosting research productivity by expanding their network of coauthors have additional commitments that can impede their own research productivity. Furthermore, an increase in collaborator diversification implies greater effort at understanding and integrating different coauthors' knowledge to find the best combination and complementarity for each research project (Katz and Martin, 1997). Although these concerns can be manageable up to a point, individuals with highly collaborator diversification might struggle to use their coauthors network effectively for raising their research productivity (Belkhouja and Yoon, 2018; Dahlander et al., 2016; Lee et al., 2015).

Taken together, we form our baseline hypothesis (BH):

**BH:** Diversification (of knowledge and collaborators) and scholars' research productivity have an inverted U-shaped relationship.

### *2.2. Moderating Role of Attention Allocation*

Although prior studies have hypothesized a curvilinear relationship between diversification and individual performance (Belkhouja and Yoon, 2018; Dahlander et al., 2016; Mannucci and Yong, 2018), they have not considered its contingencies due to attention allocation. Our study is original in this sense because explaining the moderating role of attention allocation adds novel nuances to the debate between advocates of diversification and its detractors. Subsequently, the overarching reasoning in our predictions relies on the attention-based view (Ocasio, 1997, 2011), whose roots go back to William James (1890). The original view explains that the *selective processing* of information is required for individuals to cope with complex and uncertain environments. For this reason, our analysis focuses on the structural distribution of attention (Ocasio, 1997).

Attention allocation involves the focusing of time and effort on a stimulus (James, 1890; Kahneman, 1973). Academic researchers and scholars, like other individuals, have limited attention when searching for novel ideas and collaborators to produce scientific outputs (Foster et al., 2015). To advance our understanding of scholars' attention allocation strategy with respect to knowledge (i.e., cognitive attention) and collaborators (i.e., collaborative attention), we theorize (a) the moderating effect of cognitive attention allocation on the knowledge diversification-research productivity relationship and (b) the moderating effect of collaborative attention allocation on the collaborator diversification-research productivity relationship.

In a cognitive realm, the allocation of attention reflects how scholars distribute their attention across research domains, which has implications on the costs of knowledge search and integration with the increase in a knowledge base. In this sense, if we consider two scholars exposed to the same number of research domains, one would distribute attention more or less equally across a number of different research domains (divided attention), while the other would distribute attention unevenly by focusing on only a few familiar domains (focused attention) (Rhee and Leonardi, 2018, p. 1194). In other words, as cognitive attention increases, individuals focus more on their core knowledge domains (repeated publications) than other peripheral knowledge domains (occasional publications) and vice versa.

At a lower level of knowledge diversification, the benefits of knowledge diversification on research productivity are accentuated when cognitive attention increases. Focused cognitive attention (i.e., high-level attention allocation) allows individuals to use the same knowledge elements repeatedly in a selective manner to publish in their core research domains, reduces the likelihood of errors, increases efficiency, and consequently saves time and efforts (Haas et al., 2015). Individuals who draw on the same knowledge domain or academic discipline can be more productive because repetitive and in-depth experience in a few core fields confers benefits from efficiency (no extra learning cost) and legitimacy (Leahey, 2007). Because each academic discipline and its journals have their own preference in terms of writing styles, theory, and methods, scholars who have repetitive publication experience in few core disciplines can be more productive by being more efficient due to their familiarity with implicit publication requirements (Seibert et al., 2017; Leahey, 2007). At the same time, knowledge diversification under focused cognitive attention can also provide occasional access to new or peripheral knowledge, leading to the generation of novel ideas. In other words, at a lower level of knowledge diversification, occasional exposure to peripheral research domains can help individuals to apply new ideas and methods to their core research easily and vice versa. In this sense, the benefits from occasional experience in less familiar or peripheral academic disciplines can outweigh the search and integration costs under a relatively small knowledge base. Thus, a lower level of knowledge diversification, coupled with focused cognitive attention, strengthens the benefits of knowledge application and recombination for research productivity.

Nevertheless, at a higher level of knowledge diversification, the pitfalls of knowledge diversification on research productivity are accentuated when cognitive attention increases. Focused cognitive attention can create difficulties for individuals with a higher level of knowledge diversification in switching between core and peripheral disciplinary research projects (Leahey et al., 2017). This configuration increases knowledge search and integration costs without necessarily generating complementarities or synergies to boost one's research productivity (McBee and Leahey, 2016). Furthermore, given the coordination challenges under a high level of knowledge diversification, individuals with focused attention can miss opportunities for fostering interaction between their core research domains and peripheral research domains. As such, interaction can increase research originality by sparking individuals' creativity, and individuals who overlook interaction opportunities can experience stagnation in their research production. Thus, a higher level of knowledge diversification, coupled with focused cognitive attention, can induce inefficient and ineffective learning, magnifying the costs of knowledge search and integration in research productivity (Olson and Olson, 2000).

Collectively, these arguments suggest that both the benefits and the costs of knowledge diversification are greater, respectively, when cognitive attention increases (i.e., is more focused). In other words, the inverted U-shaped curve between knowledge diversification and research productivity (as stated in the BH) can be expected to become steeper when cognitive attention is greater. Hence, we formally predict that:

**Hypothesis 1 (H1):** Cognitive attention moderates the curvilinear relationship between knowledge diversification and scholars' research productivity, such that when cognitive attention increases, the initial positive effect of knowledge diversification as well as its latter negative effect on research productivity are accentuated.

Next, allocation of collaborative attention reflects how scholars distribute their attention across their coauthors, which has implications for the cost of coordinating communications and employing resources with an increase in structural arrangements (Bidault and Hildebrand, 2014; Landry and Amara, 1998). We can consider two scholars with the same number of coauthors: the first distributes attention relatively equally across coauthors (divided attention), while the second distributes attention to coauthors unevenly by collaborating mainly with just a few of them (focused attention) (Rhee and Leonardi, 2018, p. 1194). In other words, as collaborative attention increases, individuals focus more on strong ties (repeated collaboration) than weak ties (occasional collaboration) in their co-authorship network, and vice versa.

At a lower level of collaborator diversification, the benefits of collaborator diversification on research productivity are accentuated when collaborative attention increases. Increasing (i.e., more focused) collaborative attention is characterized by saliency in one's network with strong ties, which entails a good fit between coauthors over weak ties. By increasing collaborative attention, individuals obtain more benefits from familiarity with their main coauthors. For instance, the presence of mutual trust and support and frequent reciprocal interactions (e.g., friendly reviews) makes communication and creative processes smoother, thereby enhancing one's research productivity (Colquitt et al., 2007; Gonzalez-Brambila et al., 2013, Wang, 2016). Trust built through coauthorship (Bercovitz and Feldman, 2011) also serves as a channel for constructive feedback, which significantly enhances the probability of research to be published in journals and subsequently increases research productivity (Wang, 2016). Concurrently, focused collaborative attention does not prevent individuals from taking advantage of their network's weak ties, even though occasional and new collaborations entail higher coordination costs. These occasional opportunities offer access to new information and resources beyond those available in their own close circles of coauthors, leading to the generation of new research projects (Burt, 1992; Granovetter, 1973; Uzzi, 1996; Uzzi and Spiro, 2005, Wang, 2016). Likewise, adding new coauthors in a relatively small network with focused collaborative attention does not take much attention and time from their main coauthors with strong ties. Furthermore, this configuration can foster high-quality and complementary interactions between their principal and occasional coauthors, thereby creating new research projects. Thus, a lower level of collaborator diversification, coupled with focused collaborative attention, strengthens the benefits of reciprocity and access to new resources for research productivity.

Nonetheless, at a higher level of collaborator diversification, the pitfalls of collaborator diversification on research productivity are accentuated when collaborative attention increases. Focused collaborative attention can cause individuals with an already extensive coauthor network configuration to experience more coordination challenges in switching between main collaborators and occasional collaborators, which reduces the overall benefits of collaborator diversification on research productivity. In particular, this configuration can make individuals miss some opportunities for collaboration with new coauthors and/or strengthen ties with existing occasional coauthors. This means that realizing synergy between strong and weak ties for research productivity is challenging under such a configuration. In addition, occasional collaborations, in general, entail low trust, familiarity, and interaction (Crescenzi et al., 2016). That being said, a lack of attention to weak ties can cause a focal scholar to experience difficulty in managing potential conflicts and friction with occasional collaborators (Lovelace et al., 2001), which is harmful to the overall research production process. Thus, a higher level of collaborator diversification, coupled with focused collaborative attention, can reduce the synergy and complementarity between strong ties and weak ties in a coauthorship network and cause conflict with occasional collaborators, which can magnify the pitfalls of coordination for research productivity.

