AN IVORY TOWER OF BABEL? THE IMPACT OF SIZE AND DIVERSITY OF TEAMS ON RESEARCH PERFORMANCE IN BUSINESS SCHOOLS

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Abstract

Despite the prevalence of teams in research, we lack a good understanding of how their size and diversity affects their performance. We develop a theoretical framework that distinguishes two dimensions of research performance for an academic paper: *impact* (i.e., subsequent citations) and *prestige* (i.e., ranking of the journal where research gets published). We propose that, while larger teams will enhance linearly the impact of research, they will affect its prestige in a non-linear fashion. We further contend that these effects will be moderated by knowledge and international diversity of the teams. We test these hypotheses using bibliometric data between 1990 and 2020 on more than 1.4 million papers and 18 million citations across 22 subfields in Management. Our results confirm significant benefits for *research impact* from both team size and diversity but also highlight drawbacks when teams become very large and heterogeneous. Moreover, we find a non-linear positive effect of team size on *research prestige* which can be offset only by high levels of knowledge diversity. These findings are robust to a variety of proxies, controls, and estimation techniques, including instrumental variables and propensity score matching. We discuss practical implications for stimulating research performance in business schools.

Keywords: *Team size; Research performance: Team diversity; Citations; Top journals.*

INTRODUCTION

Research performance is paramount for academics' recognition, impact, and reputation (Adams et al., 2005; Baruch, Point and Humbert, 2020; Ryazanova, McNamara and Aguinis, 2017). Although historically, individual geniuses were instrumental in the production of cutting-edge research (Bowler and Morus, 2010; Merton, 1968; Simonton, 1999), nowadays collaboration within larger, diverse teams is the norm for production of scientific knowledge (Currie, Davies and Ferlie, 2016; Hibbert, Siedlok and Beech, 2016; Wuchty, Jones and Uzzi, 2007).[1] And while larger research units (e.g., labs, teams) have ubiquitous advantages in terms of greater knowledge, skills and competences, they exhibit also many inefficiencies, including difficulties in coordination and knowledge exchange, dilution of effort and dissonance of individual incentives, all of which hamper different dimensions of research performance such as productivity or knowledge diffusion (Horta and Lacy, 2005; Kwiek, 2020; Lee and Bozeman, 2005). Thus, considering these trade-offs, and the multidimensional nature of research performance, it is still unclear whether larger, and more diverse teams produce better research in terms of academic quality and impact.

Motivated by these issues, we take a closer look at the effects of the size and diversity of teams of co-authors on research performance in the context of business schools (Ashford, 2013; Ryazanova and McNamara, 2016). Several reasons recommend this setting as an ideal one for examining these questions. First, business research is much less dependent than life sciences and 'hard' sciences on capital requirements (e.g., labs, equipment, materials) to produce new knowledge (Bammer, 2008; Wuchty et al., 2007); this allows for a more thorough selection and matching of co-authors within a team, usually based on the number, type and

[1] Many scientific breakthroughs can be traced to exceptional individuals (geniuses) in each field (e.g., Nash equilibrium, Einstein's theory of relativity, Hawking radiation, etc.), and are celebrated via individual scientific accolades (e.g., the Nobel Prize, the John Bates Clark Medal, etc.).

background of researchers needed for a project (Montonen, Eriksson, and Woiceshyn, 2021) .[2] Second, Business and Management research is characterized by a slower pace of publication, with more emphasis on novelty and substantial advancements to the field than in hard or life sciences where incremental contributions and replication studies are published routinely (Adams et al., 2005). As such, business scholars working in teams tend to have well-defined, non-overlapping roles, which require significant personal commitments in terms of time and resources devoted to every project in which they participate (Babchuk, Keith and Peters, 1999; Harzing et al., 2014). Finally, business schools have been at the forefront of the diversity agenda (Bell, 2010) and this long-term orientation has affected the type of research conducted, which tends to be very diverse both in terms of internationality and interdisciplinarity of the output produced (Hughes et al., 2011; Kraimer et al., 2019; Sandhu, Perera and Sardesmukh, 2019). In sum, these reasons recommend Business and Management as one of the best settings to examine the effects of diversity on research performance (Maddi and Gingras, 2021).

Our theoretical framework conceptualizes the complexity of research performance across two distinct dimensions: *impact*, in the form of citations gathered by a research paper (Judge et al., 2007) and *prestige*, in the form of ranking of the journal where it is published (Aguinis et al., 2020). We combine elements from transaction cost economics (Landry and Amara, 1998) and the extended resource-based view of the firm (Lavie, 2006) to argue that research produced by larger teams of co-authors will have greater impact, given the additional knowledge complementarities, network opportunities, and legitimacy gains that come with scale. In turn, we conjecture that team size will also positively affect research prestige, but in a non-linear fashion such that after a certain threshold the coordination costs of having an extra co-author will outweigh the benefits, thereby reducing the chance of a paper reaching top

[2] In turn, hard and life sciences often have very large teams of co-authors (in some cases up to 1,000 even), and hyper-prolific authors (that publish on average a paper every five days) given the different norms regarding publication of research (Ioannidis, Klavans and Boyack, 2018).

journals. Finally, we propose that greater diversity (in terms of knowledge and internationality) will positively moderate the effects of team size on both dimensions (impact and prestige) of research performance. We test these hypotheses using bibliometric data from between 1990 and 2020 across 22 subfields within Business and Management. Our dataset includes over 1 million unique teams of co-authors responsible for more than 1.4 million papers and 18 million citations over this 30-year period.

We propose several contributions. First, we advance new insights on the determinants and complexity of research performance by focusing on a critical, yet less explored, dimension of performance (*prestige*), i.e., successful publication in the highest rank (top) journals. Despite the fallacies of such rankings (Adler and Harzing, 2009; Walsh et al., 2017), on average, top journals tend to outperform their peers in terms of readership and citations (Starbuck, 2005). Thus, publication in these journals has become paramount for academic progression and status, including promotion or tenure decisions, faculty pay, and research endowments (Aguinis et al., 2020; Cortina, 2019; Salter, Salandra, and Walker, 2017). Moreover, these journals are highly valued by universities as they improve visibility, reputation, and position within national and international rankings with direct repercussions for the success of student and faculty recruitment (Mangematin and Baden-Fuller, 2008; Ryazanova, et al., 2017). Given these considerations, we theorize and test the idea that the impact of team size on research *prestige* (i.e., ability to publish in top journals) will be non-linear, thereby advancing the research performance literature which, up to this point, has focused exclusively on citation-based metrics (Jeong and Choi, 2015; Lee et al., 2015).

Second, we propose two important moderators for the relationship between team size and research performance, namely the *international diversity* and the *knowledge diversity* of the team (Abramo, D'Angelo and Solazzi, 2011; Jones, Wutchy and Uzzi, 2008; Schilling and Green, 2011). Collaborative research enables teams to take advantage of their members' resources, skills, and perspectives, embedding expertise and context-specific knowledge from different countries and disciplines (Lisak et al., 2016; Pieterse, Van Knippenberg and Van Dierendonck, 2013). By focusing on the moderating effects of diversity on performance, we expand the research on the micro-foundations of knowledge production (Grigoriou and Rothaermel, 2014; Hibbert et al., 2016). This is particularly salient for business scholars who need to engage and maintain global networks of collaborators to successfully meet increasing requirements to publish, achieve impact, and secure external funding as prerequisites for academic success (Montonen et al., 2021; Sandhu et al., 2019).

Finally, we examine the drivers of research performance in business schools (Montonen et al., 2021; Ryazanova and McNamara, 2016), shifting the focus from individual- and article-specific explanations (Judge et al., 2007; Leahey et al., 2017) to the complex role of teams and their characteristics, notably size and diversity. Our findings support a much more nuanced approach in terms of balancing these characteristics with different ramifications for achieving academic status and impact (Aguinis et al., 2020; Baruch et al., 2020).

THEORY AND HYPOTHESES

Measuring Research Performance

Academia is a competitive environment characterized by increasing performance requirements, greater public scrutiny, and global pressures (Chambers and Miller, 2014; Rafols et al., 2012; Van Leeuwen et al., 2001). An important criterion for academic success and recognition is research performance: that is, the ability to produce and publish high-quality, novel, and impactful research (Schilling and Green, 2011; Wutchy et al., 2007). Research performance has significant implications for job placement and hiring (Ryazanova et al., 2017), career progression via promotion or tenure (Sauer, 1988), individual earnings (Johnson and Stafford, 1974), and the success of funding bids (Hamermesh, 2013). As such, stimulating research performance remains an issue of great interest for both scholars and practitioners (i.e., policy makers and management of higher education institutions).

In terms of assessing research performance, the most used measures in the literature include publication counts (Hamermesh, 2013; Horta and Lacy, 2005; Nederhof, 2006) and citation counts (Leahey et al. 2017; Ryazanova et al., 2017). However, more recent work in this vein considers (conceptually) other available metrics such as journal rankings (Harris, 2008) or impact factors (Garfield, 2006), as well as citations indexes such as the H-index[3] (Baruch et al., 2020; Hirsch, 2005) or the i10-index[4] (Chambers and Miller, 2014). Nevertheless, when it comes to empirical examinations, the most widely employed indicator remains paper citation counts (Rafols et al., 2012). While all these proxies come with advantages and caveats, from a practical and scholarly angle it is difficult to argue that research performance should not include citations and number of top publications, as these are the generalized, core criteria for academic success worldwide (Aguinis et al., 2020; Schilling and Green, 2011).

Teamwork and Research Performance

Over the past decades, collaboration became a prerequisite for research success across all disciplines (Adams et al., 2005; Bowler and Morus, 2010; Katz and Martin, 1997; Simonton, 2013; Wutchy et al., 2007). This trend is driven by a variety of factors, including technological progress (Hamermesh and Oster, 2002; Teasley and Wolinsky, 2001), the cumulative burden of knowledge (Jones et al., 2008), the gains from specialization and division of labour (Lee, Walsh, and Wang, 2015), and the rising importance of interdisciplinary agendas (Yegros-Yegros, Rafols, and D'Este, 2015).

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[3] A scientist has index *h* if *h* of their 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).
[4] The index, introduced by Google, represents the number of publications by a scientist that have at least ten citations each. This is reported in the Google scholar profiles of researchers.

