Research performance of teams in Business and Management: The impact of team size, knowledge diversity and international diversity

Krammer, Sorin M.S. and Belkouja, Mustapha and Yoon, David

2 March 2019

RESEARCH PERFORMANCE OF TEAMS IN BUSINESS AND MANAGEMENT: THE IMPACT OF TEAM SIZE, KNOWLEDGE DIVERSITY AND INTERNATIONAL DIVERSITY

Abstract

Despite inherent differences across disciplines, collaboration in general and larger teams of co-authors in particular, are prevalent strategies to increase research performance via academic publications. We take a more fine-grained view of this relationship by distinguishing between two dimensions of research performance, namely impact (i.e., subsequent citations of a paper) and prestige (i.e., top academic journals). Different from prior literature, we argue that there are both benefits and pitfalls in having larger teams, and these trade-offs will affect differently the impact and prestige of academic research. Specifically, we propose that while team size will enhance linearly the impact of a paper, it will contribute in a non-linear fashion to its prestige. Furthermore, these relationships will be moderated by the knowledge and international diversity of the team. We test these hypotheses using bibliometric data on more than 40,000 publications between 1994 and 2013 papers across 21 sub-fields within the realm of Business and Management. Our results broadly support our theoretical assertions. We discuss some practical implications for assessing and stimulating the research performance of academics in business schools.

Keywords: Team size, citations, co-authorship, research performance.

"No grand idea was ever born in a conference, but a lot of foolish ideas have died there."

F. Scott Fitzgerald

INTRODUCTION

Historically, the pivotal role of individual geniuses in the production of major scientific discoveries has been emphasized by historians, psychologists and sociologists (Merton, 1968; Fox and Faver, 1984; Simonton, 1999; Bowler and Morus, 2010). Broadly, this tradition equates a number of significant breakthroughs with exceptional individuals in a given field (e.g., Nash equilibrium, Einstein's theory of relativity, Hawking radiation), and celebrated through prestigious scientific accolades (e.g., the Nobel Prize, John Bates Clark medal, etc.). In contrast, recent findings suggest that the paradigm of a lonely genius is a relic of the past (Simonton, 2013), and that collaborations within larger and more geographically dispersed teams (Adams et al., 2005; Wuchty, Jone and Uzzi, 2007) are the current norms in the production of cutting-edge scientific knowledge, given today's lower collaboration costs and tendency towards more division of scientific tasks (Katz and Martin, 1997; Lee and Bozeman, 2005). Nevertheless, larger teams are known to bring in greater coordination problems and potential inefficiencies, even in the case of highly complex tasks such as production of scientific knowledge (Williams and O'Reilly, 1998; Guimera et al., 2005). Subsequently, we still lack a good understanding on whether larger teams produce better research, and if these effects are consistent across various disciplines that differ in terms of requirements to produce scientific breakthroughs.

Motivated by these issues, we take a closer look at the effects of team size on research performance of academic papers in the realm of Business and Management. Given the small size of investment needed for production of scientific knowledge (Wutchy et al., 2007;

Bammer, 2008), and the increasing pressure to produce scientific knowledge that this also interdisciplinary in nature (Rafols et al., 2012), Business and Management provides an appropriate context to identify and better isolate the effects of team size. To capture fully the research performance of an academic paper we focus on two dimensions: *research impact* - i.e., the subsequent citations of a paper, as a widely used metric in the field (Judge et al., 2007)- and *research prestige* -i.e., top academic journals in which the paper get published (Tahai and Meyer, 1999; Harris, 2008). Employing theoretical elements from transaction costs economics and legitimacy theory we argue that larger teams will have positive and linear effects on the research impact of an academic paper, given the benefits drawn by team size in terms of knowledge complementarities, network opportunities, and legitimacy gains. In turn, we suggest that the effects of team size on research prestige will be positive but in a non-linear fashion, such that the coordination costs of having an extra co-author outweigh the scientific benefits, thereby reducing a paper's chances of reaching top journal outlets. In addition to the direct effects of team size, we examine also the interaction between size and diversity of teams in relation to research impact and prestige, suggesting that greater international and knowledge diversity of teams will moderate positively the effects of team size on both dimensions of research performance.

We test these hypotheses using bibliometric data on more than 40,000 publications between 1994 and 2013 papers across 21 subfields within the realm of Business and Management. While prior work on the determinants of research performance has focused mostly on sciences (Schilling and Green, 2011; Leahey et al., 2017) due to the significant research investments and benefits (Bammer, 2008), we examine these questions in the context of Business and Management journals for which financial constraints (e.g., labs, equipment, materials) are far less important (Rafols et al., 2012). In this way, we seek to better identify and isolate the effects of team characteristics on performance. Our empirical results support the idea that while team size has a positive and linear relationship with the research impact (i.e., citations) of a paper, it has a curvilinear (inverted U-shape) relationship with the research prestige (i.e., publishing in top journals) of a paper. The results also show that the linear relationship between team size and research impact is contingent on team international diversity and the curvilinear relationship between team size and research prestige is contingent on team knowledge diversity.

Subsequently, we propose several contributions. First, we advance the existing literature on the determinants of research performance. While prior studies have focused predominantly on citations and the role of individual characteristics of authors, articles or journals (Judge et al., 2007; Rafols et al., 2012; Leahey et al., 2017), we expand the set of possible explanations by focusing on team-related characteristics (e.g., size, diversity) and two related, yet distinct dimensions of research performance (e.g., impact through citations, and prestige through publication in top outlets). In this regard, our study contributes to the literature by theorizing and validating empirically the non-linear effects of team size in determining a paper's chances to make it into a top journal. Therefore, we advance a more fine-grained view of the relationship between team size and performance (Bechky, 2006; Singh and Fleming, 2010).

Second, we augment this view by looking into some of the contingencies of this relationship. In particular we focus on diversity in terms of international backgrounds and respectively knowledge, as two sources for moderating effects of the relationship between team size and research performance (Schilling and Green, 2011; Jones, Wutchty and Uzzi, 2008). Indeed, collaborative research enables teams to coordinate their tasks across geographically dispersed zones and benefit from the large pool of diverse knowledge, skills, and perspective of their team members (Lisak et al., 2016). In this way, we are building on a growing body of research calling for better understanding of the micro-foundations of organizational learning and performance (Felin and Foss, 2005; Miron-Spektor et al., 2018; Raisch et al., 2018).

Third, this study contributes to the literature on performance of temporary organizations (Bakker and Janowicz-Panjaitan, 2009; Cattani et al., 2011). Research teams provide a natural and complex setting to examine the determinants of their performance given the internal processes, tasks' characteristics, and the internal and external tensions across networks and research fields (Katz and Martin, 1997; Hulscheger, Anderson and Salgado, 2009). In this way, we are answering research calls in the field (Burke and Morley, 2016) by disentangling the complex relationship between the characteristics of a temporary organization and its subsequent performance.

THEORY AND HYPOTHESES

To build our arguments we draw on elements from transaction costs economics (TCE) and legitimacy theory (LT). The role of the TCE (Williamson, 1975, 1985, 1996) in affecting collaboration outcomes is well-recognized, because it is concerned with the costs of coordinating communications and making choices on deploying resources with the increase in the size of the structural arrangements (Landry and Amara, 1998). Complementarily, LT is intrinsically related to social justification, validation or endorsement of a certain actor or its activities (Perrow, 1961). Such processes usually abide to a general perception that the actions of this actor are "desirable, proper or appropriate with some socially constructed systems of norms, beliefs and definitions" (Suchman, 1995: 574). In this way, academic work is particularly subject to legitimacy constraints stemming from peers, journal editors, grant funding bodies and general readership (Kacperczyk and Younkin, 2017; Thomas and Wilson, 2011). By using these two theoretical lenses, we are able to probe theoretically deeper into the perceived benefits and pitfalls associated with larger teams and research performance.

Measuring research performance

The interest in employing bibliometric data and techniques to measure research performance has strongly increased in recent years along with decreasing research budgets, public accountability and the drive for efficiency in the scientific research system (Chambers and Miller, 2014; Rafols et al., 2012; Van Leeuwen et al., 2001). Prior studies found that research performance has important implications for job placement and hiring (Ryazanova et al., 2017), career progress via promotion and tenure (Diamond, 1986; Sauer, 1988), individual earnings (Hansen et al., 1978; Johnson et al., 1974), and attracting research grants (Hamermesh, 2018). Subsequently, a variety of measures on research performance has been introduced which ranges from productivity measure using publication count (Moed et al., 1985; Nederhof, 2006) to impact measures including citation counts (Leahey et al. 2017; Ryazanova et al., 2017; Belkhouja and Yoon, 2018), the h-index[1] (Bar-Ilan, 2008; Hirsch, 2005; Marchant, 2009) or the i10-index[2] (Chambers and Miller, 2014) now reported in the Google scholar profiles of academics.

Despite the simplicity of publication count (i.e. number of articles published in indexed journals), many higher education institutions care less about quantity and emphasize the importance of research impact (e.g. visible or vanish). This institutional change is in response to a popular belief that research output is not valuable unless it is cited (Rafols et al., 2012). Commonly, the impact of a research piece reflected in citations can be viewed as 'frozen footprints on the landscape of scholarly achievements' (Cronin, 1984). Citation indicates usefulness and influence of a research because it contributed, in some way, to a subsequent work (Leahey et al. 2017). While not all highly cited papers are correct or social-welfare

[1] "A scientist has index h if h of his/her Np papers have at least h citations each, and the other (Np - h) papers have no more than h citations each" (Hirsch, 2005: pp16569).
[2] The index introduced by Google represents the number of the scientist's publications that have at least ten citations each (Chambers and Miller, 2011).

enhancing, it is not hard to argue that they have on average, played very important role in scientific progress (Schilling and Green, 2011).

With the growing importance of citations as a research performance metric, several studies found that article, author, and journal attributes (research plot, affiliation of the first author, journal impact factor, etc.) influence citations (Judget et al., 2007; Leahey, 2007; Leahey et al. 2017; Mingers and Xu, 2010). Despite their contributions to our understanding of research impact, there is relatively little understanding of what makes a research to be published in a top journal outlet (Trieschmann et al., 2000). Publishing in prestigious or highly-ranked journals with high impact factors requires the endorsement of journal reviewers who have strong expertise relevant to the submitted paper to assess the significance and rigor of a study. Although not all the papers published in prestigious journals are impactful to garner a high number of citations, the rigorous review process in these journals ensures that only the very best and competitive papers are accepted for publication (Mingers and Xu, 2010).

In sum, our analysis is focused on how team-level attributes influence impact and prestige of team research outputs. Whereas research impact is reflected in the number of forward citations (Leahey et al. 2017), research prestige refers to publishing research in highly-ranked journals that shows comparable attributions of an output's relative worth or standing (Elsbach and Kramer 1996, Fombrun and Shanley 1990; Trieschmann et al., 2000). Distinguishing between research impact and research prestige is theoretically valuable, because there is a large variation in the number of citations that individual articles within the same top journal outlet receive.

Team size and research performance

We argue that larger teams will attract more citations than smaller teams and that the relationship between team size and research impact will be a linear one for the following reasons. First, larger teams will offer more opportunities for team members to specialize and increase the overall efficiency of a team both in terms of production and diffusion of research (Adams et al., 2009). Thus, the more specialized members decided to collaborate they can benefit more from economies of scale (in terms of efficiency of delivering certain tasks or functions) and scope (in terms of combining these tasks successfully). Moreover, having more co-authors will likely imply tapping more easily into a greater number of networks (e.g., collaborators, conferences, colleagues) which will ensure greater dissemination and higher chances of research being cited by more people (Ding, 2011; Lee et al., 2015; Otte and Rousseau, 2002; Bentley, 2007; Valderas, 2007).