Taken together, these arguments suggest that both the costs and benefits of collaborator diversification are greater when collaborative attention increases (i.e., focused attention). In other words, the inverted U-shaped curve demonstrating the relationship between collaborator diversification and research productivity (as stated in the BH) can be expected to become steeper when collaborative attention is greater. Hence, we formally predict that:

**Hypothesis 2 (H2):** Collaborative attention moderates the curvilinear relationship between collaborator diversification and scholars' research productivity, such that when collaborative attention increases, the initial positive effect of collaborator diversification as well as its latter negative effect on research productivity are accentuated.

## 3. Methods

### *3.1. Data and Sample*

We retrieved raw data from the Clarivate Analytics Web of Science (WoS) database consisting of 159,169 articles published in 320 peer-reviewed business and management (a subdomain of the social sciences research domain) journals from 1994 to 2013. The extracted data contain detailed information on each journal article, such as the author name, author affiliation, article title, year of publication, type of publication, journal name, and citations number. After filtering the original data, removing all journal articles with missing information such as author names or affiliations, and checking for other inconsistencies, we obtained a dataset of 116,270 journal articles with complete information (73% of the initial raw data). These journal articles are in 20 disciplines based on the Association of Business Schools (ABS) academic journal guide classification in 2015.

Because the level of our analysis is individuals, we standardized the names of all the institutions (i.e., affiliation) and disambiguated (co)authors' names to identify unique scholars.[1] By doing so, we built panel data with yearly records for each author in our dataset. Specifically, we credited scholars with the number of publications, citations, and collaborations on an annual basis from the beginning of their research career—the year of their first publication—until 2013. For instance, if a journal article with three authors received ten citations in a particular year, each author is credited with one publication, ten citations, and two collaborations for that year. Moreover, to measure prior knowledge and experience accurately (e.g., prior research, citations, collaborations, and research age), we restricted our sample to scholars who started publishing in 1997 to have complete information on their production until the end of 2013. In other words, our sample excluded scholars who published journal articles before 1997 to avoid any left-censoring bias. We also identified all authors who published in disciplines other than business and management (according to the Clarivate Analytics WoS) and dropped them from our analysis to ensure homogeneity and computational accuracy. We further limited our sample to scholars who published at least three articles over the period of analysis (1997-2013) to ensure that our results are not driven by unproductive individuals (especially when testing the effect of diversification and

[1] We follow the approach in Belkhouja and Yoon (2018).

attention allocation). An alternative minimum threshold of five articles was also employed that dramatically reduced the sample size but did not change our main findings. After considering these issues and restrictions, we obtained unbalanced panel data for our analyses with 244,915 yearly observations, consisting of 27,379 authors over the period 1997 to 2013.

### *3.2. Variables*

#### *3.2.1. Dependent Variable*

To measure the research productivity of individual scholars, we relied on the yearly number of journal articles, from the beginning of a scholar's career—the year of his/her first publication—until 2013, weighted by the journal ranking where these articles were published according to the journal ranking list in the 2015 ABS Guide. This weighted measure of research productivity is more accurate than simply counting journal articles because it accounts for both quantity and quality. Specifically, each publication is coded as 1 if the journal ranking is ABS 1 (the fourth-highest quality), 2 if the journal ranking is ABS 2 (the third-highest quality), 3 if the journal ranking is ABS 3 (the second-highest quality), and 4 if the journal ranking is ABS 4 or 4* (the highest quality). For instance, if a scholar has two publications in 2000, one in an ABS 4* journal and the other in an ABS 2 journal, his/her research productivity for 2000 is 6 (4+2).

#### *3.2.2. Independent and Moderating Variables*

To construct our independent variable "diversification," we first assigned the 20 subject areas or disciplines provided in the 2015 ABS Guide to the 320 journals included in our dataset and then counted how many different disciplines are covered by a given author according to his/her journal publications over the prior five years (moving window). Our approach is in line with prior studies showing that exposure to diverse knowledge domains affects the quality and impact of research (Dell'Era and Verganti, 2010; Mitchell et al., 2009; Wang et al., 2017). Similarly, our second independent variable, “collaborator diversification”, is the total number of unique coauthors with whom each focal scholar has published over the prior five years (moving window).

Our moderating variable “attention allocation” measures unevenness in an individual’s attention allocation across different disciplines and coauthors (Gupta et al., 2018; Ozbas and Scharfstein, 2010; Rajan et al., 2000). We operationalize attention allocation with the disparity index (Gupta et al., 2018; Harrison and Klein, 2007). The disparity is conceptualized as vertical differences in the concentration of individuals' attention at their extreme, privileging a few over many (Harrison and Klein, 2007), which has been widely used to capture “allocation” behaviors of organizations (Ozbas and Scharfstein, 2009; Rajan et al., 2000). For instance, whereas high disparity means focused attention, low disparity indicates divided attention. Specifically, following the approach used in previous studies (e.g., Harrison and Klein, 2007; Wang et al., 2015), we calculated the disparity in the allocation of a scholar's attention to disciplines over the prior five years (moving window) using the coefficient of variation (CV), defined as:

$$\boldsymbol{Cognitive\ attention}_{\boldsymbol{t}} = \sqrt{\left[\sum_{i=1}^{n}(P_i - P_{mean})^2/n\right]\Big/P_{mean}}$$

where $P_i$ is the number of papers published by the focal scholar in discipline $i$ over the prior five years[2] (from year $t$-4 to year $t$), $P_{mean}$ is the average number of papers published by the focal scholar

[2] We ran models with a shorter moving window (two and three years) and the results are qualitatively similar to the main analysis using a five-year moving window.

per discipline over the previous five years, and $n$ is the number of disciplines in which the focal scholar has published over the previous five years.

This measure captures the asymmetry that is fundamental to the conceptualization of disparity (Harrison and Klein, 2007) and reflects the dominance of certain disciplines over others. The higher the value of CV, the greater the disparity across disciplines, which reflects focused attention. The lowest value of disparity is zero, characterizing researchers with equally divided attention across disciplines. The highest possible value of CV is the square root of the number of disciplines in which a given scholar has published minus one. This is the case when most of the scholar's publications are in one particular discipline, and only one publication is in each other discipline. For example, a scholar who published eight papers over the past five years, four in one discipline and four in another, would have a CV score of zero. In contrast, an equally productive colleague over the same period who published seven papers in one discipline and one paper in another would have a CV score of 0.75. In our sample, the highest CV score for cognitive attention is 1.38, and the lowest is 0.

We also quantify the allocation of a scholar's attention to coauthors using the same measure of disparity. To operationalize collaborative attention, we calculate the CV for each scholar by considering his/her collaborations over the past five years (moving window) as follows:

$$Collaborative\ attention_t = \sqrt{\left[\sum_{i=1}^{n}(C_i - C_{mean})^2/n\right]} \Big/ C_{mean}$$

where $C_i$ is the number of collaborations of the focal scholar with coauthor $i$ over the past five years (from year $t$-4 to year $t$), $C_{mean}$ is the average number of collaborations per coauthor over the past five years, and $n$ is the number of unique coauthors with which a scholar has collaborated over the past five years.

Similarly, CV captures the inequality, unevenness, and imbalance of the distribution of collaborations across coauthors over the past five years. In our sample, the highest CV score for collaborative attention is 0.94, and the lowest is 0.

*3.2.3. Control Variables*

We used several control variables to rule out alternative explanations of the variations in research productivity and to better isolate the effects of the main independent variables if they are correlated with these control variables, which could lead to estimation bias.

At the author level, we first control for an author's research age, as it may explain an upward bias in research productivity (Lee and Bozeman, 2005; Dahlander et al., 2016), and, at the same time, it might increase exposure to different disciplines and collaboration opportunities. Research age is calculated as the current year minus the year that the focal scholar first published a journal article. For the same reason, we control for prior performance, which is operationalized as prior research volume and prior research impact. We include these two control variables because prolific and highly cited scholars will be more productive in the future (Parker et al., 2013). Such high-performing researchers can easily establish connections with new coauthors and gain access to resources (e.g., database, funding), thereby activating the self-reinforcing dynamic of success known as the Matthew effect (Merton, 1968). To construct these measures of accumulative advantages, we traced all the authors and calculated their prior research publications as the lagged cumulative number of publications and, similarly, their prior research impact as the lagged cumulative number of citations. In addition, we control for individual mobility by counting how many times the focal scholar has changed institution after the first affiliation (identified in the first publication) up to the focal year. Mobility is correlated with both diversification and research productivity because it helps scholars to expand their scholarly network and enhance their research production (Mortensen and Neeley, 2012).