Prior studies in this vein provide some important insights into both the benefits and the potential drawbacks of pursuing research in large, heterogeneous teams. For instance, an increase of team knowledge means that narrower, more manageable, bands of expertise are required for individual researchers (Jones, 2009). Moreover, bigger teams appear to be more successful in terms of pushing scientific frontiers (Mesmer-Magnus and De Church, 2009) and drawing upon diverse international backgrounds (Abramo et al., 2011; Joshi and Roh, 2009). Finally, bigger teams are associated with greater creativity (Schilling, 2005; Uzzi et al., 2007), more balanced workload, female leadership, outsourcing of tasks (Jeong and Choi, 2015), better information (Horta and Lacy, 2005), and greater benefits from specialization and division of labour (Lee et al., 2015), all of which will stimulate the potential and performance of the team.

On the other hand, teamwork comes also with significant challenges and costs. First, larger teams face more coordination problems and potential inefficiencies, especially when working on highly complex tasks, such as knowledge production (Guimera et al., 2005). Second, involvement in many teams and projects often results in a dilution of effort and resources, with negative effects on research excellence (Jeong and Choi, 2015). Third, there is a significant disconnect between incentives for research performance (clearly favouring team collaboration) and those related to the academic reward systems (e.g., tenure, prizes, promotions, etc.), which are still very much individually evaluated. This may yield consistent bias in terms of giving credit, and perpetuate the pervasive 'Matthew effect'[5], which is often linked to low diversity and to discrimination in academia (Jones, 2021). Fourth, larger, diverse teams do not automatically equate to better or more innovative scientific output (Barjak and Robinson, 2008; Lee et al., 2015; McFadyen and Cannella Jr., 2004) .[6] Fifth and final, the value

[5] The Matthew effect of accumulated advantage means that those that perform better will also benefit from superior resources and treatment which will further increase their performance vis-à-vis unperforming peers.
[6] McFadyen and Cannella Jr. (2004) examined over 7,000 scientific discoveries by 173 biomedical scientists over 11 years and found a non-linear relationship between social capital (the number of co-authors) and the amount of

of the team is often a non-additive function of the value of its components (i.e., members) and recent evidence on this issue suggests that the value of a team is usually reflected by the value of its weakest link (Ahmadpoor and Jones, 2019).[7] As such, the size and composition of research teams appears to affect their performance in many intricate ways.

Considering all these complexities, it is clear that we still lack a good understanding of *whether* and *when* larger and more diverse teams of co-authors produce better, more ground-breaking, and impactful research. To answer the first question (*whether*), we investigate whether the size of a team of collaborators has systematic effects on research performance by focusing on two dimensions: *research impact* (i.e., the citations received by a paper; the most widely used metric in the field) (Judge et al., 2007) and *research prestige* (i.e., the ranking of the academic journal in which a paper is published) (Harris, 2008; Tahai and Meyer, 1999). Distinguishing between research impact and research prestige is both *theoretically valuable* (given their differences in terms strategizing, resources, and approaches required) and *practically relevant* (given the difference between them[8], and the differences in terms of emphasis as a requirement for career advancement). To answer the second question (*when*), we focus on the role of international and knowledge diversity within teams that have the potential to strengthen or weaken the effect of team size on research performance (Abramo et al., 2011; Barjak and Robinson, 2008; Joshi and Roh, 2009).

Team Size and Research Performance

In our theoretical framework we combine elements from transaction cost economics (TCE) and the extended resource-based view of organizations (RBV) to analyze the effects of the size and

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knowledge created (proxied by the weighted impact factor count of publications). Lee et al. (2015) found out that team size is also not linearly affecting the novelty of science produced (as measured by rarity in terms of combinations of citations of prior work).

[7] Nevertheless, they still document significant gains from collaboration (compared to working separately) even in the case of working with lower-impact collaborators.

[8] There are many examples of top publications with very little impact (citations) and vice-versa, namely high-impact papers published in B- and C-level journals.

diversity of a team of co-authors on research performance. Our rationale is two-fold: (1) neither of them alone can fully explain the complexities of these relationships, and (2) they complement each other providing an appropriate theoretical mix for examining this relationship. Team collaborations are subject to typical transaction costs and frictions, e.g., coordination, communication, knowledge creation and recombination (Landry and Amara, 1998). Complementarily, following the RBV tenet (Arya and Lin, 2007; Lavie, 2006), research teams can be conceptualized as organizational forms that employ the advantage of bundles of resources and capabilities, such as knowledge stocks, reputation, personal networks, or the managerial abilities of members, to spur their performance. By combining these two theoretical lenses, we can probe more comprehensively the potential benefits and pitfalls associated with research performance in larger and diverse teams.

We argue that larger teams will attract more citations than smaller teams, and that this positive relationship between team size and *research impact* will be a linear one for several reasons. First, from an RBV perspective, bigger teams benefit from larger knowledge stocks (aggregated across all team members) that are paramount for producing and showcasing impactful research. Thus, the more co-authors a paper has, the greater scope there is for pooling distinct knowledge resources, which yields a higher propensity to develop new scientific propositions (Hauptman, 2005; Söderbaum, 2001) that have a better chance of making more research impact in the form of citations (Li, Liao, and Yen, 2013; Ryazanova et al., 2017). Second, having more co-authors will automatically improve dissemination opportunities for this work, as all team members will publicize it within their personal networks (e.g., collaborators, conferences, colleagues) (Lavie, 2006), thereby increasing citation rates (Bentley, 2007; Lee et al., 2015). Third, teams with more co-authors will also benefit more from aggregating intangible resources (i.e., reputation) to better signal the validity and legitimacy of the project to an academic audience (Claxton, 2005). Research prowess is an important component of academic reputation (O'Loughlin, MacPhail and Msetfi, 2015) and having multiple co-authors implies that this research was vetted by many experts, and thereby yields higher citation rates than papers with one, or a few co-authors (Abramo, D'Angelo and Di Costa, 2009).

In addition to superior resources and capabilities, larger research teams can also benefit from a reduction in transaction costs associated with the production and performance of research. First, larger teams offer more opportunities for team members to specialize and increase the overall efficiency of the team, in terms of both production and diffusion of research (Adams et al., 2005) through economies of scale (efficiency of tasks or functions) and scope (combining these tasks successfully). Second, larger teams have a better ability to create new knowledge, as collaborations allow team members to build off each other's expertise and knowledge to create something new (Lee et al., 2015). Taking advantage of larger pools of resources and expertise, larger teams have more opportunities for knowledge recombination, thus increasing the team's chance of producing new research ideas (Stewart, 2006). These benefits are available for both 'fresh' team members (i.e., those who lack prior teamwork experience) and more 'seasoned' ones, suggesting that there are important gains to be made by working in larger teams vis-à-vis working in small ones or individually (Zeng et al., 2021).

Considering all these factors, we hypothesize that:

Hypothesis 1a. Team size has a positive effect on the research impact (i.e., citations) of a paper.

In turn, given the number and complexity of factors that affect a paper's chance of being published in a top journal, we propose that the benefits of team size with respect to research prestige will be non-linear in nature, and that an increase in the size of the research team will likely yield diminishing returns when it comes down to targeting a very competitive outcome like research prestige.[9] Our intuition builds on several TCE rationales as follows.

First, while larger teams benefit from sizeable stocks of knowledge, potential complementarities, and cross-feeding opportunities across disciplines (Bechky, 2006; Singh and Fleming, 2010), the cost of integrating efficiently these resources to produce novel, robust and appealing research is equally substantial. Although specialization and expertise within a team raises the overall productivity of the team, it does not contribute directly to the prominence (i.e., prestige) of the research produced (Whitley, 1984). As the size of a team increases, the effort required to coordinate, manage, and successfully integrate these components also increases significantly (Landry and Amara, 1998). Thus, larger teams may find it more difficult to develop radical new ideas (Hackman, 1992), and the coordination costs of accruing and disseminating new and heterogeneous knowledge will increase, at least after a certain point, faster than the benefits it brings to the project, therefore reducing its quality (Horta and Lacy, 2005; Louis et al., 2016; Yamane, 1996) [10].

Second, in addition to knowledge integration diseconomies, larger teams also require well-developed communication and management tools, which often translate into more bureaucratic procedures, and preassigned, fixed roles for team members that match closely their expertise, availability, and preferences (Katz and Martin, 1997; Singh and Fleming, 2010). While such structures are clearly needed for successful management of large teams, they often stifle the creativity and autonomy of their members, thus reducing the team's chances of producing innovative, radical findings (Krammer, 2021; Lee et al., 2015).

[9] For instance, communication costs (a common TCE aspect of teamwork) will increase as the size of the team increases. However, this additional cost will affect research impact very differently (marginally and with relatively small consequences) as opposed to research prestige (major impact) which is a very competitive endeavour where the tiniest of differences could mean success or failure in getting into a top journal.
[10] Horta and Lacy (2005) show that there is a non-linear relationship between the size of the research lab (unit) and the degree of information exchange between members in the context of Portuguese scientists. Similarly, Louis et al. (2016) find in the US Sciences' context that, while larger labs tend to produce more publications, their members are likely to be less willing to share knowledge and expertise in this (large team) context.

Furthermore, large teams provide lower incentives for individual members, given the dissipation of benefits and reputation across a larger number of co-authors. This also provides more opportunities for free riding that hamper the potential of a project (Wagner, 1995; Yamane, 1996). Finally, larger teams have more difficulties in reaching a consensus (in terms of academic aims and strategies) given their significant heterogeneity across members in terms of status, experience, and individual characteristics. As a result, papers with many co-authors will be, on average, more risk-averse in terms of contesting existing paradigms or proposing radically new ideas (Chambers, 1994). This relative risk aversion will reduce their chances of reaching top outlets (Hülsheger, Anderson and Salgado, 2009; Lee et al., 2015).

In conclusion, we propose that:

Hypothesis 1b. Team size has a curvilinear (inverted U-shape) effect on a paper's research prestige (i.e., publishing in top journals), with the highest research prestige occurring in medium-sized teams.

The Moderating Role of Knowledge Diversity

A major benefit of working in a team is the access to diverse knowledge and expertise across its members. We argue that knowledge diversity positively moderates (i.e., strengthens) the effect of team size on the impact of research.