Second, a larger number of co-authors will implicitly boost the legitimacy of the research undertaken both within and across disciplinary fields. Given that every research is an accurate reflection of an academic's reputation, having more co-authors signals that this research has been vetted from multiple angles and by multiple experts in the field, which in turn will also provide a higher level of legitimacy vis-à-vis existing knowledge in the field. In turn, this will trigger higher citation rates than single-authored papers that implicitly benefit from lower average levels of legitimacy (Abramo, D'Angelo and Di Costa, 2009). Moreover, a paper with counterintuitive claims or results is more likely to be accepted by the academic community (and therefore cited more frequently) if it is produced (and implicitly endorsed) by a large number of authors. In contrast, a paper with a single author if it carries a message that deviates substantially from the established scientific paradigm, it is less likely to be accepted and therefore cited in a given field. Thus, radical research is more likely to move or shift the academic consensus on the subject, and therefore be cited much more than the average piece in this area as the size of the team behind the project is larger.

Third, larger teams can increase the novelty and the potential for radical scientific contribution to the field. From a transactions-cost perspective, the more co-authors a paper has the greater scope for pooling risks and efforts, both of which are commonly associated with a higher propensity to develop novel scientific propositions (Soderbaum, 2001; Hauptman, 2005). Therefore, larger teams have more leeway in terms of investing time and effort into projects that are perceived to be riskier, but with greater potential impact on the field and peer research (Li, Liao, and Yen, 2013). In this way, projects involving larger teams of co-authors stand a greater chance of diverging from existing scientific paradigms and creating new ones, thereby generating more subsequent citations (Ryazanova, McNamara and Aguinis, 2017).

Finally, larger team size means also less potential for both unethical behaviours and honest mistakes (Brass, Butterfield, & Skaggs, 1998). Given the existing pressures and direct benefits associated with research performance, "honest mistakes" and fraud/misconduct are becoming more common in academic research (Azoulay et al., 2015). Furthermore, the penalties associated with such incidents remain relatively minor in terms of legitimacy (e.g., according to Azoulay, Bonatti and Krieger (2017) retractions lead to an only 10% average drop in citations to prior work of the authors) but bear significant effects in terms of reputation of those involves. More co-authors imply automatically larger potential reputational pitfalls for all parties involved in a research project, which suggests more reassurance and lower chances for unethical behaviour of authors (Crippen and Robinson, 2013).

Summing up all the above we postulate that there will be several tangible benefits from having larger teams of contributors to an academic paper. Hence:

H1a. Team size will have a positive effect on the research impact (i.e., citations) of a paper.

While our expectation is that larger teams will benefit more in terms of research impact, the relationship between team size and the prestige of research is likely to be more complex given the variety of factors determining a paper's chances of being published in a top-tier journal. Therefore, encompassing these complexities, we posit that the benefits of team size with respect to research prestige are non-linear in nature, and that increases in terms of the size of the research team may be subject to diminishing returns when it comes down to research prestige. Our intuition builds up on several key rationales from TCE and LT, as follows.

First, the coordination costs of accruing new and heterogeneous pieces of knowledge may increase, at least after a certain point, faster than the benefits when it comes to producing a highly-rated research output (Yamane, 1996). In this regard, while the distribution and division of work among team members benefits the overall productivity of the team, it does not contribute directly to the prominence (prestige) of the research (Whitley, 1984). Larger teams may present significant benefits from pooling more and diverse resources and expertise while maximizing the benefits from complementarity and cross-feeding across disciplines and sub-disciplines alike (Bechky, 2006; Singh and Fleming, 2010). Nevertheless, as the size of the team grows, the effort required to coordinate efficiently various resources, manage and integrate different knowledge, as well as ensure a proper communication and functioning of the research project increases significantly as well (Landry and Amara, 1998). This means that if a team is interested in boosting the research prestige of a project adding more people to the team will not automatically ensure this. Instead they need to add researchers that are cognitively distant enough to provide novelty to the project. Thus, resource requirements and ability to integrate new and diverse knowledge sources become progressively less efficient, given the unbalance between these efforts and potential benefits.

Second, as team size increases, coordination costs of division of the work and matching the tasks appropriately with team members' expertise will be more difficult to achieve when it comes to targeting top-tier outlets. For instance, the number of researchers within a team can significantly enhance the quality of the paper through the within-team peer review and filtering processes (Singh and Fleming, 2010). Moreover, co-authorship provides opportunities for teams to easily gain the commitment of star researchers to an on-going research project (Barnett et al., 1988; Hagen, 2010) thereby increasing its research novelty and implicitly its chances of making a significant contribution to the field (i.e., a highly-rated publication). However, larger teams imply greater efforts regarding the distribution of tasks within the team and matching each team member with their particular expertise (Katz and Martin, 1997). While these concerns could be manageable up to a point, very large teams may struggle in terms of achieving efficiently this objective and making good use of the existing heterogeneous expertise within the team. Moreover, larger teams imply lower incentives for individual members given the dissipation of benefits and reputation from the project, as well as an increase in the opportunities for free-riding (Yamane, 1996; Wagner, 2005). In the case of very large teams these effects will likely trump the aforementioned benefits.

Third, while larger teams provide an opportunity for finding new knowledge, its assimilation and adaptation will still be costly, and after a certain size threshold, these costs will outweigh the benefits. As teams seek out additional members with more diverse and distant expertise and knowledge to increase their novelty potential, they are also more likely to be subject to greater coordination and communication costs as they are likely not to share a common language or a common way of researching a particular issue (Szulanski, 1996). Such lack of common ground results in extra effort and resources devoted to understanding, assimilation and embedding of this new knowledge, which ex-post may outweigh the actual research or publication benefits (Bruce, Tait and Williams, 2004). Moreover, most elite journals remain rather focused on discipline specific topics and research agendas (Rafols et al., 2012). Moreover, integrating a very large base of knowledge might be extremely costly and may yield much lower benefits (or even negative effects) in terms of a team's ability to publish this research in a top publication.

Finally, from a LT perspective, while larger teams may acquire legitimacy more easily, they might find it more difficult to develop radical new ideas (Hackman, 1992), which will reduce the paper's ability to land in a top journal. Larger team size involves achieving greater academic consensus, which in turn will increase a paper's positioning closer to the scientific consensus in this area. As a result, papers with more co-authors will be less risk-averse, in terms of contesting existing paradigms or proposing radically novel ideas (Chambers, 1994). Subsequently, this increasing conformity with existing paradigms due to larger teams will reduce the novelty and creativity of their work (Hülsheger, Anderson and Salgado, 2009), and ultimately their chances of publishing it in the top scientific outlets.

In conclusion, as team size increases the costs of acquisition, assimilation and adaptation of new knowledge, coordination issues stemming from division of work and pooling of resources, as well as pressures to comply with existing scientific paradigms are likely to overtake the benefits in terms of achieving greater scientific novelty, commonly required to publish in prestigious outlets. Therefore, we maintain that while having larger teams could be beneficial to improve research prestige, after a certain level these benefits will be completely outweighed by additional costs and challenges. Hence:

H1b. Team size will have a curvilinear (inverted U-shape) effect on the research prestige (i.e., publishing in top journals) of a paper, with the highest research prestige occurring at intermediate levels of team size.

The moderating role of knowledge diversity

A ubiquitous benefit of working in teams is the diversity of existing knowledge that can be employed in a project. Formally, knowledge diversity refers to cognitive complementarity in a team or difference in academic disciplines covered by research team members (Nelson and Winter, 1982; Nooteboom, 2009) and prior studies postulate it as a key determinant of productivity (Reagans and Zuckerman, 2001), creativity, and innovative exploration behaviour (Bantel and Jackson, 1989; McLeod, Lobel, and Cox, 1996). However, increasing the size of the research team does not necessarily imply achieving greater knowledge diversity for a project. Given all its positive attributes of knowledge diversity, we will consider its contingent effects on the relationship between team size and research performance and argue that knowledge diversity will moderate the effects of team size on both impact and prestige of research.

First, knowledge diversity increases the benefits of specialization on research impact, because highly diverse and specialized individuals within large teams can cover more topics and draw on various expertise to produce a high impact research (Adams et al., 2009). A rich set of diverse knowledge available in teams can also accelerate the speed of absorbing new knowledge and ideas, thereby increasing the overall efficiency and providing numerous opportunities for envisioning novel associations and linkages to produce a high impact research (Moreira, Markus, & Laursen, 2018). In this sense, larger teams that also have access to greater knowledge diversity can take more risks to pursue atypical and novel combinations of diverse ideas by benefiting from division of labour, economies of scale, and absorptive capacity to generate breakthrough research output with greater impact (Hauptman, 2005; Schilling and Green, 2011; Soderbaum, 2001; Uzzi et al., 2013).

In addition, knowledge diversity further increases the benefits of reputation because large teams of co-authors from diverse intellectual domains can reach broader audiences through their networks (Leahey et al., 2017). More authors from diverse knowledge domains increase the chance that the paper will be found by those searching for work related to any given author, thereby enhancing the propensity for the paper to be (found and) read, and eventually cited (Lee et al., 2015). In this respect, having more co-authors from a variety of academic disciplines helps teams to leverage upon a greater number of disciplinary network of co-authors which will ensure greater publicity for research output and therefore more subsequent citations (Otte and Rousseau, 2002; Bentley, 2007; Valderas, 2007).

Finally, knowledge diversity enhances also the positive effects of team size on research impact via the legitimacy channel. Since large teams with co-authors from diverse academic disciplines signals a higher level of credibility from a LT perspective, they can attract a high number of citations. In fact, highly cited research outputs are derived from not only brokering knowledge by bridging structural holes across social contexts, but also from a large and credible network structure capable of supporting and protecting those ideas from skeptical scrutiny (Cattani and Ferriani, 2008). In this sense, endorsements from a variety of disciplines through co-authorship can legitimize a research output by validating and improving research from multiple angles that result in attracting more citations (Abramo, D'Angelo and Di Costa, 2009). Research outputs produced by large teams with highly diverse knowledge backgrounds will likely have a greater legitimacy across scientific fields and be able to garner citations from distant and diverse disciplines.

In light of all these arguments, greater knowledge diversity will effectively increase the ability of large teams to produce impactful research outputs that will attract a high number of citations given the combined effects of size and diversity. Hence, we posit that:

H2a. The knowledge diversity of the team will positively moderate (i.e., strengthen) the relationship between team size and research impact (i.e., citations).

While our expectation is that larger teams with knowledge diversity will benefit more in terms of research impact, the moderating role of knowledge diversity on the relationship between team size and the prestige of research is likely to be more complex given its curvilinear shape. Subsequently, we argue that the cost of recombining heterogeneous pieces of knowledge for teams may increase up to a certain point, faster than the benefits when it comes to publishing in prestigious journal outlets.