Moreover, we include three additional measures to capture the characteristics of their research network (e.g., average tie strength, centrality, and structural holes), which can influence research productivity and affect the relationship between collaborator diversification and research productivity. First, average tie strength is operationalized as the frequency or the intensity of collaborations between a given author and his/her coauthors in past years. Precisely, the average tie strength of a given author is measured as the number of all previous collaborations, divided by the number of unique coauthors up to the year [*t*-1]. Second, the centrality of individuals in networks can be measured in several different ways. Because we are interested in the movement of information across a collaborative network, we chose the eigenvector centrality measure. This calculation method considers central nodes (focal authors) that are connected to other nodes (coauthors), which are also well connected, so it is well-aligned with our interest (Borgatti, 1995). As argued by Ferriani et al. (2009, p. 1549), unlike closeness and betweenness measures of centrality, which account only for geodesic paths, the eigenvector measure assumes that "traffic is able to move in an unrestricted manner rather than being constrained by trails, paths or geodesics." (Borgatti, 2005, p. 62). We, therefore, calculated a yearly measure of centrality for each author based on the normalized eigenvector (Bonacich, 1972) and used it as a lagged variable in the analyses. Third, structural holes can influence an author's likelihood of identifying valuable coauthors by providing access to more diverse and less redundant information and resources. Burt (2004) suggests that good ideas originate disproportionately with individuals who span structural holes and are connected across different groups. Thus, we operationalized the variable structural holes using Burt's (1992) classic network constraint index. We inverted Burt's constraint measure, such that a value close to one indicates the author's superior brokerage position in a network. To avoid simultaneity with the dependent variable, we also lagged one year this variable.

At the institution level, we control for the high-status institution effect because prestigious institutions provide a combination of abundant resources, high-quality peers, and incentives to motivate researchers, which in turn enhances individual research productivity (Ryazanova and McNamara, 2016). Thus, we created a binary variable coded as 1 if the focal scholar is affiliated with a high-status institution, in a given year, based on the annual Top 100 worldwide business school research ranking made by the University of Texas at Dallas (UTD)[3], and 0 otherwise.

Finally, we included year dummies to control for differences in productivity and competition over time, with 1997 as the reference category and used the natural logarithm on specific variables to facilitate interpretation of their estimates and mitigate their high skewness.

### *3.3. Econometric Model*

As our dependent variable "research productivity" is a non-negative count variable with overdispersion, we adopted a negative binomial model with a conditional maximum likelihood estimation in our main analysis (Hausman et al., 1984). In the robustness check, we used the quasi-maximum likelihood Poisson model instead of the pure Poisson model because the latter underestimates the standard errors and inflates the statistical significance of variables (Cameron and Trivedi, 2013).

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[3] The UTD has created a database to track institutions publishing in 24 leading business journals and ranks research-intensive business schools since 1990 (Jensen and Wang, 2018).

Moreover, we employed a random-effects specification to test our hypotheses because it accounts for both within and between individual variations when calculating the standard errors. Nevertheless, we run additional analyses using both fixed-effects and population-averaged specifications, as reported in the robustness tests section.

## 4. Results

Descriptive statistics and Spearman correlations are reported in Table 1. The bivariate correlations are generally moderate, except between prior research publications, prior research impact, and research age. In addition, the maximum variance inflation factors (VIF) score is 3.64, which is below the recommended tolerance level of 10, showing that multicollinearity is not a concern.

***Insert Table 1 here***

Table 2 lists the full sample regression results using a random-effects negative binomial estimator. Model 1 represents the relationships between control variables and research productivity. Models 2 and 3 test the curvilinear effects of knowledge diversification and collaborator diversification on research productivity, respectively. Model 4 simultaneously tests the curvilinear effects of knowledge diversification and collaborator diversification on research productivity. Model 5 tests the moderating effect of cognitive attention on the knowledge diversification-research productivity relationship, while Model 6 tests the moderating effect of collaborative attention on the collaborator diversification-research productivity relationship. Model 7 shows the fully specified model. We have fewer observations for Models 5, 6, and 7 because the disparity measures (cognitive attention and collaborative attention) require scholars to have publications in at least two disciplines or with at least two co-authors. The Wald measure of overall fit indicates a significant chi-square for each model ($p < 0.01$), meaning that the four models are significant and acceptable for interpretation.

Starting with the control variables, we observe consistent effects across all the models. The estimates suggest that scholars with longer research experience, a higher prior research impact, frequent mobility, and affiliated with a prestigious institution have, on average, higher research productivity. However, the negative effect of prior research volume on research productivity is interesting. This implies that, as researchers advance their career while accumulating some publication experience, they tend to be more selective by targeting higher-ranked journals that will prolong the research process thereby decreasing their research productivity (Gonzalez-Brambila and Veloso, 2007). Regarding the network characteristics, the results indicate positive and significant effects of average tie strength and structural holes on research productivity.

***Insert Table 2 here***

Turning our attention to the effect of knowledge diversification on scholars' research productivity, the results of Model 4 in Table 2 and Figure 1 suggest an inverted U-shaped relationship ($\beta = 0.67$, $p < 0.01$; $\beta = -0.07$, $p < 0.01$), as stated in the BH.

***Insert Figure 1 here***

Likewise, the results of Model 4 in Table 2 ($\beta = 0.24$, $p < 0.01$; $\beta = -0.01$, $p < 0.01$) and Figure 2 are consistent with the BH, predicting an inverted U-shaped relationship between the diversification of collaborators and research productivity.

***Insert Figure 2 here***

To test H1, Model 7 in Table 2 includes interaction terms between knowledge diversification and cognitive attention. The linear effect of knowledge diversification on research productivity is positive and significant ($\beta = 0.73$, $p < 0.01$), whereas its squared effect is negative and significant ($\beta = -0.06$, $p < 0.01$). By contrast, the interaction between knowledge diversification and cognitive attention is negative and significant ($\beta = -0.78$, $p < 0.01$), while the interaction between knowledge diversification squared and cognitive attention is positive and significant ($\beta = 0.08$, $p < 0.01$). These results suggest that the initial positive effect and the latter negative effect of knowledge diversification on research productivity are mitigated as cognitive attention increases.

To illustrate these results, Figure 3 demonstrates the relationship between knowledge diversification and research productivity at three different levels of cognitive attention allocation (low, moderate, and high). The curve representing the inverted-U-shaped relationship between research productivity and knowledge diversification is observed at a low level of cognitive attention. The curve flattens as cognitive attention increases, with its turning point moving to the right (see Figure 3, when cognitive attention is moderate), and then turns into a U-shaped relationship when the level of cognitive attention is high. This phenomenon is called a "shape flip" because the shape of the curves flips from an inverted U-shape to a U-shape (Haans et al., 2016).

More explicitly, while a moderate level of knowledge diversification is optimal for research productivity when cognitive attention is divided (see Figure 3, when cognitive attention is low), a higher level of knowledge diversification is more beneficial for research productivity when cognitive attention is focused (see Figure 3, when cognitive attention is high). Although these findings show the moderating role of cognitive attention with a shape flip, they do not support H1, which predicts a steepening of the inverted U-shaped curve.

This result suggests that when cognitive attention increases under a larger knowledge base, the benefits derived from knowledge diversification on research productivity outweigh the costs of various knowledge combination and integration. This positive moderating effect of cognitive attention on the latter negative relationship between knowledge diversification and research productivity could be explained by the complementarity and synergy between core and peripheral research domains. Specifically, the exposure to peripheral research domains offers individuals the opportunity to apply new ideas and methods to their core research easily and vice versa, as do many sociologists who go back and forth between management and sociology while publishing their work (Moody, 2004). In other words, scholars can always revive their core discipline after working on different peripheral disciplines.

***Insert Figure 3 here***

Model 7 in Table 2, which also tests H2, shows the moderating effect of collaborative attention on the relationship between collaborator diversification and research productivity. The interaction effect between collaborator diversification and collaborative attention is positive and significant ($\beta = 0.14$, $p < 0.01$), indicating that the initial positive effect of collaborator diversification on research productivity becomes larger when collaborative attention is greater. In contrast, the interaction effect between collaborator diversification squared and collaborative attention is negative and significant ($\beta = -0.004$, $p < 0.05$), indicating that this negative effect of collaborator diversification on research productivity becomes stronger with greater collaborative attention.

***Insert Figure 4 here***

Figure 4 illustrates the relationship between collaborator diversification and research productivity across different levels of collaborative attention (low, moderate, and high). The inverted U-shaped relationship between collaborator diversification and research productivity demonstrates a steeper upward and downward curve when collaborative attention increases, but the turning point of this relationship does not change. This suggests that scholars with focused collaborative attention can get more benefit from collaborator diversification, to achieve a higher level of research productivity on average (see Figure 4, when collaborative attention is high vs low). Nevertheless, increasing collaborative attention allocation has its limits because, beyond a certain level of collaborator diversification, its effect on research productivity becomes even more detrimental compared with a lower level of collaborative attention. In line with Ryazanova and McNamara (2016), we find that this changing pattern reveals the reinforcing double-edged sword effects of collaborator diversification on research productivity, which are triggered by the increase in collaborative attention. In sum, the findings from Model 7 in Table 2 and Figure 4 strongly support H2.