First, from a TCE angle, knowledge diversity increases the benefits of specialization, as highly diverse individuals within a large team can cover more topics, and draw on various expertise, to produce more impactful research (Adams et al., 2005). It also allows teams to maximize the benefits of larger knowledge reservoirs by reducing the overlap between team members and providing more opportunities for knowledge recombination (Lee et al., 2015). A large, diverse knowledge stock can also accelerate the speed at which a team absorbs new ideas and trends in academic areas, thereby increasing the chances of their making relevant contributions to these fields (Moreira, Markus, and Laursen, 2018). Larger knowledge-diverse teams can pursue more combinations of existing ideas to generate original research output that has a greater potential to be cited by other academics (Schilling and Green, 2011; Uzzi et al., 2013; Wagner, Whetsell and Mukherjee, 2019).

Second, knowledge diversity is a useful resource when it comes to knowledge dissemination, since large teams from diverse intellectual domains can reach broader audiences through their members' personal networks (Leahey et al., 2017). Papers with more co-authors, especially from diverse fields/disciplines of activity, will attract attention from multiple communities, thereby enhancing a paper's chances of being read (Lee et al., 2015) and cited (Bentley, 2007) by more researchers.

Finally, knowledge diversity enhances the positive effect of team size via other intangible capabilities, such as reputation, which results in more credibility across different disciplines, and, therefore, more impact (Yegros-Yegros et al., 2015). Highly cited research output derives not only from brokering knowledge by bridging structural gaps across social contexts, but also from a large, credible network capable of supporting and protecting these ideas from sceptical scrutiny (Cattani and Ferriani, 2008). Hence, endorsements (via co-authorship) from a variety of disciplines can legitimize research output, resulting in more citations and recognition across the relevant fields (Abramo et al., 2009).

Considering all these arguments, we propose that:

Hypothesis 2a. The knowledge diversity of a team positively moderates (i.e., strengthens) the relationship between team size and research impact (i.e., citations).

There are several reasons that suggest that ability of teams to take advantage of their members' knowledge diversity will differ, albeit in different ways, across different team sizes.

First, greater knowledge diversity will increase the costs associated with searching and recombining new knowledge for a top publication, making it a hindrance for small, resource-scarce teams (Park, Lew, and Lee, 2018). Moreover, smaller, heterogeneous teams will also struggle with the internal division of labour. Thus, members of such small teams must often cover, or venture into, areas of research in which they feel less comfortable, impacting negatively the quality of their output (Lee et al., 2015). Lastly, communication in small teams is more informal and less structured than in large teams, and this makes the implementation of ‘big’ (risky) ideas less efficient (Desanctis and Gallupe, 1987).

Second, knowledge diversity decreases the benefit of reputation for small teams when it comes to targeting top journals, as the reputation of the team is spread across several domains, and sends a weaker legitimacy signal (Siedlok, Hibbert and Sillince, 2015; Walsh, Lee, and Tang, 2019). Although the double-blind review process is designed to reduce the effect of reputation (and its extremes, e.g., star scientists and top institutions), this bias is still present through editorial actions (Rupp, 2015; Tomkin, Zhang, and Heavlin, 2017) and the wealth of information available to reviewers seeking to identify authorship details during a review (Yankauer, 2011).

Finally, small teams face resource and time constraints that prevent them from allocating the optimum level of attention to radical knowledge development (Dahlander et al., 2016), and it is challenging for them to gain legitimacy by forming collaborations with researchers from other disciplines (Liu et al., 2017; Uzzi et al., 2013). This means that they will have difficulty in efficiently implementing novel ideas, due to less balance and greater disparities in terms of co-authors’ expertise, which will diminish the legitimacy of their work when targeting prestigious journals (Yegros-Yegros et al., 2015).

Nevertheless, while knowledge diversity can be detrimental for small research teams, thereby attenuating the positive relationship between team size and research prestige, for large teams it may boost research prestige by lowering the transaction costs of implementing division of labour and recombining the existing knowledge stock of the team. This is mainly because knowledge diversity in large research teams can motivate researchers to pursue new opportunities to recombine their knowledge to generate novel research ideas (Mitchell et al., 2009) that are appreciated by prestigious journal outlets. Large research teams with knowledge diversity can leverage not only their diverse expertise and resources but also efficient division of labour to carry out research and achieve breakthroughs in a timely manner (Singh and Fleming, 2010). More importantly, large research teams may identify important trends and opportunities, thanks to their team members' diverse knowledge and expertise, so they can develop research projects faster than individuals or small teams of peers, thereby significantly reducing the development cycle of projects (Aldrich and Al-Turk, 2018). Therefore, knowledge diversity gives large teams first-mover advantages so they can take more risks and introduce pioneering research towards publication in top outlets.

Summing up these arguments, we hypothesize that:

> *Hypothesis 2b. The knowledge diversity of a team weakens the positive relationship between team size and research prestige for smaller teams and attenuate the negative relationship between team size and research prestige for larger teams.*

The Moderating Role of International Diversity

Another advantage of working in a larger team is being able to tap into diverse international resources and audiences (Stahl et al., 2010), which will improve both scientific quality (Presser, 1980) and originality of academic work (Larivière et al., 2015). Subsequently, we propose that international diversity of a team of co-authors will enhance the benefits of having a large team when it comes to research impact. This is driven by several rationales.

First, international diversity increases the benefits of specialization, taking advantage of authors' context-specific knowledge and expertise (Barjak and Robinson, 2008; Merton, 1968). A large research team with limited international representation (e.g., all team members come from a single country) may find limited use for its acquired knowledge, while knowledge developed in a large, yet internationally diverse team may have multiple applications in several contexts, thus garnering more impact (Lahiri, 2010). In this respect, from a TCE perspective, greater international diversity will help teams to better exploit the division of labour and produce high-impact research across different national contexts.

Second, from an RBV lens, larger and more international teams have access to greater and more diverse pools of resources, e.g., specialized expertise, local knowledge, and cultural insights (Zellmer-Bruhn and Gibson, 2006). Sourcing a variety of inputs and rich contextual knowledge from co-authors located in multiple countries increases creativity of team members (Stahl et al., 2010) and enhances the applicability of a research output, and, therefore, its impact (Barjak and Robinson, 2008; Meyer-Krahmer and Reger 1999).

Third, international diversity increases the benefits of intangible resources, such as reputation and networks of individual team members, amplifying dissemination and public interest in the research findings of a team (Bentley, 2007; Lee et al., 2015). Hence, papers produced by large teams with international diversity can garner more citations if the co-authors utilize their networks to receive state-of-art knowledge and diffuse their output (Arya and Lin, 2007; Confraria et al., 2017). Moreover, international diversity is linked to reputation and legitimacy (Stahl et al., 2010), and this is particularly true in academia where the academic community is virtually global (Eisend and Schmidt, 2014). As such, large and internationally diverse teams can exploit economies of scale and employ their global orientation and international legitimacy (Ghoshal and Nohria, 1989) to garner greater scholarly interest and subsequently, more citations.

We therefore propose that:

Hypothesis 3a. The international diversity of a team positively moderates (i.e., strengthens) the linear relationship between team size and research impact (i.e., citations).

Lastly, we argue that international diversity also moderates the effect of team size on research prestige via several RVB and TCE mechanisms. In line with the latter, small teams that are internationally diverse will face fewer challenges, in terms of coordination, collaboration, and consensus-building (Harryson et al., 2008), which usually escalate with increasing differences in terms of cultural background and language (Stahl et al., 2010). This effect is also present for knowledge recombination: in smaller teams, members take part in frequent, informal interactions that become long-standing relationships which capitalize on existing, localized know-how and expertise within the team (Hsiehchen, Espinoza, and Hsieh, 2015). Since smaller teams have a less defined hierarchical structure, international diversity does not stop team members from freely exchanging ideas that often develop into new research projects (Cramton and Webber, 2005). Finally, RBV-wise, reputational benefits from international diversification have a modest effect in terms of promoting research prestige, absent of the ability to identify and use existing local settings to examine a fundamental question in the field (Van Raan, 1998).

In essence, while the benefits of international diversity are important, in the context of large teams it increases the cost of coordinating the division of labour and communications, making it more difficult to target successfully top journals for publication (Barjak and Robinson, 2008). Despite recent improvements in connectivity, large international teams may face significant challenges in terms of scheduling meetings across multiple time zones (Freeman et al., 2014) and maintaining good communication and engagement of all team members (Cummings and Kiesler, 2005; Okdie et al., 2011). In addition, despite major advancements in communication technologies, face-to-face (in person) interactions remain paramount for research excellence (Jeong and Choi, 2015).[11] International diversity in large teams can impede team members' ability to interact, share information, and receive feedback (Cramton and Webber, 2005). In turn, this will influence knowledge sharing (Crescenzi et al., 2016), so that large, heterogeneous international teams will find it harder to coordinate in-depth sessions for developing and refining research ideas (whether sessions are done physically or virtually) to the extent required by top journals (Aguinis et al., 2020).

Thus, our last prediction states that:

[11] This study finds that face-to-face meetings have a significant effect on subsequent citations, suggesting that despite the technological improvements in communication, "face-to-face meetings are still influential" (p.469).

Hypothesis 3b. The international diversity of a team strengthens the positive relationship between team size and research prestige for smaller teams and reinforces the negative relationship between team size and research prestige for larger teams.

The conceptual model summarizing all hypotheses of our study is presented in **Figure 1**.

-- Insert Figure 1 here --

METHODS

Data Sources and Sample

We collected data on peer-reviewed business and management journal articles from the Scopus database over the period 1990 to 2020. Scopus contains detailed information on authors' names, article titles, publication year, journal names, authors' affiliations, and annual number of forward citations. Furthermore, compared with other alternatives (notably, Web of Science) it has better coverage of journals both cross-sectionally (i.e., number of titles) and longitudinally (i.e., number of years). Our final sample, in its most restrictive specification, is roughly 1.4 million articles (papers) published in more than 1,500 journals (based on the CABS list) by approximately 1 million unique teams of co-authors. For these papers, we record more than 18 million citations over the period 1990–2020. Finally, we include several other control variables, which are detailed in **Table 1**.

-- Insert Table 1 Here --

Dependent Variables

Following our theoretical framework, we use two indicators to capture different facets of research performance, namely impact (citation counts) and prestige (dummy for top-tier publication). *Research impact* is computed as the yearly number of (forward) citations a paper received from all other publications in the Scopus (Azoulay, Stuart, and Wang, 2013; Furman and Stern, 2011). *Research prestige* is coded as 1 if the paper is published in top-tier journals and 0 otherwise. We refer to the Academic Journal Guide (various editions) produced by the CABS (UK) which provides five categories: 4*, 4, 3, 2, and 1 and consider the 4* category as top journals. In addition, we employ alternate rankings (e.g., University of Texas Dallas -UTD- from the USA, and the ABDC list from Australia); for more details, please see the Robustness Checks section below.