Knowledge diversity increases the costs of implementing division of labour and searching and recombining new knowledge for small teams in terms of research prestige, because integrating a large knowledge base is a challenging task for small teams. Small teams struggle in terms of achieving labour efficiency to implement diverse ideas and complete the project in a timely manner ahead of their competitors (peers). Communication in small teams is more informal and less structured than that of large teams that makes idea implementation inefficient (Desanctis and Gallupe, 1987). In addition, knowledge diversity decreases the benefits of legitimacy for small teams in terms of research prestige. With the upward trends in co-authorship practices and in greater scrutiny for interdisciplinary projects from the scientific community (Walsh, Lee, & Tang, 2019), many researchers add additional authors from other disciplines to secure more endorsements and enhance the legitimacy of their work (Liu et al., 2017; Uzzi et al., 2013). Since small teams tend to have resource and time constraints to allocate a proper level of attention to a variety of knowledge (Dahlander et al., 2016), it is challenging for small teams to gain legitimacy by forming collaborations with researchers from other disciplines. Taken together, small teams with knowledge diversity will have difficulties in efficiently implementing novel ideas and appealing the legitimacy of their work to prestigious journal outlets.

While knowledge diversity can be detrimental up to a certain point (i.e. for small teams) by attenuating the relationship between team size and research prestige, knowledge diversity lowers the costs of implementing division of labour and recombining new knowledge for large teams in terms of research prestige. This is mainly because knowledge diversity in large research teams can motivate them to pursue new opportunities to search and recombine a variety of knowledge for the generation of novel research ideas (Mitchell et al., 2009) that are appreciated by prestigious journal outlets. Large research teams with knowledge diversity can leverage upon not only their diverse expertise and resources but also efficient division of labour to implement novel research ideas and achieve breakthroughs in a timely manner (Singh and Fleming, 2010; Fleming, Mingo, and Chen, 2007). More importantly, large research teams may identify trends and opportunities from their team members' diverse knowledge and expertise to develop research projects in advance of their peers and reduce the development cycle of projects (Aldrich and Al-Turk, 2018). Therefore, knowledge diversity provides large teams with first mover advantages to take more risks and introduce a pioneering research to prestigious journals outlets.

In sum, as team size increases, its diminishing returns to research prestige will be mitigated through more effective leveraging of the team's knowledge diversity (Wales et al., 2013). Hence, we posit that knowledge diversity will moderate the proposed curvilinear relationship between team size and research prestige so that:

H2b. The knowledge diversity of the team will attenuate the positive relationship between team size and research prestige for smaller teams and mitigate the negative relationship between team size and research prestige for bigger teams.

The moderating role of international diversity

Another advantage of working in teams are the subsequent benefits of employing diverse international resources, as team members disperse across different locations, cultural and social environments (Stahl et al., 2010). As such, prior studies postulate it as a key determinant of scientific quality (Presser, 1980) and atypical academic work (Lariviere et al., 2015). However, increasing the size of the research team does not necessarily imply achieving greater international diversity of a project. Given all its positive attributes of international diversity, we will consider its contingent effects on the relationship between team size and research performance and argue that international diversity will moderate the effects of team size on both impact and prestige of research.

First, international diversity increases the benefits of specialization to research impact because large teams composed of co-authors from multiple national locations can increase the scope of resources (e.g. expertise, knowledge, and language) that are needed to produce a high impact research (Zellmer-Bruhn and Gibson, 2006). Sourcing a variety of inputs and rich contextual knowledge from co-authors located in multiple countries can enhance the applicability of a research output (Meyer-Krahmer and Reger 1999; Lavie and Miller 2008). In fact, a geographically concentrated research team may not always find use for the knowledge it has acquired, but the knowledge developed by internationally dispersed large research teams may have an application in more distant and diverse locations to garner a higher number of citations (Lahiri, 2010). In this respect, international diversity helps teams to exploit the division of labour to produce a high impact research from a transactions-cost perspective (Merton, 1968; Barnett et al., 1988; Kafouros et al., 2018).

In addition, international diversity further increases the benefits of networking on research impact, because co-authors from multiple national locations in large teams can use a larger number of available diffusion channels and networks that can help disseminate and communicate the research findings (Lee et al., 2015; Otte and Rousseau, 2002; Bentley, 2007; Valderas, 2007). International collaboration in large teams often implies a considerable 'broadening' of the audiences around the authors, enhanced by more intensive 'networking' which is characteristic for 'internationality' of research (Van Raan, 1998). Likewise, research impact is enhanced primarily through the way in which a number of individuals within teams gain access to external parties for exchanging knowledge (Nahapiet and Ghoshal, 1998). In this sense, network also provides opportunities for teams to be provided with new sources of knowledge for their projects. Subsequently, research outputs produced by large teams with international diversity can garner more citations by utilizing their network to receive state-of-art knowledge and diffuse their output (Confraria et al., 2017).

Finally, international diversity also enhances the positive effect of team size on research impact via the legitimacy channel. Since the internationalization of business and management research community has been encouraging researchers to be more inclusive through international collaborations and to produce research outputs aimed at global audiences (Corbett et al., 2014), research outputs produced by large teams with international diversity can be well-received by academic community from a LT perspective. In fact, business and management research community is becoming more global by having editors, reviewers, researchers, and readers from across the world who are collaborating and contributing to the advancement of business and management research (Eisend and Schmidt, 2014). In this context, large teams with international diversity can exploit economies of scale or scope across the world and appeal their global orientation and legitimacy in research to attract readers and eventually garner more citations (Ghoshal & Nohria, 1989).

In light of all these arguments, greater international diversity will effectively increase the ability of large teams to efficiently appeal and diffuse their work to audiences that will attract a high number of citations. Hence, we posit that:

H3a. The international diversity of the team will positively moderate (i.e., strengthen) the linear relationship between team size and research impact (i.e., citations).

While our expectation is that larger teams with international diversity will benefit more in terms of research impact, the moderating role of international diversity on the relationship between team size and the prestige of research is likely to be more complex given its curvilinear shape. Subsequently, we argue that the cost of international collaborations for teams will outweigh the benefits after a certain point when it comes to publishing in prestigious journal outlets.

International diversity decreases the costs of coordinating division of labour for small teams in terms of research prestige. Small teams with international diversity have fewer challenges to coordinate scheduling and solve communication problems derived from language and cultural distance of their team members from various countries. This is natural because small team size is ideal to encourage active reciprocal interaction and sharing of information among team members. With less hierarchical structure in small teams, international diversity will not hinder team members to freely exchange ideas to develop innovative research outputs (Cramton and Webber, 2005). In fact, the typical managerial problems derived from diverging opinions and time-frames of internationally diverse teams can be easily solved in small teams (Harryson et al., 2008). These elements show that for small teams, international diversity will be of a less concern, as in-depth interactions among the team members will not be hampered which is one of the most important drivers to ensure the quality of research for top tier journal outlets.

While international diversity can be beneficial up to a certain point (i.e. for small teams), international diversity increases the costs of coordinating division of labour and communications for large teams to publish their work in prestigious journal outlets. Despite recent enhancements in connectivity, large teams collaborating across national borders may have challenges derived from scheduling with team members across different time zones (Freeman et al., 2014) and communication problems complicating academics' deep engagement in projects (Buenstorf and Schacht, 2013; Cummings and Kiesler, 2005). International diversity in large teams can impede the ability to regulate interaction, express information, and monitor feedback from others, thus negatively affecting the establishment of mutual understanding (Cramton and Webber, 2005). Such tendency affects the cost and quality of knowledge sharing by limiting opportunities for face-to-face contact between the scholars involved in the research project (Crescenzi et al., 2016). Although technological advances have vitalized distant collaborations, they cannot substitute the face-to-face research conversations, as in-depth interaction (e.g. within-team peer review and filtering processes) plays an important role in enhancing the quality of a research to be published in prestigious journal outlets (Ryazanova and Mcnamara, 2016). For these reasons, a greater degree of international diversity in large collaborative research networks is generally associated with higher coordination and transaction costs thereby reducing the ability of the teams to publish the work in prestigious journal outlets.

In sum, as team size increases, its diminishing returns to research prestige will be strengthened by the team's international diversity. Hence, as a moderator within the proposed curvilinear relationship between team size and research prestige we posit that:

H3b. The international diversity of the team will strengthen the positive relationship between team size and research prestige for smaller teams and reinforce the negative relationship between team size and research prestige for bigger teams.

METHOD

Data sources and sample

We have collected the data from the Web of Science over the period 1994-2013 by focusing on peer-reviewed business and management journal articles that are the most relevant scholarly outputs for business researchers. The data contain detailed information on published articles such as authors' names, article titles, publication year, journal names, authors' affiliations, and annual number of forward citations. We restricted our sample to authors who started publishing from 1997 - to properly account for their historical outputs - and up to 2012 to ensure at least two years for these papers to be cited. The final core sample used for our analyses comprises of 98,776 articles appeared in 319 journals, co-authored by 133,072 different authors who are affiliated with 13,460 different institutions worldwide. With the yearly citations received by each paper up to 2013, we end up with 727,030 article-year observations for our analysis. Recall that the unit of our analyses is the output of a research team, which is composed of business researchers that have co-authored a paper published in a peer-reviewed journal. Finally, we complemented our dataset by referring to other sources as shown in Table 1.

-- Insert Table 1 Here --

Dependent variable

Following our theoretical framework, we use two indicators to measure research performance. While there is an inherent correlation between the prestige and the impact of research, there are also examples of papers that have relatively low research prestige (i.e., not published in top-tier journals) but excellent research impact in terms of citations. Therefore, to capture both facets of research performance we incorporate these two dimensions of research performance (Leahey et al., 2017).

First, '*Research impact'* is computed as the yearly number of (forward) citations a paper received until 2013 from all the publications in the Web of Science database (Furman and Stern, 2011; Azoulay, Stuart, and Wang, 2013). Second, '*Research prestige'* is a binary variable coded as "1" if the paper is published in top-tier journals and coded as "0" otherwise. We refer to the ABDC (Australian Business Deans Council) journal ranking of 2013 which provides four categories: A*, A, B, and C. A* journals refer to the highest quality category and are used as a proxy for our '*research prestige*' measure. We preferred ABDC journal ranking list than ABS journal ranking list, because the ABDC's journal coverage was much more comprehensive (e.g. 2,777 journals on ABDC journal ranking list and 1,583 journals on ABS journal ranking list).

Independent variables.

Our main explanatory variable is '*Team size'* measured as the number of authors collaborating on the focal paper. To compute *diversity* measures for knowledge and geographic locations, we employ the Jaccard index (Jaccard, 1912). While a common way to capture heterogeneity in the literature is to use the Blau index (1997), we preferred to use the Jaccard index instead because in our context scholars often have prior knowledge or expertise in many sub-fields of Management (non-exclusive categories) which can result in negative values for the Blau index. Jaccard dissimilarity index is a common normalized measure of diversity (Luukkonen et al.,1993) that captures the variations within a group of people where the value ranges from 0 to 1, higher the value is, less generic and common exists between team members. Moreover, the Jaccard index meets the four criteria for a good measurement of diversity: a higher index value indicates a higher level of diversity; the index does not allow negative values; the zero (0) value of the index represents perfect homogeneity; and the index is not unbounded. For our analysis, the Jaccard index (at team level) was calculated as the average of the Jaccard distance between each pair of co-authors in a given team. A Jaccard distance between two co-authors A_i and A_j with N binary attributes is given as follows:

$$J(A_i, A_j) = \frac{b + c}{a + b + c}$$

where *a* is the number of common attributes to both co-authors, b is the number of attributes present in A_i but not in A_j, c is the number of attributes present in A_j but not in A_i.