**5. Robustness Tests**

To ensure the robustness of our findings, we conducted several additional analyses. First, in addition to the negative binomial models used in our main analysis, we employed alternative estimation methods, such as a quasi-maximum likelihood Poisson model, a fixed-effects negative binomial model, and a population-averaged negative binomial model (see Table 3).

***Insert Table 3 here***

Second, we used alternative measures of research productivity, including the yearly number of publications, the yearly number of publications weighted by the Australian Business Deans Council (ABDC) journal ranking, and the yearly number of publications weighted by the journal impact factor (see Table 4).

***Insert Table 4 here***

Finally, we conducted the same set of analysis using first an alternative sample including scholars with at least five articles [4](see Appendix Table 1), and then excluding control variables to show that our main findings are not driven by the inclusion of the control variables (see Appendix Table 2). In all cases, the supplementary results are consistent and qualitatively similar to our main results.

**6. Discussion and Conclusion**

Despite the prevalence of skilled individuals' heavy reliance on knowledge outside their domain of expertise and new collaborators to produce scientific research outputs, prior research on diversification and the attention-based view has focused on an organization's ability to use a variety of knowledge and partners (Fleming, 2001; Chatterji and Fabrizio, 2014). Understanding the performance implications of diversifying knowledge and collaborators at the individual level is important, as scientists, engineers, and researchers drive value creation and the competitive advantage of many knowledge-based organizations (Agrawal et al., 2017). Thus, our study makes several contributions by providing a microfoundational framework that explains how attention allocation can play a moderating role in shaping the relationship between diversification and research productivity.

First, it contributes to prior research on diversification and the attention-based view by exploring the interplay between an individual's level of diversification (diversification of knowledge and collaborators) and attention allocation as a mechanism through which the

[4] We also tested the same models using alternative samples including scholars who published at least eight articles and eleven articles, respectively. The estimated results derived from the alternative samples are consistent with our main findings.

performance of skilled individuals is manifested. Rather than merely accounting for differences in cognition and collaborators, we theorize how the curvilinear relationship between diversification and research productivity is moderated by attention allocation. Although mechanisms through which diversification leads to successful performance outcomes have been investigated (Belkhouja and Yoon, 2018; Dahlander et al., 2016; Mannucci and Yong, 2018), less is known about the mechanism of attention allocation through which individuals screen, process, and act upon a variety of knowledge and collaborators. This is an important contribution because of the dilemma between diversification and attention due to the overabundance of knowledge and collaborators. In turn, this enables us to develop a deeper understanding of the relationship between diversification and individual performance, which is in line with a growing body of research calling for work on the micro-foundations of attention allocation (Dahlander et al., 2016; Shin et al., 2012; Taylor and Greve, 2006).

Second, although the role of the individual or human attention system in responding to stimuli to our senses has been widely investigated in academic disciplines such as cognitive psychology and neuroscience (Bundesen, 1990; Desimone and Duncan, 1995; Pashler and Sutherland, 1998), in contemporary management studies the notion of attention has been mainly theorized and tested in the context of organizational studies (Fleming, 2001; Chatterji and Fabrizio, 2014). Subsequently, our analysis takes a different perspective by addressing the role of attention allocation by individuals. It shows that increasing attention can change the relationship between diversification and individual performance. Thus, this study enhances our understanding of individuals' search and attention allocation behavior in the context of skilled individuals, which has been underexamined (Nagle and Teodoridis, 2019).

Specifically, our findings on the moderating effect of cognitive attention highlight two optimal research strategies. First, research productivity increases in general by either publishing in domains other than one's core domain or by borrowing ideas and knowledge from other domains to apply them to one's core domain. In line with the coordination costs argument, managing projects across different disciplines with equal attention (divided cognitive attention) is very challenging for researchers, but they can optimize their research productivity if their knowledge diversification is moderate. Second, scholars can be even more productive by focusing on a few disciplines while limiting their attention to other disciplines (focused cognitive attention) without compromising their scholarly identity, even if their knowledge diversification is high. In other words, being a specialist in a few domains while seizing occasional opportunities to publish in other domains will increase the benefits of the combinatorial search and decrease the pitfalls of the coordination costs on research productivity.

Furthermore, our findings show that collaborative attention strengthens the initial positive effect of collaborator diversification on research productivity through two mechanisms. First, focused collaborative attention allowing repeated collaboration (strong ties) leads to higher research productivity (Colquitt et al., 2007; Gonzalez-Brambila et al., 2013; Wang, 2016). Second, focused collaborative attention permitting occasional collaboration (weak ties) helps individuals access new ideas and resources, which also increase their research productivity (Burt, 1992; Granovetter, 1973; Uzzi, 1996; Uzzi and Spiro, 2005, Wang, 2016). These two mechanisms enable scholars to optimize their research productivity when collaborator diversification is moderate.

Moreover, we recognize that focused attention has its limits when it comes to managing a large coauthorship network. In this sense, our findings reveal that the focused attention strategy represents an "asset" for individuals only to a limited extent because the inverted U-shaped relationship between collaborator diversification and research productivity persists when collaborative attention increases. Furthermore, while the increase in cognitive attention changes the shape of the curve between knowledge diversification and research productivity from an inverted U-shape to a U-shape, increasing collaborative attention steepens the inverted U-shaped relationship between collaborator diversification and research productivity. This implies that although searching and recombining new knowledge in a large knowledge base is challenging, it is easier than managing relationships with different coauthors in a large network. For instance, many sociologists publish in multiple fields in business and management by applying theoretical frameworks and quantitative methods across other fields (Moody, 2004). After working across different peripheral disciplines, scholars can always return to their core discipline. In fact, the extent to which individuals can engage in knowledge diversification depends mainly on whether they successfully incorporate diverse knowledge with sufficient attention to each body of knowledge (Dahlander et al., 2016). In contrast, it is more difficult to revive "paused" collaboration with co-authors, because maintaining a good coauthorship relationship requires an enduring commitment and building trust (Steinmo and Rasmussen, 2018). As occasional collaborations can become salient in increasing the network of coauthors, they can prevent a focal scholar under time constraints from maintaining strong ties, which mainly contribute to one's research productivity (Huo et al., 2019).

Overall, our study contributes to the call for further research on the micro-foundations of strategies, specifically at the individual level (Felin and Foss, 2005; Gavetti, 2005; Teece, 2007; Foss, 2011), by broadening the conceptualization of specialists and generalists. Notably, prior research has focused on the scope of knowledge, whether an individual is working on narrower or wider knowledge areas (Melero and Palomeras, 2015). As a result, existing studies have paid little attention to the impact of attention allocation on the ability to recombine knowledge and work with different collaborators. Thus, the present study goes beyond recent conversations on the diversification-performance relationship (Belkhouja and Yoon, 2018; Dahlander et al., 2016; Mannucci and Yong, 2018) by introducing the moderating role of attention allocation on the relationship between diversification (knowledge and collaborator) and research productivity by individuals.

The current study also offers practical implications for managing the research performance of academics, especially with the growing demand and opportunity for interdisciplinary research and research collaboration, respectively. Although institutional norms in research organizations frequently emphasize specialization, our results show that, in general, diversification is more beneficial than specialization for research productivity, and the benefits of that knowledge diversification can be magnified when cognitive attention is focused. In particular, the findings are highly relevant for researchers early in their career who have been increasingly encouraged to hyperfocus to become the world's expert in one specific domain (Stephan, 2012). Our results offer grounds for adjusting this practice by showing that simultaneously focusing on core domains and allocating little attention to other domains is an effective strategy for optimizing research productivity (Nagle and Teodoridis, 2019). Therefore, cognitive attention allocation is an essential way for individuals to increase the benefits of knowledge diversification on their performance.

Furthermore, our analysis reveals how academics can achieve greater research productivity. For coauthors in a network that is small or moderate in size, the benefits derived from the diversification of collaborators outweigh the costs of coordinating these collaborators. By adopting a focused collaborative attention strategy (i.e., continued collaboration with the main coauthors and taking advantage of occasional collaboration opportunities), scholars can benefit from combinatorial search while, at the same time, reducing their coordination costs. In this way, scholars can use their coauthorship network efficiently and optimize their research productivity. Overall, our findings offer a complete account of how, why, and under what circumstances individuals can be more productive, with the input of diverse ideas and collaborators, by considering how they strategically or unintentionally allocate their attention.

Naturally, our study is not without limitations. Although the distance between disciplines can play a crucial role in driving atypical combination and determining the level of an individual's cognitive attention, our operationalization of disparity in measuring cognitive attention strictly captures the dominance of specific disciplines over others, relying on Harrison and Klein (2007). In addition, because the connections among the collaborators of a focal individual can have an information-processing implication by highlighting a network's redundancy, incorporating Burt (1992)'s constraint measure as a moderator in our research model could enrich the analysis and make the findings more compelling. Furthermore, as individuals can take advantage of "team science practices (collaborator diversification)" that cover a larger breadth of knowledge (knowledge diversification) without compromising much on their attention (Jones, 2009), future studies could investigate the multiple interactions among them (e.g., collaborator diversification, knowledge diversification, and attention). Finally, although interdisciplinary and collaborative research has become a widespread practice at many research institutions, we know little about their career implications. Thus, future studies could investigate the impact of interdisciplinary and collaborative research on career outcomes, such as academic promotion and research leadership (e.g., being elected as a fellow of a research community).