Independent Variables

The main explanatory variable (*team size)* is measured as the total number of authors collaborating on a paper. To derive measures for knowledge and international *diversity* we rely on Jaccard indexes, which are commonly employed to capture similarity between different sets of characteristics in many disciplines (Krammer, 2016; Leydesdorff, 2008; Ruef, 1997; Zhang et al., 2017). For our particular purpose, we employ a modified version of the Jaccard index (i.e., the Jaccard distance) which captures the dissimilarity or distance between co-authors across knowledge (by looking at the distribution of their prior publications across various subdisciplines as classified in the CABS list) and across institutional affiliation (in terms of country of the home institution). For knowledge diversity, we use the list of 22 subdisciplines listed in the Academic Journal Guide and track prior publications of all authors in each of these categories to be able to compare the knowledge profile of co-authors. We then compute a Jaccard distance (JD) between a pair i of co-authors (X and Y) within a team in year t using this formula:

$$JD\ (X, Y)_{it} = (b + c)_t \ / \ (a + b + c)_t$$

where b is the number of subdisciplines in which X published by year t but Y had not, c is the number of disciplines in which Y published by year t but X had not, and *a* is the number of disciplines in which both X and Y published by year t. We apply this formula to all unique pairs of co-authors within a team and we average them to obtain the average knowledge diversity for the team (*team knowledge diversity*) which we will use in our econometric estimations. Similarly, *team international diversity* is computed as an average of the Jaccard dissimilarity coefficients of all the pairs of co-authors and considering the differences in terms of nationality of their home institutions. Greater values for these indexes imply greater diversity along knowledge, and respectively, internationality.

Control Variables

Following prior literature (Judge et al., 2007; Leahey et al., 2017; Ryazanova and McNamara, 2019), we incorporate three different sets of control variables at different levels (paper, team, and journal) in our regressions, as well as discipline and year fixed effects to control for any systematic differences between papers published in different fields and periods of time.

Thus, in the *research prestige* regressions (paper level), we include several measures as follows: *Team tenure* is the average number of years since the first publication for each co-author proxying more experience in terms of publication. *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 research experience* is reflected by the number of publications for all team members up to the publication year of the focal paper. Given the well-documented Matthew's effect (i.e., spillovers in terms of impact and prestige by including a prolific co-author or one from a very reputable institution, Judge et al., 2007), we control for this using 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 UTD Top 100 business school research ranking, and 0 otherwise. We also include a dummy for *general journals* given that such journals are more likely to be classified as top journals and generate more scholarly interest (i.e., citations). This taxonomy comes from the CNRS (the National Committee for Scientific Research in France) since neither CABS nor ABDC nor UTD lists make this distinction. Finally, to allow also for high performing, but not general journals, we also control directly for the impact factor of the journal, for the publication year, under the assumption that a journal which has high impact is automatically more likely to be considered as "top" in these lists.

In the *research impact* regressions (paper-year level), we include all the aforementioned control variables, plus other paper characteristics given that citation performance is likely to be also paper-specific. Specifically, we have *paper prior citations* (i.e., the lagged yearly cumulative number of citations received by a given paper up to the focal year of the analysis), and *paper age* (i.e., number of years since an article was published). As for the *research prestige* models, we employ both year and discipline fixed effects because *research impact* can also vary systematically, both by field and by year.

Estimation Technique

Given the distinctive nature of our dependent variables, we used two different empirical estimation techniques. Specifically, we adopted a negative binomial panel regression with random-effects to predict *research impact* since the number of citations is a count variable (Wooldridge, 2002). In turn, we employed a probit model to predict the probability of publication in top journals. Each model includes slightly different sets of control variables since prestige and impact have different determinants. Specifically, control variables such as *paper prior impact*, *paper age*, and *journal impact factor* are used exclusively for *research impact* analysis. Other than these three variables, common sets of variables are used to explain both outcomes.

RESULTS

Descriptive statistics and pairwise correlations for all the variables are provided in **Tables 2 and 3**. Some correlations between a couple of regressors are relatively high but this does not affect the efficiency of our estimates, as suggested also by VIF values which are below 10 in all models. To avoid multicollinearity, we also test the interactions between diversity measures and team size in separate regressions.

-- Insert Tables 2 and 3 here--

Table 4 reports the negative binomial regression results for '*research impact*' as proxied by the yearly number of forward citations received by a paper. The alpha value (in log transformation) is statistically significant throughout all models indicating the presence of over-dispersion in the data, and thus the proper use of a negative binomial estimator in these cases. In Model 1 we test our first hypothesis namely that team size will have a positive linear effect on research impact. The coefficient of team size is positive and significant while the coefficient of team size squared is indistinguishable from zero in statistical terms, thereby supporting our H1a hypothesis namely that the size of the team will affect positively and linearly the number of citations garnered by a co-authored paper. Subsequently, we drop the squared term from the remaining regressions that explain research impact. Next, in Model 2 we include also the two proposed moderators together with team size to see whether there are additional benefits from diversity. The positive and significant coefficients suggest that both international and knowledge diversity contribute additively to research impact, as proxied by citations, in addition to the effect of having larger teams of co-authors. Furthermore, the magnitude of these coefficients is comparable and suggest that benefits from knowledge diversity are much greater than those from international diversity when it comes to impact. In Model 3 we test the interaction between team size and knowledge diversity while in Model 4 we test the interaction of team size and international diversity. Both coefficients are negative and highly significant suggesting that when teams are large and very heterogeneous in terms of international and knowledge diversity it can function as a deterrent for yearly citations of a given paper. These results do not support a simple positive moderation as per our H2a and H3a. Instead, they suggest that in very large and diverse teams research impact is decreasing.

-- Insert Tables 4 and 5 here—

Next, we examine our hypotheses with respect to research prestige (**Table 5**). In Model 5, the coefficients of both team size (0.311) and team size squared (-0.039) are highly significant, confirming a non-linear, inverted U-shape relationship (as hypothesized in H1b) between team size and the probability to publish in top journals as proxied by CABS 4* category. This suggests that the benefits of adding additional co-authors on a collaborating team are increasing only up to a point, and then decrease. **Figure 2** shows this effect graphically suggesting that the optimal number of co-authors for a top publication is roughly three, after which the slope becomes negative, and that after this point, adding more co-authors effectively decreases the chances of a paper to make it into a top outlet.

-- Insert Figure 2 here--

In Model 6 we include again both our proposed moderators- their direct effect suggest that diversity is overall beneficial to research prestige in addition to the effects of team size. In Model 7 we interact knowledge diversity with both the linear and squared term of team size. The first interaction is negative yet not statistically significant (β =- 0.047) while the second one is positive (β = 0.038) and significant at 1 percent supporting our hypothesis H2b. 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 when teams are larger. Finally, in Model 8 we test H3b, namely the moderating effect of international diversity on the relationship between team size and research prestige. In this case both the first and second order interactions are significant, albeit with different signs, suggesting that international diversity will further enhance the relationship between team size and research prestige and thus supporting our H3b.

To interpret better our moderating effects, we also present them in a graphical format. **Figure 3** illustrates these trade-offs between team size and knowledge diversity. Thus, for highly diversified teams in terms of knowledge domains, these gains are more incremental (from 3.37 average yearly cites in a team of 2 co-authors to 3.66 in a team of 9), for low knowledge diversity ones they increase drastically as a result of larger teams (1.88 average cites per year for a team of 2 versus 4.90 cites per year in a team of 9). The graph also suggests that for larger and knowledge-diverse teams, beyond 6-7 persons, greater diversity will result in a lower impact. Similarly, albeit with smaller margins, **Figure 4** shows that for smaller teams the positive effects of international diversity in terms of research impact are more pronounced than for larger teams[12]. However, when teams become large (i.e., beyond 6-7 co-authors) the effects of team size appear to be offset by diversity, and there is a reversal so that very large teams are marginally better in terms of yearly yields of citations at intermediate or lower levels of international diversity.

-- Insert Figures 3 and 4 here--

Figure 5 shows how the inverted U-shape relationship between '*research prestige*' and '*team size*' flattens as '*team knowledge diversity*' increases, and then turns into a negative relationship as '*team knowledge diversity*' increases further to prominent levels, resulting in what is called a "shape-flip" (Haans et al., 2016). As a result, we can conclude that high knowledge diversity is able to reverse the decreasing returns to scale, and when it comes to larger teams and chances to publish in top journals greater knowledge diversity is mandatory. In turn, upon graphical examination of the interactions with international diversity, we can see that the U-shaped relationship is maintained (now with an inflexion point around 4), yet the gains from international diversity are still very much present (particularly in larger teams) – see **Figure 6**.

-- Insert Figures 5 and 6 here--

Robustness checks

To ensure the robustness of our findings, we have performed several additional analyses as follows[13].

Different controls, proxies, and estimation techniques.

[12] For instance, a paper with two authors from different countries will garner on average 37% more (0.78) yearly cites than one with two authors that share the same nationality.
[13] Some of these are not reported in the paper given the space constraints but are available upon request.

First, we ran our specifications using additional information from Scopus on some of our control variables. Thus, we used a more restrictive (recent) three- and a five-year window to calculate authors' prior publications and citations to reflect recent research performance that might bear more immediate benefits in terms of both impact and prestige. Furthermore, we have employed different proxies for our controls, including prior citations from CABS papers only, prior publications in CABS journals only, and years since team members have published in CABS journals (as opposed to our baseline variables which include citations, publications, and time lapses by/since any publication that is indexed by Scopus). In all these cases our main conjectures are still supported. Finally, we have employed different estimators (i.e., OLS for paper impact and ordered probit estimation for paper prestige). The OLS results with log transformed yearly citations (to reduce skewness of our DV) mimic our negative binomial ones, while the ordered probit estimations suggest that the effects of team size differ across different tiers of journals as proxied by the CABS ranking.