Thus, to operationalize '*Team knowledge diversity*', we first assigned each paper in our dataset to one of the 21 subject areas provided by the "ABS Guide 2015". Second, we traced all the authors publications in our database and recorded all the discipline areas that they published in. Third, we computed the Jaccard dissimilarity coefficient for each pair of co-authors of a given paper according to their knowledge background. Finally, we calculate the '*Team knowledge diversity*' as a mean of all the coefficients previously calculated for the different pairs of co-authors of a given paper. Hence, greater values of this index imply greater knowledge diversity across the team. Similarly, '*Team international diversity*' was computed as an average of the Jaccard dissimilarity coefficients of all the pairs of co-authors in the team by considering the differences among the countries of their home institutions. Greater values of this index imply greater international diversity within the team.

Control variables.

Following prior research, we incorporated three different sets (paper, team, and journal) of control variables in the regression specifications of the two measures of research performance: whereas some of them affect both *'Research prestige'* and *'research impact'*, others only influence the latter.

In the model employed to explain '*research prestige*' (paper level), we thus include the following measures: '*Team research experience'* capturing the ability/productivity of authors composing the team by counting the number of their publications since 1997 (the starting year of our dataset) up to the publication year of the focal paper. '*Team research impact'* is the number of citations received by the team members' prior work, accumulated up to the year of publication of the focal paper. '*Team tenure'* is the average number of years since the first publication year of each author up the publication year of the focal paper. This variable should capture also a part of authors' experience and should have a positive (or at least non-decreasing) effect on publication quality. Since the inclusion of a highly reputable institution into a team signals the potential quality of the research output and subsequently increases its impact (Judge et al., 2007), known as the Matthew's effect, we used a dummy variable '*Team affiliation prestige'* coded as "1" if the focal paper includes at least one author affiliated to an elite institution based on the University of Texas Dallas Top 100 business school research Ranking, and "0" otherwise. The UTD has created a database to track publications in 24 leading business journals in order to provide a top 100 business school rankings since 1990 based on the total contributions of faculty in research. Lastly, a dummy variable '*General journals*' was created to indicate whether the corresponding paper is published in a general business journal based on the CNRS Journal categorization (a national committee for scientific research in France).

Although the ABS Academic Journal Guide contains the categorization of academic disciplines, the classification for general journals includes not only general management journals but also journals in the domain of ethics and social responsibility. To overcome this issue, we evaluated additional lists of journal rankings (e.g., Harzing Journal Quality List, SCImago journal rankings) to select the right categorization of general management journals. After a thorough review, we selected the categorization of general management journals provided by the French national committee of scientific research (CNRS). We also manually checked the scope of journals by visiting their websites and those of relevant associated academic societies to ensure the appropriateness of our measure. Finally, to account for possible heterogeneities in the reviewer pool or preferences across years and disciplines, we included fixed-effect specifications (for year and discipline).

Turning our attention to the '*research impact*' model (paper-year level), we controlled for all the aforementioned control variables besides additional ones to tease out possible alternative explanation of paper's research impact. First, we included 'Paper prior citations' computed as the yearly lagged cumulative number of citations received by a given paper until the focal year. This is necessary, since the dependent variable ('*Research impact*') is highly dependent on the number of citations a paper received in the previous years. '*Paper age*', counted as the number of years since an article has been published (to capture the awareness/diffusion influence) is also included in our analysis of '*research impact*'. Moreover, we considered the potential effect of journal reputation on '*research impact'*, because we expect that audiences seeking for legitimacy are more likely to read and cite papers published in impactful journals (Judge et al., 2007). For this reason, we controlled for '*Journal impact factor*' which is provided by SCIMAGO over the period 1997-2013 (the journal impact factor is calculated as the average number of citations received in one year by the articles that had appeared in the focal journal during the two previous years). As for the '*research prestige*' model, we included the year and the discipline fixed effects since '*research impact'* can vary by field (referencing norms) and by year (increasing audience size).

Estimation technique

We use two different empirical models, because whereas our data for '*research prestige*' analyses are cross-sectional (paper level), our data for '*research impact*' are unbalanced panel (paper-year level). This allows us to model research outcomes at the most appropriate level, incorporate level-specific control variables, and ensure the robustness of our results. As mentioned earlier, each model includes different sets of control variables, because research prestige and research impact are distinctive measures of research performance. Recall that we used additional control variables such as '*paper prior impact'*, '*paper age*', and '*journal impact factor*' for '*research impact*' analyses. Other than these three control variables, common sets of variables were used to explain '*research prestige*' and '*research impact*'.

We adopted a negative binomial regression to predict '*research impact*', because the number of citations received by a paper in a given year is a count variable. A negative binomial regression is more appropriate than a Poisson model because the former can better deal with over-dispersion issue commonly found in the latter (Wooldridge, 2002). Moreover, to capture the within and between entities effects, we employed a random effect specification. Another advantage of random effects specification is that it includes time invariant variables. In the fixed effects model these variables are absorbed by the intercept and thus cannot be used to investigate their influence on the dependent variables. Finally, the random-effects specification does not exclude papers that had no citations during the observation period, which is not the case for the fixed-effects model. Accordingly, we used the following model to explain '*research impact*':

Research impact = β_0 + β_1*Team size + β_2*Team knowledge diversity + β_3*Team international diversity + β_4*Paper prior citations + β_5*Paper age + β_6* Team research experience + β_7* Team research impact + β_8*Team tenure + β_9*Team affiliation prestige + β_{10}*General journals + β_{11}*Journal impact factor + Year fixed effects + Discipline fixed effects + Errors

To address the non-linear relationships between the '*research prestige*' and the aforementioned explanatory and control variables, we use a logit model to predict the probability to publish in top-tier journals. Following, is the general equation of the model to explain '*research prestige*':

Y* = log[P(Y=1)/P(Y=0)] = β_0 + β_1*Team size + β_2*Team knowledge diversity + β_3*Team international diversity + β_4*Team research experience + β_5*Team impact + β_6*Team tenure + β_7*Team affiliation prestige + β_8*General journals + Year fixed effects + Discipline fixed effects + Errors

Where Y* is the continuous (latent) level of the dependent variable '*research prestige*' based on the logit link function. Thus, the relationship between our binary dependent variable '*research prestige*' (Y) and the underlying latent variable (Y*) can be written as:

$$Y = \begin{cases} 0 & \mathit{if} \quad Y^* \leq 0 \\ 1 & \mathit{if} \quad Y^* > 0 \end{cases}$$

RESULTS

Standard descriptive statistics and pairwise correlations for all the variables are given in **Tables 2 and 3**. Moderate bivariate correlations and the variance inflation factors (VIF) tests suggest that multicollinearity is not a threat in our models. The mean VIF of the full model is 2.49 for 'research impact' and 1.77 for 'research prestige'. The maximum VIF score for any individual variable across all models is 5.29 which is well below the acceptable threshold of 10.

-- Insert Tables 2 and 3 here--

Table 4 reports the negative binomial regression results for '*research impact*' as proxied by the yearly number of citations a paper receives, whereas **Table 5** shows the binary logistic regression results for '*research prestige*' as proxied by an acceptance in a top-tier journal. Models 1 in **Tables 4** and **5** examine the effects of the control variables as well as the linear effect of '*team size*'. Models 2 in **Tables 4** and **5** test the quadratic effect of '*team size*' on respectively '*research impact*' and '*research prestige*'. Models 3 in **Tables 4** and **5** include '*team knowledge diversity*' and '*team international diversity'* variables**.** Models 4 and 5 in **Tables 4** and **5** test the moderation role of these variables on the relationships between '*team size*' and respectively '*research impact*' and '*research prestige*'. It is worthwhile to note that the effects of the control and explanatory variables are consistent across all the models predicting '*research impact*' and '*research prestige*'. Furthermore, the Wald measures of the overall fit indicate significant chi-square statistics for all models ($p < 0.01$), confirming that the results are acceptable for interpretation.

-- Insert Tables 4 and 5 here—

As indicated in Model 1 of **Table 4**, '*team size*' has a positive and significant effect on '*research impact'* ($\beta = 0.09$, $p < 0.01$), as predicted in **H1a**. Furthermore, Model 2 of **Table 4** reveals that the quadratic effect of '*team size*' on '*research impact'* is not significant confirming that the relationship between these variables is linear.

On the other hand, while Models 1 of **Table 5** shows a negative and non-significant linear effect of '*team size*' on the probability to publish in top-tier journals, the significant coefficients of '*team size*' and '*team size squared*' (β =0.32, $p < 0.01$; β =-0.06, $p < 0.01$), reported in Model 2 of **Table 5,** support the curvilinear relationship (inverted-U) between '*team size*' and the likelihood a paper appears in a top-tier journals, supporting therefor **H1b.** As illustrated in **Figure 1**, the positive effect the team size on the likelihood of publishing in prestigious journals is present until a given point and then becomes negative after reaching the optimal level (three co-authors), which also confirms **H1b**.

-- Insert Figure 1 here--

By adding team diversity measures in Models 3 (see **Tables 4** and **5**), we limit our analyses to papers including at least two authors, which explains the decrease of the number of observations (all the single-authored papers were excluded from the sample). The findings from Models 3 suggest that while '*team knowledge diversity*' and '*team international diversity*' are beneficial for '*research impact*', they are detrimental for '*research prestige*'. Turning our attention to the potential moderation roles that may play '*team knowledge diversity*' and '*team international diversity*', Model 4 in **Table 4** shows a non-significant moderation effect of '*team knowledge diversity*' on the relationship between '*team size*' and '*research impact*' (No support for **H2a**), however a positive and significant interaction between '*team international diversity*' and '*team size*' (β =0.05, $p < 0.01$) in Model 5 of **Table 4**. As depicted in **Figure 2**, '*team size*' has a negative effect on '*research impact*' at a low level of '*team international diversity*', but this relationship becomes positive and stronger at a higher level of the latter. This suggests that '*team international diversity*' may be viewed as a leverage for the relationship between '*team size*' and '*research impact*' by expanding the scope of professional networks to disseminate the research team's output more widely (Lee et al., 2015). The observation from **Figure 2** coupled with the results reported in Model 5 of **Table 4**, suggest that '*team international diversity*' moderates positively the linear relationship between '*team size*' and '*research impact*', which is consistent with our prediction in **H3a**.

-- Insert Figure 2 here--

As for 'research prestige' (See **Table 5**), Model 4 reports the results with the inclusion of the interaction between '*team size*' and '*team knowledge diversity*'. The linear effect of '*team size*' on the likelihood of publishing in top tier-tier journals is positive and significant ($\beta = 0.22$, $p < 0.01$) whereas its squared effect is negative and significant ($\beta = -0.05$, $p < 0.01$). By contrast, the interaction between '*team size*' and '*team knowledge diversity*' is negative and significant ($\beta = -0.47$, $p < 0.05$), while the interaction between '*team size squared*' and '*team knowledge diversity*' is positive and significant ($\beta = 0.08$, $p < 0.05$). This suggests that the shape of the curvilinear relationship between '*team size*' and '*research prestige*' observed for a low level of '*team knowledge diversity*' is changing for a higher level of the latter. In other words, the relationship between '*team size*' and the probability to publish in the highest ranked journals is contingent upon '*team knowledge diversity*', as expected in **H2b**. Since interpreting the results of non-linear models is not trivial, we included **Figure 3** which to show how the inverted U-shape relationship between '*research prestige*' and '*team size*' flattens as '*team knowledge diversity*' increases and then turns into U-shape relationship when '*team knowledge diversity*' increases further. 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). However, '*team international diversity*' does not show any significant moderation effect on the curvilinear relationship between 'team size' and the probability to publish in top-tier journals (See Model 5 of **Table 5**), which does not support **H3b**.