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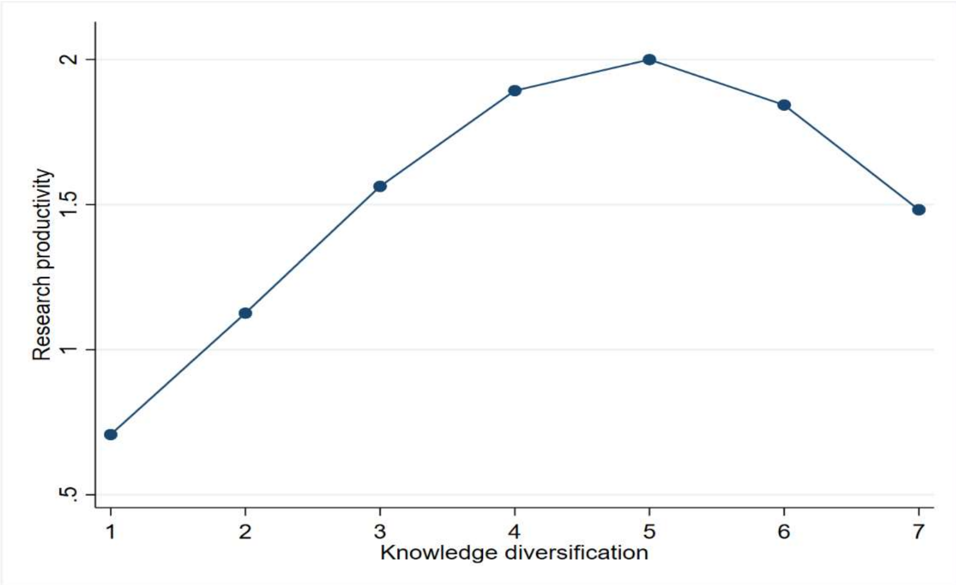


**Figure 1**. The effect of knowledge diversification on research productivity (based on Model 4 in Table 2)

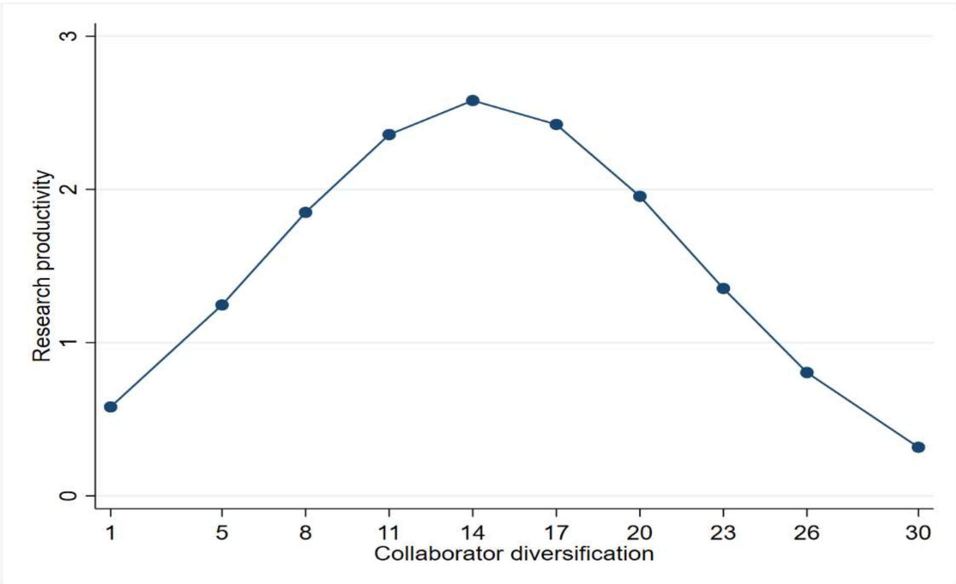


**Figure 2**. The effect of collaborator diversification on research productivity (based on Model 4 in Table 2)

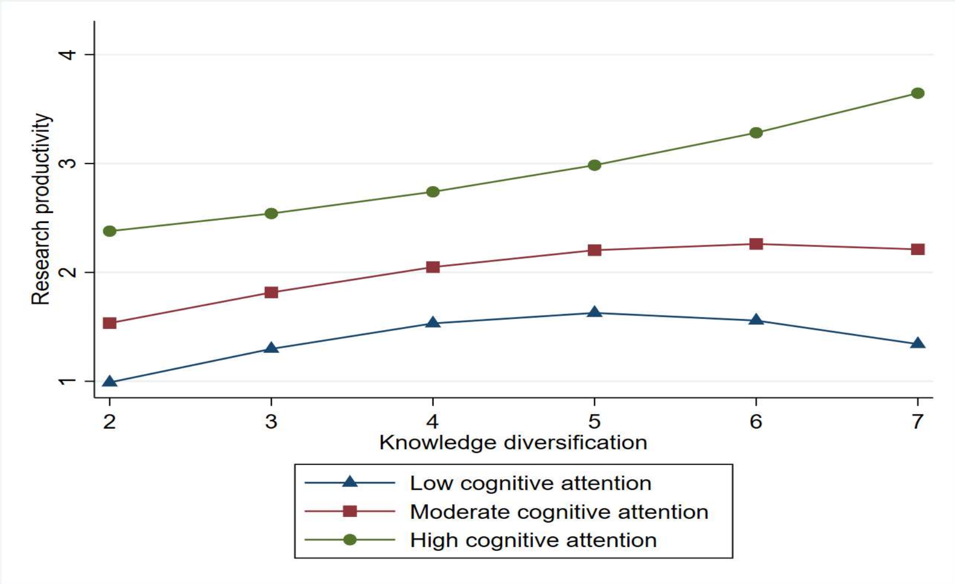


**Figure 3**. The moderating effect of cognitive attention on the relationship between knowledge diversification and research productivity (based on Model 7 in Table 2)

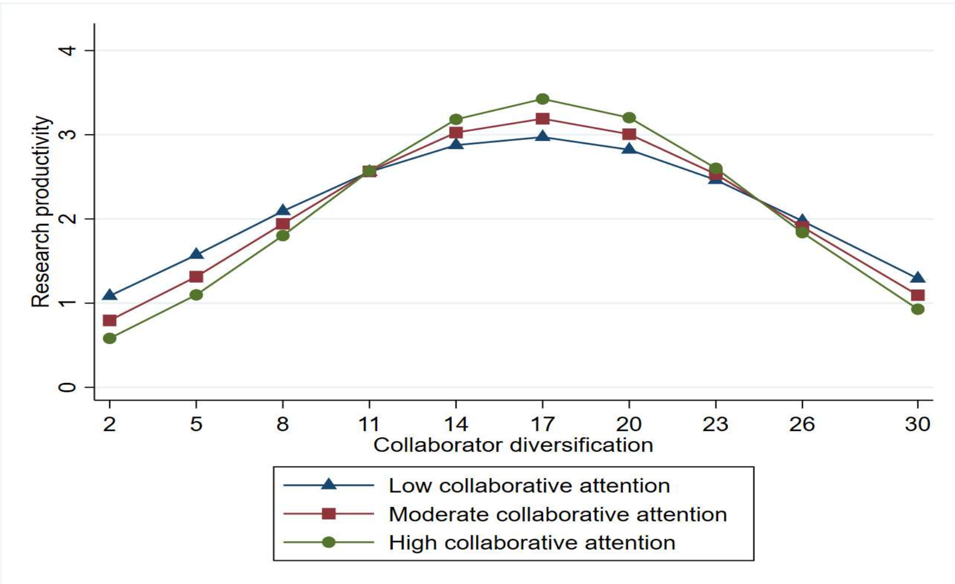


**Figure 4**. The moderating effect of collaborative attention on the relationship between collaborator diversification and research productivity (based on Model 7 in Table 2)