Different top journal rankings

Second, in the case of prestige, to ensure that these results are not driven by the nature of our DV we have also used two alternate, well-regarded, journal rankings in our field: the UT Dallas list of journals employed for compiling the top 100 Business Schools worldwide in terms of research output, and the ABDC (Australian Business Deans Council) journal list constructed (similarly to CABS list for the UK) for its members and reviewed by independent chair and discipline-specific panels. Overall, there stark differences across these rankings in terms of what constitutes a top journal: across our sample of journals according to CABS about 2.8% of journals are listed as "top", in contrast to 10.6% (ABDC list) and 1.6% (UTD list). Despite these differences, the results of these robustness checks confirm a positive and non-linear effect of team size on research prestige (**Table 6**, Appendix A).

Different proxies for internationality

Besides measuring internationality by comparing the nationality of the institutions of all co-authors in a team, international business and allied social sciences (e.g., economics and geography) propose also cultural and geographical distances as two important variables that can explain international interactions (Hofstede, Hofstede, and Minkov, 2005; Berry, Guillén, and Zhou, 2010)[14]. Thus, we have also computed similar team diversity measures using the longitude-latitude central point of countries of co-authors (*geographic diversity*), and country-level data on Hofstede's six cultural dimensions (*cultural diversity)*[15]. For more details on these variables see **Appendix B**. We have re-run our analyses using these alternative proxies for international diversity. Results confirm our main conjectures (**Tables 7** and **8**, **Appendix A**).

Endogeneity: Instrumental variables and Propensity Score Matching

Finally, from a methods point of view, one of the major issues that could affect our results is endogeneity. To address it, we have implemented two strategies to tease out a clear and causal effect of it on research impact and prestige: 1) instrumental variable (IV) regressions, and 2) propensity matching score techniques (PSM).

Regarding the former, we have scanned the literature for potential instruments (Yitzhaki, 1994) for team size which will be highly correlated with the endogenous variable but relatively independent from our outcomes (e.g., prestige and impact). Given the exceptional dimensionality of our dataset we have examined the meta data available from Scopus and selected three potential instruments namely the *length of the paper* (number of pages), the *length of the title* of the paper (number of words separated by space) and the *number of references* in the article. Subsequently, we have performed IV regressions using various combinations of these three variables as instruments for team size and respectively team size squared (**Table 9,** Appendix A). In these tests, we have adopted a heteroskedasticity robust

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[14] We thank one of the reviewers for these suggestions.
[15] Our international diversity measure is highly correlated with both geographic (0.79) and cultural (0.85) distances, all statistically significant at 1 percent.

standard errors specification and report the following tests: Kleibergen-Paap LM statistic (for under-identification) and Kleibergen-Paap Wald F statistic (for weak instruments). The results of these tests indicate that the model is not under-identified, and the combination number of references used and number of pages of a paper is a strong instrument for the size of the team of co-authors, while the other combinations are rather weaker in terms of maximal bias that can be induced (Stock and Yogo, 2005). Moreover, they confirm our baseline hypotheses, namely that team size has a positive effect on research impact and a positive non-linear one on research prestige.

Given some potential pitfalls associated with the number of pages of a paper (e.g., different formatting standards, layouts, common practice in terms of number of tables, other field and journal specific reporting norms and requirements, etc.) we have also explored using an alternate measure for *the length of the paper* (total number of words in the paper) as an instrument[16]. However, this information is not readily available from any bibliometric source, and subsequently it needs to be manually collected. Given this issue, we have selected a random subsample, obtained the full text (in a .pdf or .html format), and counted the total number of words for 10,000 papers. Overall, the correlation between number of words and number of pages within this sub-sample was 0.739, significant at 1 percent, and relatively stable across different sub-disciplines in Management and Business, thus confirming our intuition that these two variables are highly correlated[17]. The results using this additional measure of paper length as an instrument are consistent with our main findings, albeit with lower statistical salience both from significance and instrument weakness point of view (which is expected given the smaller and random nature of this sub-sample)[18].

[16] We are grateful to one of the reviewers for this suggestion.
[17] Furthermore, there is also some variance across different publishers which accounts for differences in terms of their size, as well as heterogeneity in terms of norms and publishing formats (e.g., for Emerald papers (www.emerald.com) the correlation was 0.891 statistically significant at 1 percent, N=785).
[18] These results are not reported here due to space constraints, but are available upon request from the corresponding author.

In terms of PSM, we started by creating several treatment and control groups within our dataset along different team sizes[19]. Thus, we have created several dummies (dum1-6) which signal different control-treatment groups (2 vs. 1; 3 vs. 2; 4 vs. 3; 5 vs. 4 and all greater than 5 vs. 5) so that dum1 equals 1 if team size is 1 (single-authored) and 0 if team size is 2. We have matched papers across these subsets using the publication year, discipline, types of documents (e.g., article, editorial, letter, review), and the length of these papers. We have employed the nearest neighbour technique (Guo and Fraser, 2014) across five neighbours and a conservative caliper of 1%. With these matched subsamples (**Table 10,** Appendix A) we have re-run our regressions and examined mean differences and their statistical significance as well as the estimated effects of these dummies (**Table 11,** Appendix A). Overall, the results of this exercise confirm our original insights into non-linear effect of team size on research prestige (and linear, positive on impact, not reported here) confirming that a peak occurring when team size is 3. While it remains difficult to tackle completely the endogeneity of team size and composition, these results further attest to the validity of our prior conjectures using regression analyses.

Lastly, the robustness of our results is further supported by prior balance diagnostics conducted (**Figure 7**, Appendix). Even before matching, tests show a good balance between the sub-samples, defined by team size, with an absolute standardized mean difference (ASMD) in most cases <0.1. The largest ASMD was for publication year, reaching 0.3 for 2 co-authors vs. 1 and 3 co-authors vs. 2. These differences are considered small, indicating well-balanced sub-samples even without matching (Andrade, 2020; Stuart et al., 2013).

DISCUSSION

Theoretical Implications

[19] Again, we thank one of the reviewers for this suggestion.

Our study provides an in-depth examination of research performance in business schools by focusing on teams of co-authors and some of their core characteristics (such as size and diversity). In doing so, we advance several important contributions to the literature as follows.

First, we contribute to the literature on determinants of research performance as an integral part of the “business” of business schools (Hibbert et al., 2016; Montonen et al., 2021) by developing a comprehensive theoretical framework to explore the performance implications of having larger and more diverse teams (Abramo et al., 2011). Blending TCE and RBV rationales, our approach highlights the benefits and pitfalls associated with the research processes across different levels of team size and diversity. This framework provides a much more nuanced and accurate representation of the issues business scholars face today in the development and publication of academic research in a global market of knowledge (Ekman, 2017). Notably, we demonstrate that neither the size, nor the characteristics of teams, uniformly affect research performance, and caution about over-simplistic approaches (e.g., larger, or more diverse, is better) when it comes to stimulating it.

Second, we answer previous calls in the literature to examine the benefits of diversity in the business school context (Alvesson and Gabriel, 2013) by examining its indirect effects on research performance. We focus on two salient dimensions of diversity, i.e., knowledge and international (Jackson and Joshi, 2011), and document their moderating impact on both research impact and prestige, albeit in different ways (Hayashi, 2004; Hajro, Gibson and Pudelko, 2017).[20] Together, these findings challenge some of the conventional “linear” insights into the diversity-performance relationship (Gray et al., 2022), but resonate with prior work on international collaborations that suggest that such endeavours produce more conventional, less original knowledge (Barjak and Robinson, 2008; Wagner et al., 2019). We are therefore able

[20] For instance, a large team (i.e., of 8 co-authors) with high knowledge diversity has more than double the chance to publish in a top journal compared to a homogenous (low diversity) team of 8.

to bridge these insights and provide a more complete and generalizable view of the interplay between diversity and performance across heterogenous teams.

Practical Implications for Business Scholars

Our study also has practical implications for business school academics around the world who are under pressure to develop impactful research (Cortina, 2019) and publish it in top journals in our field (Aguinis et al., 2020). Under such pressures, engaging with large and diverse (inter-disciplinary) teams of collaborators has become a norm for achieving research excellence (Baruch et al., 2020; Liu et al., 2017). In this context, we offer several nuanced insights into the success rate of these strategies and the types of situations in which such strategies work best, making an important distinction between two dimensions of research performance (*impact* and *prestige*) in the context of business schools (Alvesson and Gabriel, 2013; Montonen et al., 2021).

One of our main findings contradicts the pervasive idea that larger teams are always better for research performance (Larivière et al., 2015) by showcasing a non-linear (inverted U-shape) effect of team size on *research prestige* (i.e., propensity to publish in a top journal) .[21] Therefore, publishing in top journals in the field is not a question of scale or resources, but likely one related to skills and matching processes that occur at the level of the team (Aguinis et. al., 2020; Hughes et al., 2011). Moreover, we document a lower success rate at top journals for single-authored papers. Contrasting the amount of time, resources, expertise, and effort required to develop such research papers that inherently have much lower success rates and impact (Hamermesh, 2013), the requirement by many schools to have such single-authored top publications as a prerequisite for tenure, promotion or career advancement appears

[21] Our models suggest that the optimum team size for publishing in top-tier outlets is on average 3 and goes up to 4 when controlling for diversity levels in the team; these numbers match closely one of the most common ways in the field to distribute research tasks within a project (i.e., one member focuses on methods, one or two members focus on theory development and hypotheses, and a third or fourth member, usually the first author, is responsible for framing, conceptual development, writing and coordination). This finding also resonates with Lee et al.'s (2015) results on the novelty of scientific output (proxied by 'atypical' citation patterns).

unwarranted and rather extreme (Harley, 2019; Salter et al., 2017) .[22] In addition, we also challenge the consensus in the field regarding the universal benefit of having larger and diverse teams of co-authors for *research impact* (i.e., citations). While both larger and more diverse teams are independently conducive of research performance, in extreme scenarios (i.e., very large and very heterogenous teams) we find that this combination reduces the impact (subsequent citations) of research.

Overall, these findings can help scholars to configure teams more effectively according to their performance goals (i.e., research impact or prestige), and to adopt a balanced, portfolio approach towards research to ensure maximum impact and research benefits.

Limitations and Future Work

This work is not without limitations, which provide some promising directions for future research. First, our focus was on achieving greater generalizability by covering as much as possible of the research landscape in the broad field of Business and Management. While this resulted in a very large empirical context (of over 1.4 million articles) across all subdisciplines and countries, the research remained focused on teams and their characteristics to explain research performance. Yet, research performance is impacted by many, complex and often idiosyncratic factors, e.g., publication conventions between doctoral students and supervisors, academic rank, professional or editorial ties of team members, self-citations, single-blind versus double-blind reviews, etc., to name a few. We would encourage researchers to undertake robust, empirical investigations of these issues, as they can provide very useful and unique insights into the drivers and hindrances of research performance.