-- Insert Figure 3 here--

Regarding the other determinants of 'research prestige', we found that '*team research impact*', '*team tenure*', and '*team affiliation prestige*' all have positive and significant effects on the likelihood of publishing in top-tier journals. These findings suggest that teams including scholars with a good reputation among their peers, scholars who are affiliated with prestigious institutions, and advanced career scholars tend to produce high-quality research outputs. Conversely, more productive teams (*'team research experience'*) are less likely to publish in high-ranked journals probably because it needs a longer time. The results also show that targeting general journals increases the paper's chances of being accepted in high-ranked journals.

Turning back our attention to '*research impact*', we found the same relations with control variables as for the '*research prestige*' except for the variable '*team research experience*' which seems to have no effect. So, authors' academic experience ('*team tenure*'), publishing success ('*team research impact*'), '*team affiliation prestige*', and targeting '*general journals*' all significantly increase the expected number of citations a paper may receive. Moreover, the inclusion of additional controls such as '*paper age*', '*paper prior citations*', and journal prestige proxied by the yearly '*journal impact factor*' does not alter or render insignificant the previous findings. Actually, the results reveal that '*paper prior citations*' and '*paper age*' influence positively and significantly the yearly number of citations a paper garners. Finally, as expected also, articles published in journals with a higher impact factor receive more citations.

Robustness checks

To ensure the robustness of our analyses, we tested a series of alternative specifications, and alternative measures for dependent, explanatory and control variables. First, we used a three- and a five-year window to calculate authors' prior publications and citations. Second, we replaced the journal impact factor in the *'research impact'* model with a binary variable equals one if the focal paper is published in one of the Financial Times top 45 journals list, and zero otherwise. Third, we used a binary Probit specification instead of the binary Logit specification for *'research prestige'* models (i.e., normal versus logistic regarding the assumed distribution of the error term). Finally, to retest the hypotheses **H1b**, **H2b** and **H3b,** we used an alternative measure of the team *'research prestige'* that we named '*research rating'* by referring to the same journal ranking provided by ABDC (Australian Business Deans Council) classification of 2013. In fact, '*Research rating'* is a categorical variable that takes the value of four (4) if the journal ranking is A* (the highest quality category), three (3) if the journal ranking is A (the second highest quality category), two (2) if the journal ranking is B (the third highest quality category) and one (1) if the journal ranking is C (the fourth highest quality category). Due to the ordinal nature of the dependent variable '*Research rating*', we employed an ordered logit specification. The results derived from all these supplementary analyses were consistent with the above reported ones and are omitted for sake of concision.

DISCUSSION AND CONCLUSION

Theoretical implications

Our study delves deeper into the relationship between team size and research performance by exploring some of the potential nonlinearities associated with larger research teams. We combine two theoretical lenses to analyze this issue. Thus, TCE elements address mainly the benefits and costs of team size for producing and diffuse new knowledge, while LT focuses on how team characteristics are perceived by academic gatekeepers (e.g. editors, reviewers) and general audiences to influence research performance. By combining these two perspectives, our study provides a more convincing picture of benefits and pitfalls associated with team size and combines production-side and reception-side arguments to theorize the effects of team size on research impact and research prestige.

Notably, contrary to the pervasive view that larger team size is always beneficial for overall research performance, we take a more nuanced view and argue that it matters differently for two distinctive dimensions of research performance (i.e., impact and prestige). Subsequently, our analysis confirms the non-linear effects of team size in determining the probability of a paper to be published in a top journal, as the positive effect of team size on research prestige becomes detrimental after a certain point. This is mainly because increase in team size entails more challenges for the large team to efficiently coordinate communication, and recombine heterogeneous pieces of knowledge and resources (Landry and Amara, 1998). Therefore, this study advances our understanding of "double-edged sword" effects of team size on performance, complementing prior research in this area which has predominantly focused on one aspect of research performance (i.e., citations) and its drivers in terms of characteristics of the research, e.g., authors, articles or target journals (Judge et al., 2007; Leahey et al., 2017).

Moreover, our contingency approach enables to enhance our understanding of the inter-relationships among size, diversity, and research performance of teams. Specifically, our analysis shows that whereas team international diversity positively moderates the linear relationship between team size and research impact, team knowledge diversity does not show a significant moderation effect. Furthermore, whereas team knowledge diversity moderates the curvilinear relationship between team size and research prestige, team international diversity does not show a significant moderation effect. These asymmetric moderating effects of team knowledge diversity and team international diversity highlight some micro-foundations for a theory on collaboration, learning, and high performance teams (Felin and Foss, 2005; Raisch et al., 2018), by proposing some interesting mechanisms that affect the relationship between size and research performance of teams in today's interdisciplinary and international landscape for research (Lisak et al., 2016).

Finally, we can conceptualize teams of authors involved in a research project as a form of temporary organizations that are active in a highly competitive, complex and dynamic environment. On one hand, the increases in terms of technology, communication and access to knowledge have stimulated the emergence of larger and more complex networks of research, thereby resulting in bigger and more diverse teams (Katz and Martin, 1997). Nevertheless, given the transitory nature of many of these projects, the investments in terms of time, efforts and search are difficult to estimate a priori. Our results suggest that knowledge and international diversity have both merits in terms of research performance of these temporary organizations (Burke and Morley, 2016).

Implications for Practice

Our study also provides practical implications for business and management academics around the world who are under pressure to not only make their work impactful (i.e., get higher citations) but also publish their research in the most prestigious journals (Baer and Shaw, 2017;

Leung, 2007). Under such mounting pressures (e.g. "visible or vanish"; and "publish or perish"), engaging in large and diverse teams of researchers has become the norm in many disciplines, as a prerequisite for research excellence (Liu et al., 2017). We offer some more nuanced insights into the success rate of these strategies and the types of contingencies under which such strategies work best. By clearly distinguishing between research impact and research prestige, we show that increasing team size matters differently for the citations of team-produced research outputs and for the probability of publishing team-produced research in prestigious journal outlets.

Specifically, we contest the consensus regarding the universal benefit of having larger research teams and suggest that there are also costs from forming a large team when boosting research prestige. Namely, as the team size grows, the efforts required to develop radical new ideas for top journal outlets by efficiently coordinating communication, and recombining heterogeneous pieces of knowledge and resources are challenged (Landry and Amara, 1998) that overtake the benefits of increasing team size in terms of acquiring greater legitimacy and achieving greater scientific novelty (Hackman, 1992). Moreover, our analysis on the moderating effect of team international diversity on the relationship between team size and research impact illuminates the social function of adding co-authors from multiple national locations that expands the international scope of professional and reputational networks to disseminate the research output more widely (Lee et al., 2015). Furthermore, the significant moderating effect of team knowledge diversity on the relationship between team size and research prestige highlights the persuasive function of adding co-authors, as large teams with knowledge diversity can benefit from specialization and pooling of task-specific resources and expertise to develop state-of-art arguments for prestigious journal outlets (Singh and Fleming, 2010). In sum, our findings can help scholars configure teams more effectively according to their research performance goals (i.e. research impact or research prestige) that they want to achieve.

Limitations and Future Work

This work is not without limitations, which provide directions for future research. The large sample size prevented us from collecting data on team members' socio-economic characteristics (e.g., salary, academic rank, etc.), the relationship between co-authors (e.g. colleague, Ph.D. supervisor), and the degree of contribution by each team member. Whereas previous studies (Eisend and Schmidt, 2014; Judge et al., 2007; Mangematin and Belkhouja, 2015; Mingers and Xu, 2010; Ryazanova et al., 2017) relied on survey and CV data confined to a single or a limited number of national environments or academic journals to consider the above elements to explain research performance, our analysis using more than 40,000 research outputs allows for greater generalizability. Nevertheless, as our focus was on explaining article citations as an outcome of collaboration within temporary research teams, we took into account multi-level factors by including article, journal, team, and affiliation-specific variables in our empirical model. Furthermore, to ensure the robustness of our findings, we tested the same empirical models on alternative temporal windows of our sample that are stable. Potential areas for future work could investigate the performance implications of social relationship between co-authors and the attention paid by each team member to research projects.

REFERENCES

Abramo, G., D'Angelo, C. A., & Di Costa, F. (2009). Research collaboration and productivity: is there correlation?. *Higher Education*, 57(2), 155-171.

Adams, J. D., Black, G. C., Clemmons, J. R., & Stephan, P. E. (2005). Scientific teams and institutional collaborations: Evidence from US universities, 1981–1999. *Research policy*, 34(3), 259-285.

Aldrich, H.E., & Al-Turk, A. (2018). Crouching Authors, Hidden Pitfalls: Collaboration in Research. *Studi di Sociologia*, 56(4), 351-368.

Andrews, F.M., 1976. Creative process. In: Pelz, D.C., Andrews, F.M. (Eds.), Scientists in Organizations. , 2nd ed. University of Michigan Institute for Social Research, Ann Arbor, MI, pp.337–366.

Azoulay, P., Furman, J. L., Krieger, J. L., & Murray, F. (2015). Retractions. *Review of Economics and Statistics*, 97(5), 1118-1136.

Baer, M., & Shaw, J. D. (2017). Falling in Love Again with What We Do: Academic Craftsmanship in the Management Sciences. *Academy of Management Journal*, 60(4), 1213-1217.

Babchuk, N., Keith, B., & Peters, G. (1999). Collaboration in sociology and other scientific disciplines: A comparative trend analysis of scholarship in the social, physical, and mathematical sciences. *The American Sociologist*, 30(3), 5-21.

Bammer, G. (2008). Enhancing research collaborations: Three key management challenges. *Research Policy*, 37(5), 875-887.

Bantel, K. A., & Jackson, S. E. (1989). Top management and innovations in banking: Does the composition of the top team make a difference?. *Strategic Management Journal*, 10(S1), 107-124.

Bar-Ilan, J. (2008). Which h-index?—A comparison of WoS, Scopus and Google Scholar. *Scientometrics*, 74(2), 257-271.

Barnett, A. H., Ault, R. W., & Kaserman, D. L. 1988. The rising incidence of co-authorship in economics: Further evidence. *The Review of Economics and Statistics*, 70(3), 539-543.

Belkhouja, M., & Yoon, H. D. (2018). How does openness influence the impact of a scholar's research? An analysis of business scholars' citations over their careers. *Research Policy*, 47(10), 2037-2047.

Bentley, R.A., 2007. Why do team-authored papers get cited more? Science (New York, NY) 317, 1496–1498, author reply 1496–1498.

Bowler, P. J., and Morus, I. R. (2010). *Making modern science: A historical survey*. University of Chicago Press.

Brass, D. J., Butterfield, K. D., & Skaggs, B. C. (1998). Relationships and unethical behavior: A social network perspective. *Academy of Management Review*, 23(1), 14-31.

Bruce, A., Lyall, C., Tait, J., & Williams, R. (2004). Interdisciplinary integration in Europe: the case of the Fifth Framework programme. *Futures*, 36(4), 457-470.

Buenstorf, G., & Schacht, A. (2013). We need to talk–or do we? Geographic distance and the commercialization of technologies from public research. *Research Policy*, 42(2), 465-480.

Burke, C. M., and Morley, M. J. (2016). On temporary organizations: A review, synthesis and research agenda. *Human relations*, 69(6), 1235-1258.