**Table 1**. Correlation matrix and descriptive statistics

| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Dependent variables** | | | | | | | | | | | | | |
| 1 | Research productivity | 1.00 | | | | | | | | | | | | |
| | **Independent variables** | | | | | | | | | | | | | |
| 2 | Knowledge diversification | 0.28*** | 1.00 | | | | | | | | | | | |
| 3 | Collaborator diversification | 0.36*** | 0.48*** | 1.00 | | | | | | | | | | |
| | **Moderating variables** | | | | | | | | | | | | | |
| 4 | Cognitive attention | 0.26*** | 0.41*** | 0.41*** | 1.00 | | | | | | | | | |
| 5 | Collaborative attention | 0.15*** | 0.14*** | 0.21*** | 0.16*** | 1.00 | | | | | | | | |
| | **Control variables** | | | | | | | | | | | | | |
| 6 | Research age [a] | 0.31*** | 0.08*** | -0.08*** | 0.12*** | -0.05*** | 1.00 | | | | | | | |
| 7 | Prior research volume [a] | -0.25*** | 0.30*** | 0.16*** | 0.33*** | 0.04*** | 0.67*** | 1.00 | | | | | | |
| 8 | Prior research impact [a] | 0.12*** | 0.21*** | 0.08*** | 0.25*** | 0.02*** | 0.66*** | 0.64*** | 1.00 | | | | | |
| 9 | Mobility [a] | 0.11*** | 0.29*** | 0.22*** | 0.28*** | 0.04*** | 0.36*** | 0.42*** | 0.40*** | 1.00 | | | | |
| 10 | Tie strength | 0.07*** | 0.17*** | 0.12*** | 0.18*** | 0.16*** | 0.18*** | 0.29*** | 0.28*** | 0.16*** | 1.00 | | | |
| 11 | Centrality | -0.00 | -0.00 | -0.00 | -0.00 | -0.00 | -0.01*** | -0.01*** | -0.01** | -0.00** | 0.00 | 1.00 | | |
| 12 | Structural holes | 0.10*** | 0.26*** | 0.29*** | 0.24*** | 0.05*** | 0.29*** | 0.35*** | 0.32*** | 0.27*** | -0.38*** | -0.01*** | 1.00 | |
| 13 | High-status institution | 0.05*** | 0.01*** | 0.02*** | 0.03*** | -0.01*** | 0.02*** | 0.08*** | 0.10*** | 0.02*** | 0.00** | 0.00 | 0.04*** | 1.00 |
| | Mean | 1.16 | 1.33 | 2.30 | 0.094 | 0.092 | 1.55 | 0.99 | 2.23 | 0.20 | 1.12 | 0.00064 | 0.42 | 0.23 |
| | S.D. | 1.87 | 0.67 | 2.70 | 0.15 | 0.16 | 0.80 | 0.52 | 1.60 | 0.37 | 0.51 | 0.022 | 0.33 | 0.42 |
| | Min | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | Max | 31 | 7 | 30 | 1.38 | 0.94 | 2.83 | 4.07 | 7.25 | 2.20 | 11 | 1 | 1 | 1 |

[a] Logarithm transformed. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 2**. Predicting research productivity with the random-effects negative binomial model

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| Research age | 0.7482$^{***}$ | 0.5319$^{***}$ | 0.3025$^{***}$ | 0.2497$^{***}$ | 0.2012$^{***}$ | 0.0572$^{***}$ | 0.2038$^{***}$ |
| | (0.0095) | (0.0098) | (0.0105) | (0.0105) | (0.0167) | (0.0124) | (0.0174) |
| Prior research volume | -0.8721$^{***}$ | -1.0470$^{***}$ | -1.1913$^{***}$ | -1.2472$^{***}$ | -1.0062$^{***}$ | -1.2368$^{***}$ | -0.9687$^{***}$ |
| | (0.0082) | (0.0086) | (0.0089) | (0.0090) | (0.0145) | (0.0104) | (0.0153) |
| Prior research impact | 0.1476$^{***}$ | 0.1403$^{***}$ | 0.1515$^{***}$ | 0.1483$^{***}$ | 0.0275$^{***}$ | 0.1129$^{***}$ | 0.0275$^{***}$ |
| | (0.0043) | (0.0043) | (0.0044) | (0.0044) | (0.0062) | (0.0050) | (0.0064) |
| Mobility | 1.3139$^{***}$ | 1.0744$^{***}$ | 1.0559$^{***}$ | 0.9646$^{***}$ | 0.3771$^{***}$ | 0.6985$^{***}$ | 0.3381$^{***}$ |
| | (0.0108) | (0.0108) | (0.0109) | (0.0109) | (0.0128) | (0.0114) | (0.0131) |
| Tie strength | 0.9776$^{***}$ | 0.7882$^{***}$ | 0.8049$^{***}$ | 0.7021$^{***}$ | 0.1806$^{***}$ | 1.0392$^{***}$ | 0.4548$^{***}$ |
| | (0.0092) | (0.0091) | (0.0100) | (0.0098) | (0.0154) | (0.0138) | (0.0202) |
| Centrality | 0.0642 | 0.0596 | -0.0166 | -0.0093 | 0.0810 | -0.0786 | 0.0804 |
| | (0.1342) | (0.1323) | (0.1338) | (0.1327) | (0.2338) | (0.1628) | (0.2388) |
| Structural holes | 1.6806$^{***}$ | 1.3159$^{***}$ | 1.2690$^{***}$ | 1.0785$^{***}$ | 0.2201$^{***}$ | 1.3624$^{***}$ | 0.3969$^{***}$ |
| | (0.0143) | (0.0144) | (0.0157) | (0.0157) | (0.0350) | (0.0254) | (0.0452) |
| High-status institution | 0.1173$^{***}$ | 0.1286$^{***}$ | 0.1095$^{***}$ | 0.1189$^{***}$ | 0.1246$^{***}$ | 0.1352$^{***}$ | 0.1321$^{***}$ |
| | (0.0080) | (0.0080) | (0.0084) | (0.0083) | (0.0119) | (0.0094) | (0.0123) |
| Knowledge diversification | | 0.9201$^{***}$ | | 0.6692$^{***}$ | 0.8071$^{***}$ | 0.4835$^{***}$ | 0.7303$^{***}$ |
| | | (0.0124) | | (0.0131) | (0.0460) | (0.0132) | (0.0460) |
| Knowledge diversification$^2$ | | -0.0833$^{***}$ | | -0.0682$^{***}$ | -0.0732$^{***}$ | -0.0413$^{***}$ | -0.0647$^{***}$ |
| | | (0.0022) | | (0.0023) | (0.0068) | (0.0023) | (0.0068) |
| Collaborator diversification | | | 0.2924$^{***}$ | 0.2419$^{***}$ | 0.1241$^{***}$ | 0.1438$^{***}$ | 0.0991$^{***}$ |
| | | | (0.0026) | (0.0027) | (0.0037) | (0.0036) | (0.0045) |
| Collaborator diversification$^2$ | | | -0.0100$^{***}$ | -0.0085$^{***}$ | -0.0034$^{***}$ | -0.0043$^{***}$ | -0.0025$^{***}$ |
| | | | (0.0001) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Cognitive attention | | | | | 2.9502$^{***}$ | | 2.7535$^{***}$ |
| | | | | | (0.1519) | | (0.1531) |
| Knowledge diversification x Cognitive attention | | | | | -0.8359$^{***}$ | | -0.7885$^{***}$ |
| | | | | | (0.0929) | | (0.0925) |
| Knowledge diversification$^2$ x Cognitive attention | | | | | 0.0832$^{***}$ | | 0.0777$^{***}$ |
| | | | | | (0.0128) | | (0.0126) |
| Collaborative attention | | | | | | -1.1556$^{***}$ | -1.0760$^{***}$ |
| | | | | | | (0.1320) | (0.1598) |
| Collaborator diversification x Collaborative attention | | | | | | 0.1552$^{***}$ | 0.1400$^{***}$ |
| | | | | | | (0.0313) | (0.0356) |
| Collaborator diversification$^2$ x Collaborative attention | | | | | | -0.0047$^{***}$ | -0.0035$^{**}$ |
| | | | | | | (0.0015) | (0.0016) |
| Constant | -0.5220$^{***}$ | -1.1062$^{***}$ | -0.5674$^{***}$ | -0.9893$^{***}$ | -0.6401$^{***}$ | -0.9743$^{***}$ | -0.7346$^{***}$ |
| | (0.0223) | (0.0240) | (0.0229) | (0.0244) | (0.0948) | (0.0337) | (0.0988) |
| Year dummies | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 244915 | 245465 | 244996 | 244915 | 62052 | 130209 | 51479 |
| Number of authors | 27379 | 27415 | 27379 | 27379 | 15158 | 24230 | 14000 |
| Log likelihood statistic | -296331.14 | -291433.12 | -287741.43 | -285044.72 | -106724.37 | -200551.93 | -93335.21 |
| $\chi2$ statistic | 102164.57$^{***}$ | 109206.41$^{***}$ | 109078.83$^{***}$ | 112577.80$^{***}$ | 16696.08$^{***}$ | 48100.87$^{***}$ | 12687.79$^{***}$ |