Second, we identified research prestige by focusing on several lists or rankings of journals (CABS, ABDC and UTD) used in the United Kingdom and respectively, Australia and the United States. The reason for this is two-fold: first it allows for the best representation

[22] We thank one of the reviewers for stressing this point.

of journals based on a global rather than continental approach, and second it achieves consistency in terms of a "top tier" category of journals across time.[23] Nevertheless, in this approach we adhere to the belief that English-speaking journals are representative in terms of both quality and impact of research in Business and Management. Moreover, given that our dataset is built on one of the most commonly use sources of bibliometric data (Scopus) it has poorer coverage of non-English journals and the Social Sciences, which might underestimate the impact of some of the research in these areas (Mongeon and Paul-Hus, 2016).

Third, there are multiple layers to international diversity. Here we examined diversity predominantly from an institutional angle, given that all researchers in a certain country are subject to the same formal and informal institutional idiosyncrasies. We also refined our variables by employing alternative proxies for internationalization using geographic and cultural distances between co-authors with very robust and similar results. However, diversity of teams is also reflected by the country of origin, ethnicity, or race of co-authors. Future studies can make significant headway on this issue if they tap into these additional dimensions and examine how they impact research productivity.

Finally, we include in our analysis only published papers. While working papers are important in certain disciplines (e.g., economics or finance) they are less so in most subfields of Management. Moreover, we lack access to working paper data on a similar (large) scale, and by analysing only published papers our findings regarding the size and characteristics of teams present conservative estimates for these effects. Overall, we are confident that within our large dataset these issues do not pose significant validity constraints for our findings.

[23] There are also small differences across different editions of these lists. For instance, the CABS 2010 (4th Edition) has less journals covered (825) compared with previous (2009 edition-1,033) and subsequent editions (2015 edition 1,401) because some of the journals failed to meet the RAE 2008 BMS unit criteria of assessment of having at least two submissions in this exercise. However, the number of areas has remained constant over time (22) while the number of journals has increased from 1,025 in 2007 to 1,703 in 2021.

CONCLUSIONS

Achieving research excellence is becoming increasingly difficult for business scholars, as current requirements include both impact (citations) and prestige (top publications, and sometimes single-authored top publications). In the light of these challenges, we have seen a proliferation of research collaboration in teams, with significant variation in terms of number of co-authors, internationality, or expertise. Taking advantage of a large, longitudinal dataset of more than 1.4 million papers and 18 million citations between 1990 and 2020, our study provides several novel insights regarding teams and research performance across two dimensions (prestige and impact). First, we document a non-linear (inverted U-shaped) relationship between the size of the team and the prestige of the research produced (i.e., its chances of being published in a top journal). Second, we show that diversity of the team in terms of internationality and knowledge affects the relationship between team size and research performance in different ways. Notably, we find that the well-documented positive and linear effect of team size on impact (subsequent citations) may be reverted in different configurations of teams. These results suggest both benefits and drawbacks involved in opting for a large, diverse team of co-authors when it comes to publishing in top journals. Moreover, they illustrate the complex trade-offs in terms of balancing size and diversity within teams when targeting research prestige or impact.

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Table 1. List of variables employed in this study

Variables	Measurement	Sources	Research prestige	Research impact
Dependent variables				
Research prestige	Dummy, equals 1 if the paper is published in top-tier journals (ABS 4*), and 0 otherwise.	CABS	X	
Research impact	Yearly number of forward citations received by a paper.	SCOPUS, OC		X
Independent variables				
Team size	Number of co-authors in the team.	SCOPUS	X	X
Moderators				
Team knowledge diversity	Jaccard distance at team-level of the differences between authors' knowledge domains.	CABS, SCOPUS, OC	X	X
Team international diversity	Jaccard distance at team-level of the differences between authors' countries of affiliation.	SCOPUS, OC	X	X
Controls				
Paper prior citations	Yearly lagged cumulative number of citations received by the focal paper until the focal year	SCOPUS, OC		X
Paper age	Number of years since an article has been published	SCOPUS, OC		X
Team research experience	Lagged cumulative number of publications of all individuals in team excluding the focal paper	SCOPUS, OC	X	X
Team research impact	Lagged cumulative number of citations received by all individuals in each team excluding the focal paper.	SCOPUS, OC	X	X
Team tenure	Average number of years since the first publication of each author in the team.	SCOPUS, OC	X	X
Team affiliation prestige	Dummy, equals 1 if the paper has at least one author affiliated with a high-status institution.	UTD1	X	X
General journal	Dummy, equals 1 if the paper has been published in a general-purpose journal.	CNRS	X	X
Journal impact factor	Yearly average number of citations received by the articles that had appeared in the focal journal during the four previous years (CiteScore).	SCIMAGO, OC	X	X
Year FE	Year fixed effects		X	X
Discipline FE	Discipline fixed effects		X	X
Additional variables				
Research prestige 2	Dummy for top journal (A*)	ABDC	X	X
Research prestige 3	Dummy for top journal	UTD 2	X	X
Cultural diversity	Quadratic mean of dyadic Euclidian distances	Hofstede, OC	X	X
Geographic diversity	Quadratic mean of dyadic geodesic distances	Nominatim API, OC	X	X

Notes:
"X" mark: variables used to predict research impact and respectively research prestige; OC- own calculations
CABS: Academic Journal Guide. Various editions. Available at: https://charteredabs.org/academic-journal-guide-2021/
UTD1: UT Dallas Top 100 Business School Research Rankings. Various editions. Available at: https://jsom.utdallas.edu/the-utd-top-100-business-school-research-rankings/ ; CNRS: https://www.gate.cnrs.fr/spip.php?article1341; SCIMAGO: http://www.scimagoir.com; ABDC: Australian Business School Deans' List of journal quality. Various editions. Available at https://abdc.edu.au/research/abdc-journal-quality-list/; UTD2: UT Dallas List of top journals. Available at: https://jsom.utdallas.edu/the-utd-top-100-business-school-research-rankings/search#rankingsByJournal

Table 2. Descriptive statistics and pairwise correlations (citation-level)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	Research impact	1											
2	Team size	0.0759*	1										
3	Team knowledge diversity	0.0679*	0.4523*	1									
4	Team international diversity	0.0357*	0.2151*	0.2753*	1								
5	Paper prior citations	0.8287*	0.0386*	0.0358*	0.0084*	1							
6	Paper age	0.0188*	-0.1377*	-0.1181*	-0.0914*	0.1867*	1						
7	Team tenure	0.0302*	0.0176*	0.0570*	0.0760*	0.0194*	-0.0761*	1					
8	Team research experience	0.0137*	0.1112*	0.0459*	0.1494*	0.0037*	-0.0299*	0.1766*	1				
9	Team research impact	0.0811*	0.3384*	0.1492*	0.1020*	0.0262*	-0.1352*	0.2415*	0.1815*	1			
10	Team affiliation prestige	0.0267*	0.0519*	0.0925*	0.0905*	0.0174*	-0.0151*	0.0247*	0.0064*	0.0309*	1		
11	General journal	0.1648*	0.1111*	0.0223*	0.0111*	0.1799*	0.0419*	0.0848*	0.0325*	0.1479*	0.0263*	1	
12	Impact factor	0.0020*	0.0064*	0.0403*	0.0362*	-0.0159*	-0.0815*	0.0226*	0.0017*	0.0309*	0.0114*	0.0104*	1
	Mean	2.33	2.13	0.36	0.13	14.98	8.41	10.04	47.55	717.95	0.05	0.07	2.05
	Std. dev.	8.61	1.24	0.41	0.30	61.38	6.87	8.10	351.07	2,523.43	0.22	0.27	2.20
	Min	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	4,705.00	9.00	1.00	1.00	29,755.00	30.00	168.00	7,351.00	294,426.00	1.00	1.00	50.01

Notes:
Significance levels * $p < 0.05$ or better.
N= 14,014,292 obs.

Table 3. Descriptive statistics and pairwise correlations (paper-level)

	Variables	1	2	3	4	5	6	7	8	9	10
1	Research prestige	1									
2	Team size	0.0015*	1								
3	Team knowledge diversity	0.0834*	0.4426*	1							
4	Team international diversity	0.0377*	0.2107*	0.3131*	1						
5	Team tenure	0.0195*	0.3595*	0.3418*	0.1679*	1					
6	Team research impact	0.0322*	0.3565*	0.1799*	0.1150*	0.3714*	1				
7	Team research experience	-0.0079*	0.2118*	0.1058*	0.1446*	0.2478*	0.3243*	1			
8	Team affiliation prestige	0.0821*	0.0527*	0.1026*	0.1012*	0.0520*	0.0433*	0.0168*	1		
9	General journal	0.1794*	-0.0811*	0.0330*	0.0198*	-0.0273*	-0.0293*	-0.0270*	0.0197*	1	
10	Impact factor	0.2303*	0.3121*	0.1774*	0.1156*	0.2124*	0.3160*	0.1370*	0.0549*	-0.0134*	1
	Mean	0.03	2.36	0.36	0.16	16.12	1,293.54	63.72	0.05	0.07	2.97
	Std. dev.	0.16	1.36	0.41	0.32	11.18	3,980.71	261.11	0.22	0.27	2.89
	Min	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Max	1.00	9.00	1.00	1.00	168.00	294,426.00	7,351.00	1.00	1.00	50.01

Notes:
Significance levels * $p < 0.05$ or better.
N= 1,367,891 obs.