Cattani, G., & Ferriani, S. (2008). A core/periphery perspective on individual creative performance: Social networks and cinematic achievements in the Hollywood film industry. Organization science, 19(6), 824-844.

Cattani G, Ferriani S, Frederiksen L and Täube F (eds) (2011) *Project-Based Organizing and Strategic Management*. Bingley: Emerald Group Publishing Limited

Chambers, R. (1994). Paradigm shifts and the practice of participatory research and development. Available: https://opendocs.ids.ac.uk/opendocs/bitstream/handle/123456789/3712/WP2.pdf
Chambers, C. P., & Miller, A. D. (2014). Scholarly influence. *Journal of Economic Theory*, 151, 571-583.
Cohen, S. G., & Bailey, D. E. (1997). What makes teams work: Group effectiveness research from the shop floor to the executive suite. *Journal of Management*, 23(3), 239-290.
Confraria, H., Godinho, M. M., & Wang, L. (2017). Determinants of citation impact: A comparative analysis of the Global South versus the Global North. *Research Policy*, 46(1), 265-279.
Corbett, A., Cornelissen, J., Delios, A. and Harley, B. (2014). Variety, novelty, and perceptions of scholarship in research on management and organizations: An appeal for ambidextrous scholarship. *Journal of Management Studies*, 51(1), 3-18.
Cramton, C. D., & Webber, S. S. (2005). Relationships among geographic dispersion, team processes, and effectiveness in software development work teams. *Journal of Business Research*, 58(6), 758-765.
Crescenzi, R., Nathan, M., & Rodríguez-Pose, A. (2016). Do inventors talk to strangers? On proximity and collaborative knowledge creation. *Research Policy*, 45(1), 177-194.
Cronin, B. (1984). The citation process: The role and significance of citations in scientific communication. London: Graham.
Crippen, J. A., & Robinson, L. C. (2013). In defense of the lone wolf: Collaboration in language documentation. Available at: https://scholarspace.manoa.hawaii.edu/bitstream/10125/4577/1/crippenrobinson.pdf
Cummings, J. N., & Kiesler, S. (2005). Collaborative research across disciplinary and organizational boundaries. *Social Studies of Science*, 35(5), 703-722.
Dahlander, L., O'Mahony, S., & Gann, D. M. (2016). One foot in, one foot out: how does individuals' external search breadth affect innovation outcomes?. *Strategic Management Journal*, 37(2), 280-302.
De Rond, M., & Miller, A. N. (2005). Publish or perish: bane or boon of academic life?. *Journal of Management Inquiry*, 14(4), 321-329.
Desanctis, G., & Gallupe, R. B. (1987). A foundation for the study of group decision support systems. *Management Science*, 33(5), 589-609.
Diamond, A. M. (1986). The life-cycle research productivity of mathematicians and scientists. *Journal of Gerontology*, 41(4), 520-525.
Ding, Y. (2011). Scientific collaboration and endorsement: Network analysis of coauthorship and citation networks. *Journal of Informetrics*, 5(1), 187-203.
Eisend, M., & Schmidt, S. (2014). The influence of knowledge-based resources and business scholars' internationalization strategies on research performance. *Research Policy*, 43(1), 48-59.
Felin, T., and Foss, N. J. (2005). Strategic organization: A field in search of micro-foundations. *Strategic Organization,* 3(4), 441-455.
Fleming, L., Mingo, S., & Chen, D. (2007). Collaborative brokerage, generative creativity, and creative success. *Administrative Science Quarterly*, 52(3), 443-475.
Floyd, S. W., Schroeder, D. M., & Finn, D. M. 1994. "Only if I'm first author": Conflict over credit in management scholarship. *Academy of Management Journal*, 37(3), 734–747.
Fox, M. F., & Faver, C. A. (1984). Independence and cooperation in research: The motivations and costs of collaboration. *The Journal of Higher Education*, *55*(3), 347-359.
Freeman, R. B., Ganguli, I., & Murciano-Goroff, R. (2014). Why and wherefore of increased scientific collaboration. In The changing frontier: Rethinking science and innovation policy (pp. 17-48). University of Chicago Press.

Ghoshal, S., & Nohria, N. (1989). Internal differentiation within multinational corporations. *Strategic Management Journal*, 10(4), 323-337.
Hackman, J. R. (1992). Group influences on individuals in organizations. In M. D. Dunnette & L. M. Hough (Eds.), Handbook of industrial and organizational psychology (Vol.3, pp. 199-267). Palo Alto, CA: Consulting Psychologists Press.
Hagen, N. T. 2010. Harmonic publication and citation counting: Sharing authorship credit equitably–Not equally, geometrically or arithmetically. *Scientometrics*, 84(3), 785-793.
Hall, J., & Martin, B. R. (2018). Towards a taxonomy of research misconduct: the case of business school research. *Research Policy*.
Hamermesh, D. S. (2018). Citations in Economics: Measurement, Uses, and Impacts. *Journal of Economic Literature*, 56(1), 115-56.
Hansen, W. L., Weisbrod, B. A., & Strauss, R. P. (1978). Modeling the earnings and research productivity of academic economists. *Journal of Political Economy*, 86(4), 729-741.
Harris, C. (2008). Ranking the management journals. *Journal of Scholarly Publishing*, 39(4), 373-409.
Harryson, S., Kliknaite, S., & Dudkowski, R. (2008). Flexibility in innovation through external learning: exploring two models for enhanced industry? university collaboration. *International Journal of Technology Management*, 41(1-2), 109-137.
Hauptman, R. (2005). How to be a successful scholar: Publish efficiently. *Journal of Scholarly Publishing*, 36(2), 115-119.
Hirsch, J. E. (2005), An index to quantify an individual's scientific research output. *PNAS*, 102(46), 16569–16572.
Hoekman, J., Frenken, K., & Tijssen, R. J. (2010). Research collaboration at a distance: Changing spatial patterns of scientific collaboration within Europe. *Research Policy*, 39(5), 662-673.
Hollingsworth, R., 2004. Institutionalizing excellence in biomedical research: the case of Rockefeller University. In: Stapleton, D.H. (Ed.), Creating a Tradition of Biomedical Research. Rockefeller University Press, NewYork.
Hülsheger, U. R., Anderson, N., and Salgado, J. F. (2009). Team-level predictors of innovation at work: A comprehensive meta-analysis spanning three decades of research. Journal of Applied Psychology, 94(5), 1128-1145.
Jaccard, P. (1912). The distribution of the flora in the alpine zone. New Phytologist, 11(2), 37-50.
Johnson, G. E., & Stafford, F. P. (1974). Lifetime earnings in a professional labor market: Academic economists. *Journal of Political Economy*, 82(3), 549-569.
Judge, T. A., Cable, D. M., Colbert, A. E., and Rynes, S. L. (2007). What causes a management article to be cited—article, author, or journal?. *Academy of Management Journal*, 50(3), 491-506.
Kacperczyk, A. and Younkin, P. (2017). The paradox of breadth: The tension between experience and legitimacy in the transition to entrepreneurship. *Administrative Science Quarterly*, 62(4), 731-64.
Kafouros, M., Wang, C., Mavroudi, E., Hong, J., & Katsikeas, C. S. (2018). Geographic dispersion and co-location in global R&D portfolios: Consequences for firm performance. *Research Policy*, 47(7), 1243-1255.
Katz, J. S., & Martin, B. R. (1997). What is research collaboration?. *Research Policy*, 26(1), 1-18.
Kiesler, C.A., 1969. Group Pressure and Conformity. Macmillan, NewYork.
Lahiri, N. (2010). Geographic distribution of R&D activity: how does it affect innovation quality?. *Academy of Management Journal*, 53(5), 1194-1209.

Landry, R., & Amara, N. (1998). The impact of transaction costs on the institutional structuration of collaborative academic research. *Research Policy*, 27(9), 901-913.

Larivière, V., Gingras, Y., Sugimoto, C. R., & Tsou, A. (2015). Team size matters: Collaboration and scientific impact since 1900. *Journal of the Association for Information Science and Technology*, 66(7), 1323-1332.

Lavie, D., & Miller, S. R. (2008). Alliance portfolio internationalization and firm performance. *Organization Science*, 19(4), 623-646.

Leahey, E. (2007). Not by productivity alone: How visibility and specialization contribute to academic earnings. *American Sociological Review*, 72(4), 533-561.

Leahey, E., Beckman, C. M., & Stanko, T. L. (2017). Prominent but less productive: The impact of interdisciplinarity on scientists' research. *Administrative Science Quarterly*, 62(1), 105-139.

Lee, Y. N., Walsh, J. P., & Wang, J. (2015). Creativity in scientific teams: Unpacking novelty and impact. *Research Policy*, 44(3), 684-697.

Lee, S., & Bozeman, B. (2005). The impact of research collaboration on scientific productivity. *Social studies of science*, 35(5), 673-702.

Leung, K. (2007). The glory and tyranny of citation impact: An East Asian perspective. *Academy of Management Journal*, 50(3), 510-513.

Li, E. Y., Liao, C. H., & Yen, H. R. (2013). Co-authorship networks and research impact: A social capital perspective. *Research Policy*, 42(9), 1515-1530.

Linton, J. D., & Thongpapanl, N. (2004). Perspective: Ranking the technology innovation management journals. *Journal of Product Innovation Management*, 21(2), 123-139.

Lisak, A., Erez, M., Sui, Y., & Lee, C. (2016). The positive role of global leaders in enhancing multicultural team innovation. *Journal of International Business Studies*, 47(6), 655-673.

Liu, C., Olivola, C. Y., & Kovács, B. (2017). Coauthorship Trends in the Field of Management: Facts and Perceptions. *Academy of Management Learning & Education*, 16(4), 509-530.

Luukkonen, T., Tussen, R. J. W., Persson, O., & Sivertsen, G. (1993). The measurement of international scientific collaboration. Scientometrics, 28(1), 15-36.

Manton, E. J., & English, D. E. 2007. The trend toward multiple authorship in business journals. *Journal of Education for Business*, 82(3), 164–168.

Marchant, T. (2009). An axiomatic characterization of the ranking based on the h-index and some other bibliometric rankings of authors. *Scientometrics*, 80(2), 325-342.

McLeod, P. L., Lobel, S. A., & Cox Jr, T. H. (1996). Ethnic diversity and creativity in small groups. *Small Group Research*, 27(2), 248-264.

Merton, R. K. (1968). The Matthew effect in science: The reward and communication systems of science are considered. *Science*, 159(3810), 56-63.

Meyer-Krahmer, F., & Reger, G. (1999). New perspectives on the innovation strategies of multinational enterprises: lessons for technology policy in Europe. *Research Policy*, 28(7), 751-776.

Mingers, J., & Xu, F. (2010). The drivers of citations in management science journals. *European Journal of Operational Research*, 205(2), 422-430.

Miron-Spektor, E., Ingram, A., Keller, J., Smith, W. K., and Lewis, M. W. (2018). Microfoundations of organizational paradox: The problem is how we think about the problem. *Academy of Management Journal*, 61(1), 26-45.

Mitchell, R., Nicholas, S., & Boyle, B. (2009). The role of openness to cognitive diversity and group processes in knowledge creation. *Small Group Research*, 40(5), 535-554.

Moed, H. F., Burger, W. J. M., Frankfort, J. G., & Van Raan, A. F. (1985). The use of bibliometric data for the measurement of university research performance. *Research Policy*, 14(3), 131-149.