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Table 3.** Predicting research productivity with alternative estimation methods

| | **Quasi-maximum likelihood Poisson model** | | **Fixed effects negative binomial model** | | **Population-averaged negative binomial model** | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| Research age | 0.2865*** | 1.0186*** | 0.0316** | 0.9077*** | 0.1808*** | 0.3262*** |
| | (0.0165) | (0.0576) | (0.0142) | (0.0366) | (0.0094) | (0.0178) |
| Prior research volume | -1.6818*** | -1.7533*** | -1.6416*** | -1.7684*** | -1.6170*** | -1.1786*** |
| | (0.0155) | (0.0382) | (0.0099) | (0.0205) | (0.0079) | (0.0136) |
| Prior research impact | 0.0529*** | 0.2185*** | 0.0742*** | 0.1511*** | 0.1617*** | 0.0696*** |
| | (0.0065) | (0.0161) | (0.0056) | (0.0119) | (0.0043) | (0.0076) |
| Mobility | 0.6619*** | 0.3487*** | 0.8695*** | 0.4586*** | 0.8121*** | 0.3160*** |
| | (0.0154) | (0.0226) | (0.0122) | (0.0187) | (0.0104) | (0.0153) |
| Tie strength | 1.3896*** | 1.4238*** | 1.1413*** | 1.3625*** | 1.1372*** | 0.6029*** |
| | (0.0357) | (0.0510) | (0.0122) | (0.0352) | (0.0095) | (0.0236) |
| Centrality | 0.0361 | 0.2145 | 0.0729 | 0.2596 | 0.0176 | 0.0073 |
| | (0.1116) | (0.2068) | (0.1430) | (0.2850) | (0.1297) | (0.2800) |
| Structural holes | 1.5580*** | 2.3492*** | 1.4918*** | 2.2651*** | 1.5375*** | 0.7657*** |
| | (0.0316) | (0.1147) | (0.0187) | (0.0838) | (0.0161) | (0.0517) |
| High-status institution | 0.0322** | 0.0278 | 0.0098 | 0.0184 | 0.1963*** | 0.1654*** |
| | (0.0148) | (0.0226) | (0.0109) | (0.0186) | (0.0089) | (0.0147) |
| Knowledge diversification | 0.5971*** | 0.5933*** | 0.7563*** | 0.8398*** | 0.6502*** | 0.7136*** |
| | (0.0216) | (0.0713) | (0.0150) | (0.0553) | (0.0137) | (0.0586) |
| Knowledge diversification$^2$ | -0.0651*** | -0.0501*** | -0.0867*** | -0.0747*** | -0.0662*** | -0.0616*** |
| | (0.0041) | (0.0111) | (0.0026) | (0.0078) | (0.0026) | (0.0089) |
| Collaborator diversification | 0.3438*** | 0.1528*** | 0.3500*** | 0.1676*** | 0.2847*** | 0.0935*** |
| | (0.0048) | (0.0072) | (0.0030) | (0.0060) | (0.0024) | (0.0054) |
| Collaborator diversification$^2$ | -0.0104*** | -0.0035*** | -0.0111*** | -0.0039*** | -0.0092*** | -0.0022*** |
| | (0.0003) | (0.0003) | (0.0002) | (0.0003) | (0.0001) | (0.0003) |
| Cognitive attention | | 2.2507*** | | 2.9432*** | | 3.0479*** |
| | | (0.2714) | | (0.1903) | | (0.1952) |
| Knowledge diversification x Cognitive attention | | -0.5791*** | | -0.8120*** | | -0.9322*** |
| | | (0.1680) | | (0.1096) | | (0.1220) |
| Knowledge diversification$^2$ x Cognitive attention | | 0.0551** | | 0.0756*** | | 0.0968*** |
| | | (0.0246) | | (0.0146) | | (0.0172) |
| Collaborative attention | | -1.1729*** | | -1.6358*** | | -1.2144*** |
| | | (0.2733) | | (0.2262) | | (0.1932) |
| Collaborator diversification x Collaborative attention | | 0.1884*** | | 0.1970*** | | 0.2192*** |
| | | (0.0551) | | (0.0456) | | (0.0446) |
| Collaborator diversification$^2$ x Collaborative attention | | -0.0047** | | -0.0048** | | -0.0066*** |
| | | (0.0023) | | (0.0019) | | (0.0021) |
| Constant | -2.3562*** | -1.6754*** | -2.0099*** | -3.0206*** | -1.0396*** | -0.7635*** |
| | (0.0924) | (0.0434) | (0.0298) | (0.1284) | (0.0295) | (0.1413) |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Number of observations | 244550.0000 | 48809.0000 | 244550 | 48809 | 244915 | 51479 |
| Number of authors | 27054.0000 | 11344.0000 | 27054 | 11344 | 27379 | 14000 |
| Log likelihood statistic | -223245.3225 | -56788.6654 | -190587.1890 | -51085.4134 | - | - |
| $\chi 2$ statistic | 36359.14*** | 6154.29*** | 141991.64*** | 24757.28*** | 114951.54*** | 14512.30*** |

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

**Table 4.** Estimation using alternative measures of research productivity

| | Yearly number of publications | | Yearly number of publications weighted by the ABDC journal ranking | | Yearly number of publications weighted by the journal impact factor | |
|---|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
| Research age | 0.1871*** | 0.5028*** | 0.2568*** | 0.2183*** | 0.5638*** | 0.5759*** |
| | (0.0103) | (0.0162) | (0.0104) | (0.0170) | (0.0073) | (0.0274) |
| Prior research volume | -1.6176*** | -1.5996*** | -1.2117*** | -0.9630*** | -1.1516*** | -1.4531*** |
| | (0.0166) | (0.0222) | (0.0088) | (0.0147) | (0.0071) | (0.0217) |
| Prior research impact | 0.0726*** | 0.0192*** | 0.1393*** | 0.0156** | 0.2531*** | 0.3271*** |
| | (0.0045) | (0.0061) | (0.0043) | (0.0063) | (0.0041) | (0.0134) |
| Mobility | 0.7760*** | 0.2525*** | 0.9725*** | 0.3464*** | 0.5744*** | 0.3677*** |
| | (0.0112) | (0.0131) | (0.0108) | (0.0128) | (0.0102) | (0.0256) |
| Tie strength | 0.6742*** | 0.3553*** | 0.6703*** | 0.4158*** | 0.6665*** | 0.8074*** |
| | (0.0101) | (0.0196) | (0.0098) | (0.0197) | (0.0093) | (0.0400) |
| Centrality | -0.0002 | 0.0130 | -0.0282 | -0.0623 | 0.1518 | 0.6108 |
| | (0.1532) | (0.2671) | (0.1316) | (0.2445) | (0.1221) | (0.4558) |
| Structural holes | 1.1757*** | 0.3840*** | 1.0297*** | 0.2991*** | 0.9459*** | 1.2471*** |
| | (0.0170) | (0.0463) | (0.0156) | (0.0441) | (0.0138) | (0.0826) |
| High-status institution | 0.0298*** | 0.0193*** | 0.1289*** | 0.1350*** | 0.3476*** | 0.5416*** |
| | (0.0088) | (0.0124) | (0.0082) | (0.0120) | (0.0087) | (0.0250) |
| Knowledge diversification | 0.4548*** | 0.5119*** | 0.6673*** | 0.7309*** | 0.3056*** | 0.4278*** |
| | (0.0131) | (0.0473) | (0.0129) | (0.0452) | (0.0144) | (0.1001) |
| Knowledge diversification$^2$ | -0.0251*** | -0.0220*** | -0.0673*** | -0.0636*** | 0.0284*** | -0.0351*** |
| | (0.0023) | (0.0068) | (0.0023) | (0.0066) | (0.0029) | (0.0055) |
| Collaborator diversification | 0.1883*** | 0.0686*** | 0.2448*** | 0.1045*** | 0.2146*** | 0.1409*** |
| | (0.0026) | (0.0046) | (0.0027) | (0.0044) | (0.0024) | (0.0092) |
| Collaborator diversification$^2$ | -0.0055*** | -0.0012*** | -0.0087*** | -0.0026*** | -0.0053*** | -0.0015*** |
| | (0.0001) | (0.0001) | (0.0002) | (0.0002) | (0.0001) | (0.0004) |
| Cognitive attention | | 2.3474*** | 2.0421*** | 2.8293*** | | 1.5556*** |
| | | (0.1592) | (0.1032) | (0.1506) | | (0.3340) |
| Knowledge diversification x Cognitive attention | | -0.3775*** | -0.5935*** | -0.8003*** | | -0.7101*** |
| | | (0.0957) | (0.0641) | (0.0909) | | (0.1119) |
| Knowledge diversification$^2$ x Cognitive attention | | 0.0275** | 0.0684*** | 0.0775*** | | 0.0571*** |
| | | (0.0128) | (0.0094) | (0.0124) | | (0.0033) |
| Collaborative attention | | -0.4224 | | -1.0083*** | | -1.4403*** |
| | | (0.1560) | | (0.1573) | | (0.3271) |
| Collaborator diversification x Collaborative attention | | 0.0738*** | | 0.1266*** | | 0.3323*** |
| | | (0.0343) | | (0.0351) | | (0.0777) |
| Collaborator diversification$^2$ x Collaborative attention | | -0.0019** | | -0.0033** | | -0.0101*** |
| | | (0.0009) | | (0.0016) | | (0.0037) |
| Constant | 3.0569*** | 3.7463*** | -1.0357*** | -0.7261*** | -0.5625*** | -0.9264*** |
| | (0.0920) | (0.1672) | (0.0242) | (0.0970) | (0.0341) | (0.2554) |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Number of observations | 244915 | 51479 | 244915 | 51479 | 244915 | 51479 |
| Number of authors | 27379 | 14000 | 27379 | 14000 | 27379 | 14000 |
| Log likelihood statistic | -162829.92 | -49956.22 | -293191.66 | -95875.73 | - | - |
| $\chi2$ statistic | 57988.47*** | 12386.84*** | 113815.85*** | 13779.39*** | 89197.41*** | 13348.69*** |
| Overall R2 | - | - | - | - | 0.17 | 0.23 |