Table 4. Team characteristics and research impact

Variables	Model 1	Model 2	Model 3	Model 4
H1a: Team size	**0.100*** **	**0.034*** **	**0.067*** **	**0.068*** **
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**
Team size square	0.000			
	[0.000]			
Team knowledge diversity		0.220***	0.392***	
		[0.001]	[0.002]	
Team international diversity		0.063***		0.235***
		[0.001]		[0.003]
H2a: Team size * Team knowledge diversity			**-0.060*** **	
			[0.001]	
H3a: Team size * Team international diversity				**-0.048*** **
				[0.001]
Paper prior citations	0.024***	0.023***	0.023***	0.024***
	[0.000]	[0.000]	[0.000]	[0.000]
Paper age	-0.041***	-0.041***	-0.042***	-0.040***
	[0.000]	[0.000]	[0.000]	[0.000]
Team tenure	0.005***	-0.006***	-0.007***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research impact	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research experience	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Team affiliation prestige	0.214***	0.096***	0.125***	0.146***
	[0.001]	[0.002]	[0.002]	[0.001]
General journal	0.338***	0.326***	0.331***	0.332***
	[0.001]	[0.001]	[0.001]	[0.001]
Impact factor	0.181***	0.030***	0.052***	0.110***
	[0.003]	[0.004]	[0.004]	[0.003]
Constant	-0.008***	0.296***	0.234***	0.061***
	[0.001]	[0.001]	[0.001]	[0.001]
Year FE	Yes	Yes	Yes	Yes
Discipline FE	Yes	Yes	Yes	Yes
N	18,804,754	14,014,292	15,147,780	16,937,753
Log Likelihood	-29,920,000	-24,190,000	-25,610,000	-27,940,000
LR Chi Square	7,869,066.45	6,260,177.44	6,715,652.11	7,251,883.33
Pseudo R-sq.	0.118	0.114	0.115	0.117
Ln alpha	0.290***	0.313***	0.344***	0.252***

Notes:
Results of negative binomial estimations are reported. Robust standard errors in parentheses. The DV is research impact (i.e., yearly count of citations for a given paper). + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All significance tests are based on two-tailed tests.

Table 5. Team characteristics and research prestige

Variables	Model 5	Model 6	Model 7	Model 8
H1b: Team size	**0.311*** **	0.148***	0.141***	0.289***
	[0.009]	[0.010]	[0.018]	[0.011]
H1b: Team size sq.	**-0.039*** **	-0.020***	-0.043***	-0.038***
	[0.002]	[0.002]	[0.004]	[0.002]
Team knowledge diversity		0.331***	0.342***	
		[0.011]	[0.039]	
Team international diversity		0.047***		0.159**
		[0.009]		[0.061]
H2b: Team size * Team knowledge diversity			**-0.047**	
			[0.029]	
H2b: Team size sq. * Team knowledge diversity			**0.038*** **	
			[0.005]	
H3b: Team size * Team international diversity				**-0.079+**
				[0.040]
H3b: Team size sq. * Team international diversity				**0.016*** **
				[0.000]
Team tenure	0.011***	0.009***	0.007***	0.011***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research impact	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research experience	-0.005***	-0.005***	-0.005***	-0.005***
	[0.000]	[0.000]	[0.000]	[0.000]
Team affiliation prestige	0.391***	0.396***	0.363***	0.406***
	[0.009]	[0.009]	[0.009]	[0.009]
General journal	1.482***	1.460***	1.444***	1.483***
	[0.011]	[0.011]	[0.011]	[0.012]
Impact factor	0.233***	0.229***	0.234***	0.229***
	[0.001]	[0.001]	[0.001]	[0.001]
Constant	-2.959***	-2.586***	-2.787***	-2.775***
	[0.025]	[0.026]	[0.028]	[0.026]
Year FE	Yes	Yes	Yes	Yes
Discipline FE	Yes	Yes	Yes	Yes
N	1,443,634	1,367,891	1,443,634	1,367,891
Log Likelihood	-110,135	-101,251	-108,750	-101,679
LR Chi Square	177,881	165,513	180,652	164,656
Pseudo R sq.	0.446	0.449	0.453	0.447

Notes:
Results of probit estimations are reported. Robust standard errors in parentheses. The DV is whether the focal paper has been published in a top (ABS 4*) journal. + p < 0.10, ** p < 0.05, *** p < 0.01. All significance tests are based on two-tailed tests.

Figure 1. Conceptual model

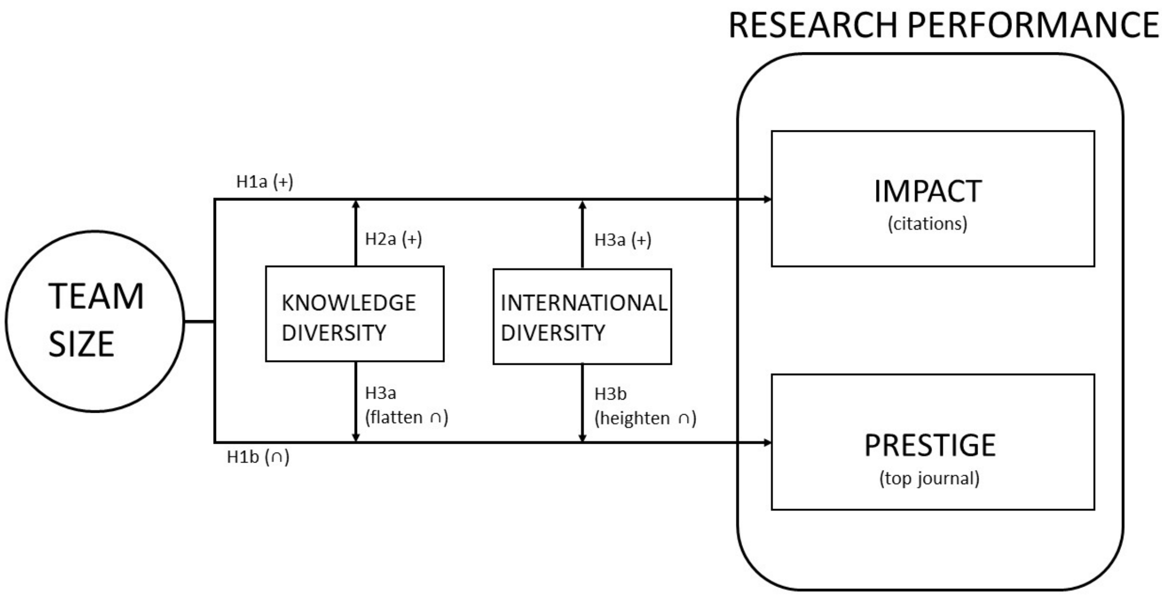
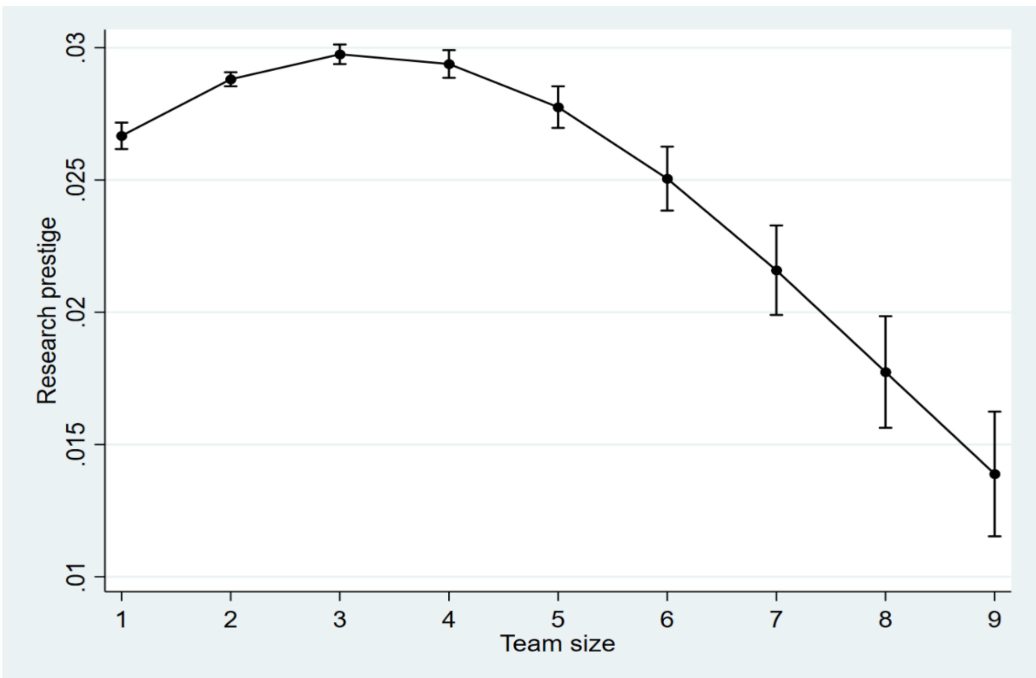
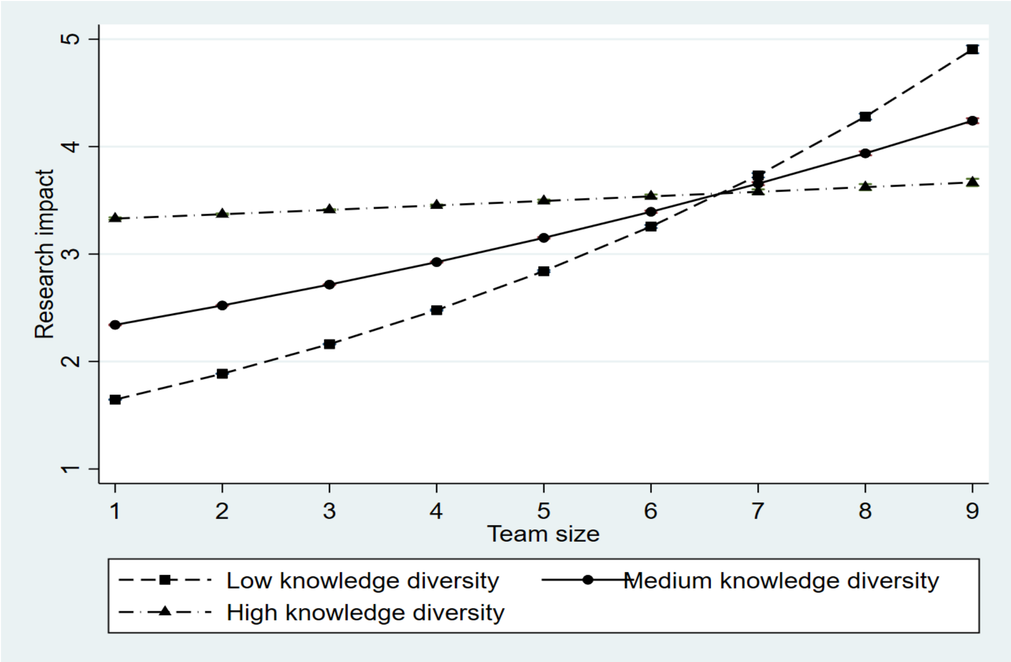


Figure 2. The effect of team size on research prestige.