Moreira, S., Markus, A., & Laursen, K. (2018). Knowledge diversity and coordination: The effect of intrafirm inventor task networks on absorption speed. *Strategic Management Journal*, 39(9), 2517-2546.
Nahapiet, J., & Ghoshal, S. (1998). Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review*, 23(2), 242-266.
Nederhof, A. J. (2006). Bibliometric monitoring of research performance in the social sciences and the humanities: A review. *Scientometrics*, 66(1), 81-100.
Nelson, R. R. and S. G. Winter (1982).An Evolutionary Theory of Economic Change. Belknap Press of Harvard University Press, Cambridge, MA.
Nooteboom, B. (2009). A cognitive theory of the firm: Learning, governance and dynamic capabilities. Edward Elgar Publishing.
Otte, E., & Rousseau, R. (2002). Social network analysis: a powerful strategy, also for the information sciences. *Journal of Information Science*, 28(6), 441-453.
Pezzoni, M., Sterzi, V., & Lissoni, F. (2012). Career progress in centralized academic systems: Social capital and institutions in France and Italy. *Research Policy*, 41(4), 704-719.
Pieterse, A. N., Van Knippenberg, D., & Van Dierendonck, D. (2013). Cultural diversity and team performance: The role of team member goal orientation. *Academy of Management Journal*, 56(3), 782-804.
Presser, S. (1980). Collaboration and the quality of research. *Social Studies of Science*, 10(1), 95-101.
Rafols, I., Leydesdorff, L., O'Hare, A., Nightingale, P., & Stirling, A. (2012). How journal rankings can suppress interdisciplinary research: A comparison between innovation studies and business & management. *Research Policy*, 41(7), 1262-1282.
Raisch, S., Hargrave, T. J., and Van De Ven, A. H. (2018). The learning spiral: A process perspective on paradox. *Journal of Management Studies.*
Reagans, R., & Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organization Science*, 12(4), 502-517.
Ryazanova, O., & McNamara, P. (2016). Socialization and proactive behavior: Multilevel exploration of research productivity drivers in US business schools. *Academy of Management Learning & Education*, 15(3), 525-548.
Ryazanova, O., McNamara, P., & Aguinis, H. (2017). Research performance as a quality signal in international labor markets: Visibility of business schools worldwide through a global research performance system. *Journal of World Business*, 52(6), 831-841.
Sauer, R. D. (1988). Estimates of the returns to quality and coauthorship in economic academia. *Journal of Political Economy*, 96(4), 855-866.
Schilling, M. A., & Green, E. (2011). Recombinant search and breakthrough idea generation: An analysis of high impact papers in the social sciences. *Research Policy*, 40(10), 1321-1331.
Söderbaum, F. (2001). Networking and capacity building: the role of regional research networks in Africa. *The European Journal of Development Research*, 13(2), 144-163.
Simonton, D. K. (1999). *Origins of genius: Darwinian perspectives on creativity*. Oxford University Press.
Simonton, D. K. (2013). After Einstein: scientific genius is extinct. *Nature*, 493(7434), 602.
Singh, J., & Fleming, L. (2010). Lone inventors as sources of breakthroughs: Myth or reality?. *Management Science*, 56(1), 41-56.
Stahl, G. K., Maznevski, M. L., Voigt, A., & Jonsen, K. (2010). Unraveling the effects of cultural diversity in teams: A meta-analysis of research on multicultural work groups. *Journal of International Business Studies*, 41(4), 690-709.
Stewart, G. L. (2006). A meta-analytic review of relationships between team design features and team performance. *Journal of Management*, 32(1), 29-55.

Suchman, M. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review*, 20(3), 571-610.

Szulanski, G. (1996). Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic management journal*, 17(S2), 27-43.

Tahai, A., & Meyer, M. J. (1999). A revealed preference study of management journals' direct influences. *Strategic Management Journal,* 20(3), 279-296.

Thomas, H. and Wilson, A. (2011). 'Physics envy', cognitive legitimacy or practical relevance: Dilemmas in the evolution of management research in the UK. *British Journal of Management*, 22(3), 443-56.

Trieschmann, J. S., Dennis, A. R., Northcraft, G. B., & Nieme Jr, A. W. (2000). Serving constituencies in business schools: MBA program versus research performance. *Academy of Management Journal*, 43(6), 1130-1141.

Valderas, J.M., 2007. Why do team-authored papers get cited more? Science (New York, NY) 317, 1496.

Van Leeuwen, T. N., Moed, H. F., Tijssen, R. J., Visser, M. S., & Van Raan, A. F. (2001). Language biases in the coverage of the Science Citation Index and its consequencesfor international comparisons of national research performance. *Scientometrics*, 51(1), 335-346.

Van Raan, A. (1998). The influence of international collaboration on the impact of research results: Some simple mathematical considerations concerning the role of self-citations. *Scientometrics*, 42(3), 423-428.

Wagner III, J. A. (1995). Studies of individualism-collectivism: Effects on cooperation in groups. *Academy of Management journal,* 38(1), 152-173.

Wales, W. J., Parida, V., & Patel, P. C. (2013). Too much of a good thing? Absorptive capacity, firm performance, and the moderating role of entrepreneurial orientation. *Strategic Management Journal*, 34(5), 622-633.

Walsh, J. P., Lee, Y. N., & Tang, L. (2019). Pathogenic organization in science: Division of labor and retractions. *Research Policy*, 48(2), 444-461.

Whitley, R., 1984. The Intellectual and Social Organization of the Sciences. Oxford University Press, Oxford.

Williamson, O.E., 1975. Markets and Hierarchies: Analysis and Antitrust Implication, New York, The Free Press.

Williamson, O.E., 1985. The Economic Institutions of Capitalism. New York, The Free Press.

Williamson, O.E., 1996. The Mechanisms of Governance, Oxford, Oxford University Press.

Wray, B. K. 2006. Scientific authorship in the age of collaborative research. *Studies in History and Philosophy of Science*, 37(3), 505–514.

Wuchty, S., Jones, B. F., & Uzzi, B. (2007). The increasing dominance of teams in production of knowledge. *Science*, 316(5827), 1036-1039.

Yamane, D. (1996). Collaboration and its discontents: Steps toward overcoming barriers to successful group projects. *Teaching Sociology*, 24(4), 378-383.

Zellmer-Bruhn, M., & Gibson, C. (2006). Multinational organization context: Implications for team learning and performance. *Academy of Management Journal*, 49(3), 501-518.

Table 1. Variables employed in this study

Variables	Measurement	Sources	Research prestige	Research impact
Dependent variables				
Research prestige	Binary variable that takes on “1” if the paper is published in top-tier journals (A* journals) and “0” otherwise	*ABDC	X	
Research impact	Yearly number of forward citations received by a paper	Web of Science, SCOPUS		X
Independent variables				
Team size	Number of authors in the team	Web of Science, SCOPUS	X	X
Moderation variables				
Team knowledge diversity	Jaccard distance at team-level of the differences between authors’ regarding their knowledge domains	*ABS	X	X
Team international diversity	Jaccard distance at team-level of the differences between authors’ regarding their countries of affiliations	Web of Science, SCOPUS	X	X
Control variables				
Paper prior citations	Yearly lagged cumulative number of citations received by the focal paper until the focal year	Web of Science, SCOPUS		X
Paper age	Number of years since an article has been published	Web of Science, SCOPUS		X
Team research experience	Lagged cumulative number of publications of all individuals in team excluding the focal paper	Web of Science, SCOPUS	X	X
Team research impact	Lagged cumulative number of citations received by all individuals in a given team excluding the focal paper	Web of Science, SCOPUS	X	X
Team tenure	Average number of years dedicated for research since the first publication of each author	Web of Science, SCOPUS	X	X
Team affiliation prestige	Dummy variable equal to “1” if the papers has at least one author affiliated with a high-status institution and “0” otherwise.	*UTD	X	X
General journal	Dummy variable equal to “1” if the paper has been published in a general-purpose journal, and “0” otherwise	*CNRS	X	X
Journal impact factor	Average number of citations received in one year by the articles that had appeared in the focal journal during the two previous years	*SCIMAGO		X
Year	Year dummy variables denoting the year (1997 is the baseline category)		X	X
Discipline	Discipline dummy variables (Accounting is the baseline category)	*ABS	X	X

*Notes:
ABDC: http://www.abdc.edu.au/pages/abdc-journal-quality-list-2013.html
ABS: https://charteredabs.org/academic-journal-guide-2015/
UTD: http://jindal.utdallas.edu/the-utd-top-100-business-school-research-rankings/worldRankings#20122016
CNRS: https://www.gate.cnrs.fr/spip.php?article1002&lang=en
SCIMAGO: http://www.scimagoir.com

Table 2. Descriptive statistics and Pearson correlations (paper-year level: N=727,030)

		1	2	3	4	5	6	7	8	9	10	11	12
1.	Research impact	1.00											
2.	Team size	0.03^{***}	1.00										
3.	Team knowledge diversity	0.14^{***}	0.02^{***}	1.00									
4.	Team international diversity	-0.01^{***}	0.04^{***}	0.04^{***}	1.00								
5.	Paper prior citations [a]	0.61^{***}	-0.02^{***}	0.13^{***}	-0.04^{***}	1.00							
6.	Paper age [a]	0.29^{***}	-0.07^{***}	0.05^{***}	-0.05^{***}	0.75^{***}	1.00						
7.	Team research experience [a]	0.23^{***}	0.34^{***}	0.54^{***}	0.03^{***}	0.20^{***}	0.07^{***}	1.00					
8.	Team research impact [a]	0.43^{***}	0.16^{***}	0.47^{***}	0.00^{*}	0.60^{***}	0.40^{***}	0.65^{***}	1.00				
9.	Team tenure [a]	0.28^{***}	-0.02^{***}	0.33^{***}	-0.02^{***}	0.60^{***}	0.72^{***}	0.47^{***}	0.65^{***}	1.00			
10.	Team affiliation prestige	0.12^{***}	0.07^{***}	0.13^{***}	-0.02^{***}	0.08^{***}	-0.01^{***}	0.25^{***}	0.24^{***}	0.11^{***}	1.00		
11.	General journal	0.07^{***}	-0.01^{***}	0.08^{***}	-0.01^{***}	0.05^{***}	-0.00^{*}	0.05^{***}	0.07^{***}	0.03^{***}	0.07^{***}	1.00	
12.	Journal impact factor	0.40^{***}	0.05^{***}	0.21^{***}	-0.02^{***}	0.36^{***}	0.14^{***}	0.28^{***}	0.44^{***}	0.28^{***}	0.19^{***}	0.18^{***}	1.00
	Mean	2.56	2.63	0.30	0.44	1.31	1.39	2.03	3.35	1.84	0.30	0.068	2.12
	S.D.	3.82	0.82	0.28	0.44	1.27	0.80	0.66	1.97	0.66	0.46	0.25	1.54
	Minimum	0	1	0	0	0	0	1.10	0	0	0	0	0
	Maximum	96	8	0.94	1	4.95	2.83	4.96	9.15	2.83	1	1	14.6

a Logarithm transformed.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 3. Descriptive statistics and Pearson correlations (paper level: N=98,776)