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

**Appendix Table 1.** Predicting research productivity with the random-effects negative binomial model using an alternative sample cut-off point (i.e., scholars who published at least five articles)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| Research age | 0.5958*** | 0.4391*** | 0.2039*** | 0.1633*** | 0.0265*** | 0.0324*** | 0.0085*** |
| | (0.0137) | (0.0145) | (0.0162) | (0.0166) | (0.0097) | (0.0108) | (0.0023) |
| Prior research volume | -0.5581*** | -0.6935*** | -0.8658*** | -0.9146*** | -0.6659*** | -0.8525*** | -0.6439*** |
| | (0.0110) | (0.0119) | (0.0129) | (0.0132) | (0.0178) | (0.0153) | (0.0188) |
| Prior research impact | 0.1045*** | 0.0905*** | 0.1070*** | 0.1022*** | 0.0192** | 0.0614*** | 0.0183** |
| | (0.0061) | (0.0062) | (0.0065) | (0.0065) | (0.0079) | (0.0070) | (0.0082) |
| Mobility | 0.6566*** | 0.5190*** | 0.4739*** | 0.4397*** | 0.2410*** | 0.3330*** | 0.2123*** |
| | (0.0131) | (0.0131) | (0.0130) | (0.0131) | (0.0145) | (0.0134) | (0.0147) |
| Tie strength | 0.5710*** | 0.5058*** | 0.5797*** | 0.5355*** | 0.1600*** | 0.7584*** | 0.3519*** |
| | (0.0114) | (0.0112) | (0.0124) | (0.0123) | (0.0189) | (0.0184) | (0.0251) |
| Centrality | 0.1546 | 0.1259 | 0.0732 | 0.0721 | 0.2499 | -0.0044 | 0.3090 |
| | (0.2074) | (0.2042) | (0.1998) | (0.1988) | (0.3018) | (0.2360) | (0.2991) |
| Structural holes | 1.4418*** | 1.1766*** | 1.0229*** | 0.9072*** | 0.1067** | 1.2377*** | 0.2689*** |
| | (0.0223) | (0.0225) | (0.0247) | (0.0249) | (0.0503) | (0.0409) | (0.0646) |
| High-status institution | 0.0825*** | 0.1075*** | 0.0837*** | 0.0942*** | 0.0982*** | 0.1026*** | 0.1075*** |
| | (0.0111) | (0.0112) | (0.0115) | (0.0115) | (0.0142) | (0.0124) | (0.0145) |
| Knowledge diversification | | 0.6538*** | | 0.4321*** | 0.5178*** | 0.2727*** | 0.4339*** |
| | | (0.0156) | | (0.0163) | (0.0542) | (0.0164) | (0.0545) |
| Knowledge diversification$^2$ | | -0.0574*** | | -0.0470*** | -0.0482*** | -0.0248*** | -0.0383*** |
| | | (0.0025) | | (0.0026) | (0.0077) | (0.0026) | (0.0076) |
| Collaborator diversification | | | 0.2456*** | 0.2163*** | 0.1341*** | 0.1494*** | 0.1108*** |
| | | | (0.0032) | (0.0034) | (0.0046) | (0.0045) | (0.0053) |
| Collaborator diversification$^2$ | | | -0.0073*** | -0.0065*** | -0.0037*** | -0.0041*** | -0.0028*** |
| | | | (0.0002) | (0.0002) | (0.0002) | (0.0002) | (0.0002) |
| Cognitive attention | | | | | 1.8807*** | | 1.6600*** |
| | | | | | (0.1776) | | (0.1800) |
| Knowledge diversification x Cognitive attention | | | | | -0.5344*** | | -0.4544*** |
| | | | | | (0.1051) | | (0.1053) |
| Knowledge diversification$^2$ x Cognitive attention | | | | | 0.0563*** | | 0.0467*** |
| | | | | | (0.0141) | | (0.0140) |
| Collaborative attention | | | | | | -0.3005* | -0.4149** |
| | | | | | | (0.1647) | (0.1950) |
| Collaborator diversification x Collaborative attention | | | | | | 0.0626** | 0.0807** |
| | | | | | | (0.0309) | (0.0411) |
| Collaborator diversification$^2$ x Collaborative attention | | | | | | -0.0013** | -0.0025*** |
| | | | | | | (0.0006) | (0.0008) |
| Constant | -0.2564*** | -0.7094*** | -0.3665*** | -0.6532*** | -0.2603** | -0.6515*** | -0.2850** |
| | (0.0330) | (0.0352) | (0.0335) | (0.0354) | (0.1143) | (0.0481) | (0.1198) |
| Year dummies | YES | YES | YES | YES | YES | YES | YES |
| Number of observations | 73230 | 73464 | 73311 | 73230 | 32192 | 49393 | 27469 |
| Number of authors | 6569 | 6570 | 6569 | 6569 | 5276 | 6358 | 5138 |
| Log likelihood statistic | -122148.97 | -120566.13 | -118118.49 | -117279.64 | -61328.71 | -91082.69 | -54713.36 |
| $\chi 2$ statistic | 19773.68*** | 22079.52*** | 25396.51*** | 26109.22*** | 6922.70*** | 12765.38*** | 5202.72*** |

Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

**Appendix Table 2.** Predicting research productivity with the random-effects negative binomial model excluding the control variables

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| Knowledge diversification | 0.4026*** | | 0.2495*** | 0.3761*** | 0.4540*** | 0.6818*** |
| | (0.0081) | | (0.0088) | (0.0449) | (0.0171) | (0.0609) |
| Knowledge diversification$^2$ | -0.0143*** | | -0.0101*** | -0.0330*** | -0.0454*** | -0.0636*** |
| | (0.0012) | | (0.0013) | (0.0066) | (0.0029) | (0.0088) |
| Collaborator diversification | | 0.1271*** | 0.0928*** | 0.1512*** | 0.2526*** | 0.2104*** |
| | | (0.0015) | (0.0017) | (0.0032) | (0.0045) | (0.0063) |
| Collaborator diversification$^2$ | | -0.0024*** | -0.0019*** | -0.0046*** | -0.0074*** | -0.0057*** |
| | | (0.0001) | (0.0001) | (0.0002) | (0.0002) | (0.0003) |
| Cognitive attention | | | | 1.3106*** | | 2.4348*** |
| | | | | (0.1450) | | (0.2010) |
| Knowledge diversification x Cognitive attention | | | | -0.4155*** | | -0.8115*** |
| | | | | (0.0899) | | (0.1181) |
| Knowledge diversification$^2$ x Cognitive attention | | | | 0.0440*** | | 0.0789*** |
| | | | | (0.0124) | | (0.0157) |
| Collaborative attention | | | | | -0.3903** | -0.2721** |
| | | | | | (0.2021) | (0.1385) |
| Collaborator diversification x Collaborative attention | | | | | 0.1013** | 0.0834** |
| | | | | | (0.0426) | (0.0422) |
| Collaborator diversification$^2$ x Collaborative attention | | | | | -0.0055** | -0.0041** |
| | | | | | (0.0023) | (0.0019) |
| Constant | | | | -0.1372 | 0.0051 | -0.0027 |
| | | | | (0.0932) | (0.0356) | (0.1197) |
| Year dummies | YES | YES | YES | YES | YES | YES |
| Number of observations | 245465 | 244996 | 244915 | 62052 | 128344 | 48809 |
| Number of authors | 27415 | 27379 | 27379 | 15158 | 22373 | 11344 |
| Log likelihood statistic | -338137.0590 | -336682.4156 | -335105.9446 | -112485.8505 | -147272.5802 | -58626.5779 |
| $\chi2$ statistic | 17242.70*** | 17495.30*** | 20568.59*** | 10076.50*** | 14954.64*** | 6900.66*** |

Robust standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.