		1	2	3	4	5	6	7	8	9
1.	Research prestige	1.00								
2.	Team size	-0.00	1.00							
3.	Team knowledge diversity	0.06^{***}	0.05^{***}	1.00						
4.	Team international diversity	-0.03^{***}	0.05^{***}	0.06^{***}	1.00					
5.	Team research experience [a]	0.13^{***}	0.40^{***}	0.59^{***}	0.07^{***}	1.00				
6.	Team research impact [a]	0.17^{***}	0.21^{***}	0.58^{***}	0.05^{***}	0.64^{***}	1.00			
7.	Team tenure [a]	0.15^{***}	0.08^{***}	0.59^{***}	0.04^{***}	0.65^{***}	0.65^{***}	1.00		
8.	Team affiliation prestige	0.26^{***}	0.07^{***}	0.14^{***}	-0.00	0.24^{***}	0.26^{***}	0.22^{***}	1.00	
9.	General journals	0.13^{***}	-0.01^{**}	0.09^{***}	-0.01	0.05^{***}	0.06^{***}	0.05^{***}	0.07^{***}	1.00
	Mean	0.36	2.20	0.27	0.46	1.93	2.13	1.07	0.30	0.07
	S.D.	0.48	1.05	0.28	0.43	0.67	2.12	0.83	0.46	0.25
	Minimum	0	1	0	0	1.10	0	0	0	0
	Maximum	1	8	0.94	1	4.81	8.99	2.77	1	1

a Logarithm transformed.
* p < 0.10, ** p < 0.05, *** p < 0.01

Table 4. Negative binomial parameter estimates for the yearly number of citations (‘*research impact*’)

Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Paper prior citations	0.0259***	0.0270***	0.0269***	0.0268***	0.0268***
	(0.0032)	(0.0032)	(0.0037)	(0.0037)	(0.0037)
Paper age	1.0502***	1.0506***	1.2058***	1.2058***	1.2059***
	(0.0074)	(0.0074)	(0.0088)	(0.0088)	(0.0088)
Team research experience	0.0072	0.0015	0.1397***	0.1391***	0.1394***
	(0.0049)	(0.0049)	(0.0063)	(0.0063)	(0.0063)
Team research impact	0.2143***	0.2123***	0.1958***	0.1957***	0.1957***
	(0.0029)	(0.0029)	(0.0034)	(0.0034)	(0.0034)
Team tenure	-0.4295***	-0.4258***	-0.5263***	-0.5265***	-0.5263***
	(0.0075)	(0.0075)	(0.0097)	(0.0097)	(0.0097)
Team affiliation prestige	0.4686***	0.4630***	0.2879***	0.2873***	0.2876***
	(0.0157)	(0.0157)	(0.0177)	(0.0177)	(0.0177)
General journal	0.1026***	0.1024***	0.0974***	0.0974***	0.0974***
	(0.0013)	(0.0013)	(0.0015)	(0.0015)	(0.0015)
Journal impact factor	0.0648***	0.0649***	0.0537***	0.0536***	0.0537***
	(0.0041)	(0.0041)	(0.0045)	(0.0045)	(0.0045)
Team size	0.0887***	0.1223***	0.0177***	0.0121*	-0.0088
	(0.0038)	(0.0117)	(0.0050)	(0.0064)	(0.0079)
Team size squared		-0.0284			
		(0.0020)			
Team knowledge diversity			0.0230**	-0.0185	0.0231**
			(0.0099)	(0.0305)	(0.0099)
Team international diversity			0.0684***	0.0682***	-0.0671**
			(0.0091)	(0.0091)	(0.0327)
Team size # Team knowledge diversity				0.0173	
				(0.0121)	
Team size # Team international diversity					0.0548***
					(0.0127)
Constant	0.0541	-0.1093*	0.0789	0.0935	0.1452*
	(0.0584)	(0.0595)	(0.0744)	(0.0751)	(0.0760)
Year dummy variables	Yes	Yes	Yes	Yes	Yes
Discipline dummy variables	Yes	Yes	Yes	Yes	Yes
Number of observations (paper-year)	727030	727030	488799	488799	488799
Number of papers	98776	98776	69818	69818	69818
Min number of observations per paper	2	2	2	2	2
Max number of observations per paper	17	17	17	17	17
Log-likelihood statistic	-1149777.81	-1149681.82	-820224.78	-820223.75	-820215.50
Wald X^2 statistic	299597.33***	299623.52***	212925.52***	212928.96***	212945.08***
D.F.	47	48	49	49	49

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. standard errors in parentheses. All significance tests are based on two-tailed tests.

Table 5. Binary logit parameter estimates for the probability of publishing in top-tier journals (‘*research prestige*’)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Team research experience	-0.1426***	-0.1984***	-0.1806***	-0.1797***	-0.1797***
	(0.0242)	(0.0248)	(0.0300)	(0.0300)	(0.0300)
Team research impact	0.1701***	0.1769***	0.1719***	0.1718***	0.1720***
	(0.0086)	(0.0087)	(0.0101)	(0.0102)	(0.0101)
Team tenure	0.0455***	0.0371**	0.0272	0.0267	0.0268
	(0.0175)	(0.0175)	(0.0225)	(0.0225)	(0.0225)
Team affiliation prestige	0.9865***	0.9850***	1.0131***	1.0130***	1.0133***
	(0.0176)	(0.0176)	(0.0198)	(0.0198)	(0.0198)
General journal	2.9132***	2.8939***	2.6522***	2.6516***	2.6529***
	(0.0459)	(0.0459)	(0.0512)	(0.0512)	(0.0512)
Team size	-0.0160	0.3255***	0.0929*	0.2196***	0.2088**
	(0.0104)	(0.0304)	(0.0531)	(0.0809)	(0.0912)
Team size squared		-0.0609***	-0.0289***	-0.0499***	-0.0443***
		(0.0051)	(0.0078)	(0.0124)	(0.0143)
Team knowledge diversity			-0.1593***	0.4902	-0.1592***
			(0.0435)	(0.3296)	(0.0435)
Team international diversity			-0.1795***	-0.1797***	0.2157
			(0.0212)	(0.0212)	(0.2219)
Team size # Team knowledge diversity				-0.4681**	
				(0.2220)	
Team size squared # Team knowledge diversity				0.0771**	
				(0.0349)	
Team size # Team international diversity					-0.2465
					(0.1521)
Team size squared # Team international diversity					0.0325
					(0.0243)
Constant	-0.1341***	-0.4663***	-0.0742	-0.2498*	-0.2605*
	(0.0417)	(0.0502)	(0.0930)	(0.1299)	(0.1416)
Year dummy variables	Yes	Yes	Yes	Yes	Yes
Discipline dummy variables	Yes	Yes	Yes	Yes	Yes
Number of papers	98776	98776	69819	69819	69819
Log-likelihood statistic	-47617.06	-47543.03	-35778.84	-35776.32	-35776.68
LR X^2 statistic	23625.04***	23773.11***	15872.48***	15877.53***	15876.79***
D.F.	33	34	36	38	38
Pseudo R^2	0.2417	0.2427	0.2186	0.2188	0.2188

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. All significance tests are based on two-tailed tests.

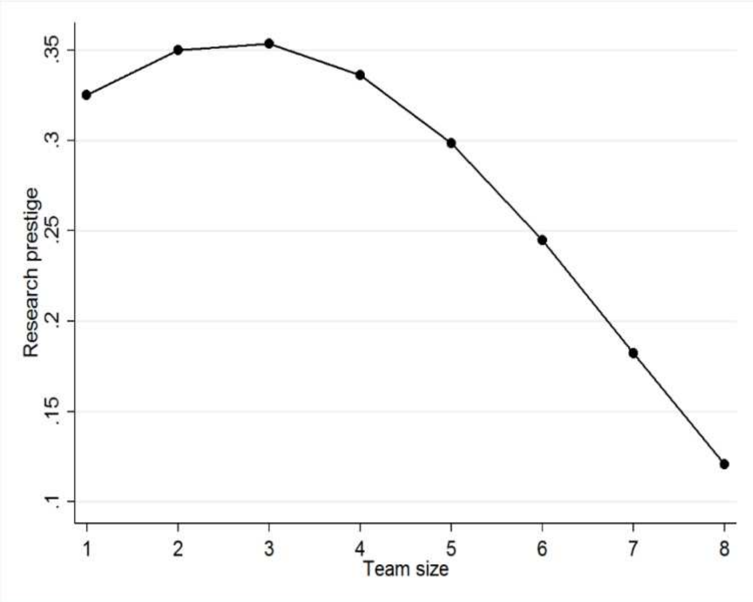

Figure 1. Marginal effect of team size on research prestige. The results are based on the estimates from Model 2 of Table 5.

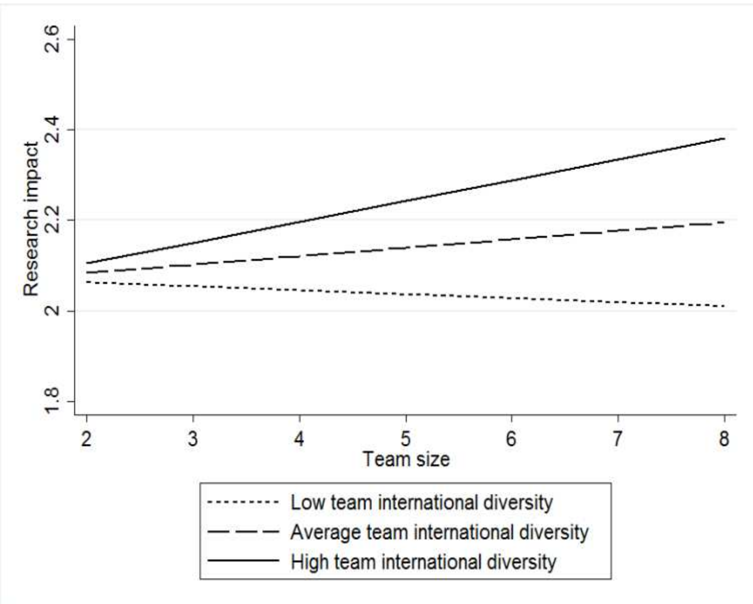

Figure 2. Moderation effects of team international diversity on the relationship between team size and research impact. The results are based on the estimates from Model 4 of Table 4

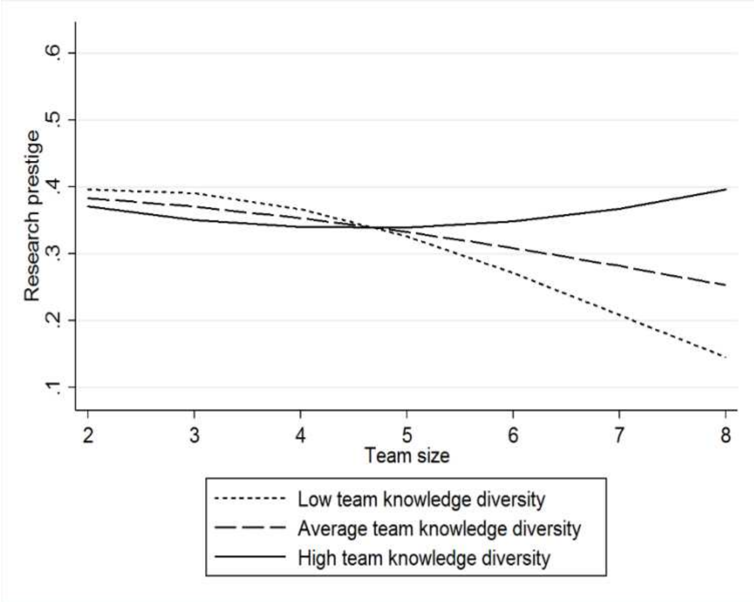

Figure 3. Moderation effects of team knowledge diversity on the relationship between team size and research prestige. The results are based on the estimates from Model 3 of Table 5.