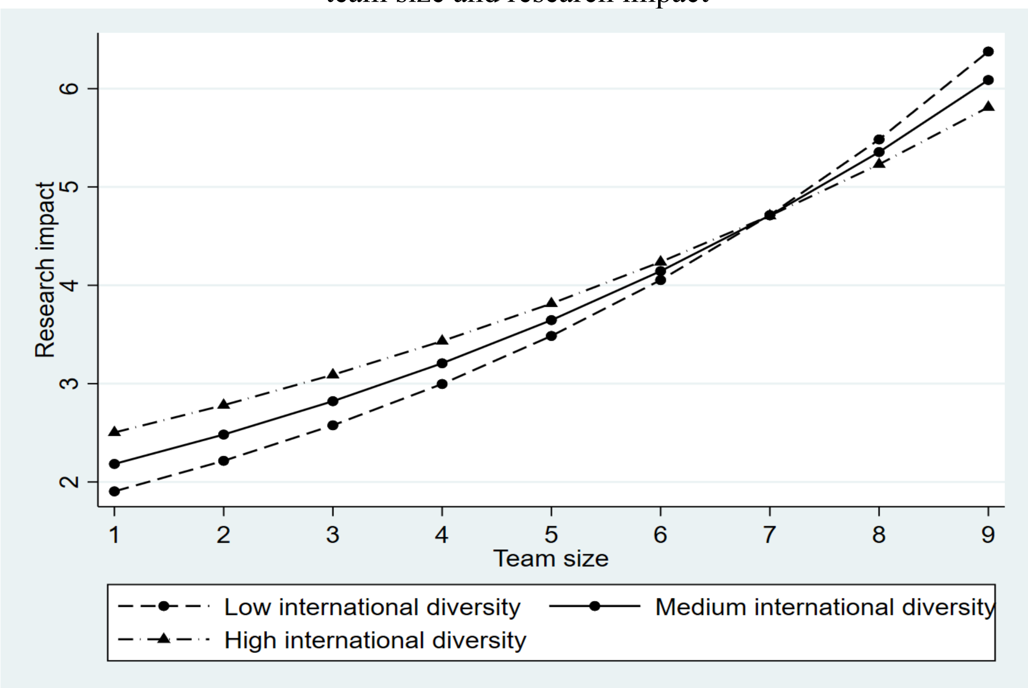
Notes: These results are based on the estimates from Model 5 of Table 5 (95% confidence intervals).

Figure 3. The moderating effect of team knowledge diversity on the relationship between team size and research impact



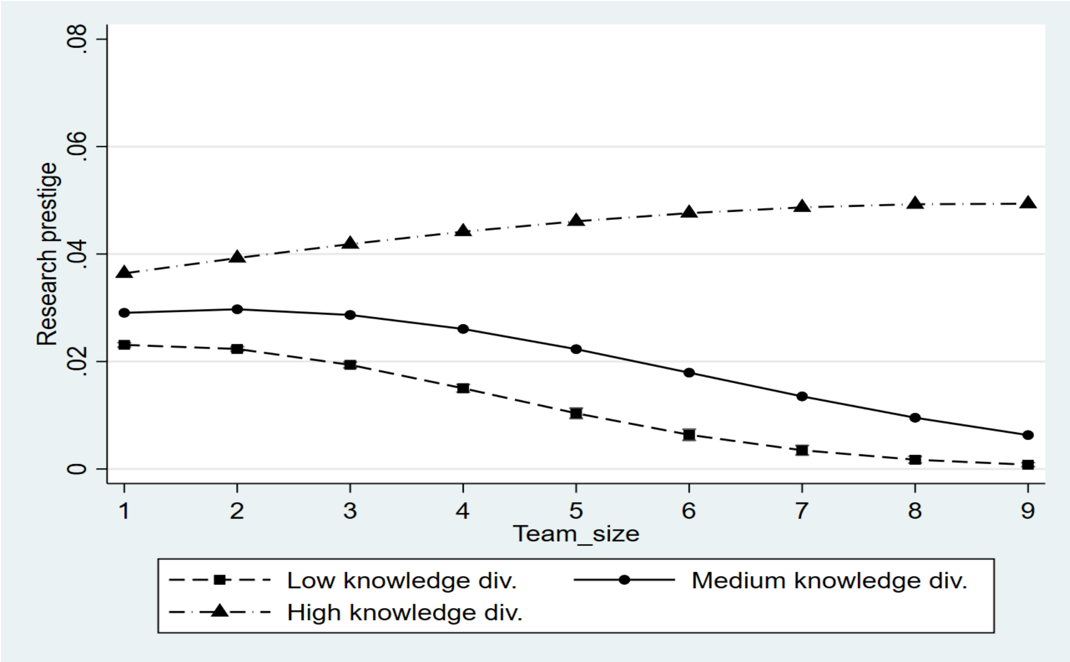
Notes: These results are based on the estimates from Model 3 of Table 4.

Figure 4. The moderating effect of team international diversity on the relationship between team size and research impact



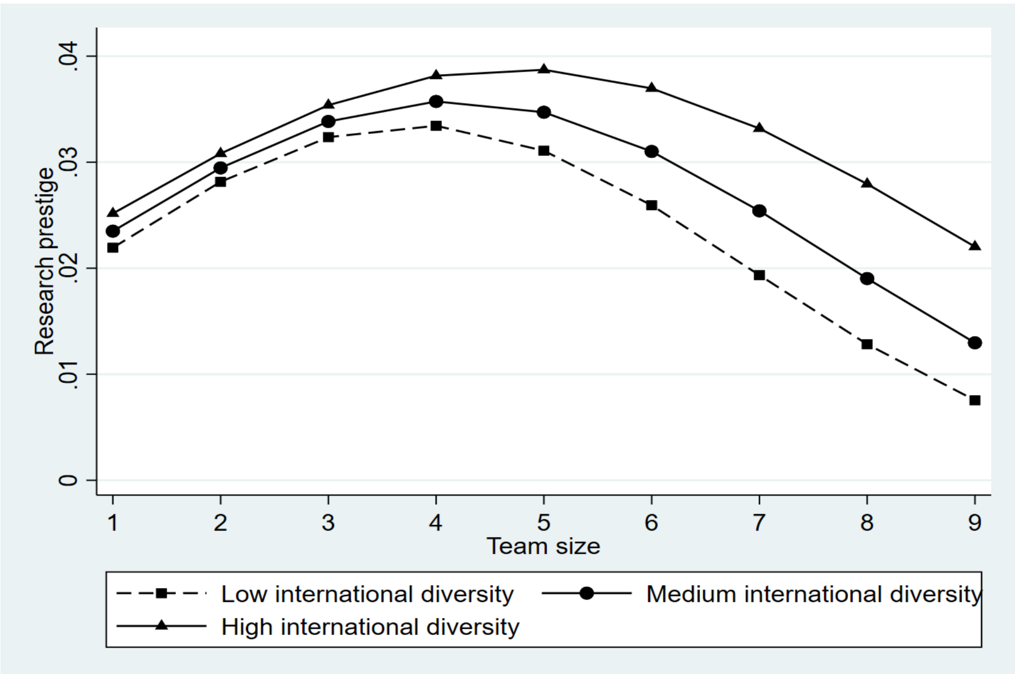
Notes: These results are based on the estimates from Model 4 of Table 4.

Figure 5. The moderating effect of team knowledge diversity on the relationship between team size and research prestige.



Notes: These results are based on the estimates from Model 7 of Table 5.

Figure 6. The moderating effect of team international diversity on the relationship between team size and research prestige.



Notes: These results are based on the estimates from Model 8 of Table 5.

APPENDIX A. ADDITIONAL RESULTS

Table 6. Alternative proxies for top journals in Business and Management- research prestige-

Variables / Proxies for top journals	**Model 5**	**Model 9**	**Model 10**
	(CABS)	(ABDC)	(UTD)
Percent top journals (of total)	2.8%	10.6%	1.6%
H1b: Team size	0.311***	0.205***	0.296***
	[0.009]	[0.004]	[0.011]
H1b: Team size sq.	-0.039***	-0.036***	-0.044***
	[0.002]	[0.001]	[0.002]
Team tenure	0.011***	0.008***	0.014***
	[0.000]	[0.000]	[0.000]
Team research impact	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]
Team research experience	-0.005***	-0.002***	-0.005***
	[0.000]	[0.000]	[0.000]
Team affiliation prestige	0.391***	0.371***	0.482***
	[0.009]	[0.005]	[0.010]
General journal	1.482***	0.343***	1.514***
	[0.011]	[0.005]	[0.015]
Impact factor	0.233***	0.292***	0.278***
	[0.001]	[0.001]	[0.001]
Constant	-2.959***	-3.475***	-3.890***
	[0.025]	[0.019]	[0.029]
Year FE	Yes	Yes	Yes
Discipline FE	Yes	Yes	Yes
N	1,443,634	1,719,785	634,084
Log Likelihood	-110,135	-565,712	-90,520
LR Chi Square	177,881	366,283	110,548
AIC	220,379	1,131,545	181,137
BIC	221,037	1,132,286	181,682

Notes:
Probit estimations with robust standard errors are reported.
ABDC: Australian Business School Deans' List of journal quality. Various editions. Available at https://abdc.edu.au/research/abdc-journal-quality-list/. The top category here is A+ journals
UTD: UT Dallas List of top journals. Available at: https://jsom.utdallas.edu/the-utd-top-100-business-school-research-rankings/search#rankingsByJournal. This list presents only one category (top journals).

Table 7. Alternative proxies for internationality: research impact

Variables	**Model 17**	**Model 18**	**Model 19**	**Model 20**
Team size	**0.066*****	**0.065*****	**0.071*****	**0.071*****
	[0.000]	**[0.000]**	**[0.000]**	**[0.000]**
Team geographic diversity	0.169***		0.447***	
	[0.002]		[0.006]	
Team cultural diversity		0.155***		0.409***
		[0.002]		[0.004]
Team size * Team geographic diversity			**-0.101*****	
			[0.002]	
Team size * Team cultural diversity				**-0.091*****
				[0.002]
Paper prior citations	0.019***	0.019***	0.019***	0.019***
	[0.000]	[0.000]	[0.000]	[0.000]
Paper age	-0.028***	-0.028***	-0.028***	-0.028***
	[0.000]	[0.000]	[0.000]	[0.000]
Team tenure	-0.001***	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research impact	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research experience	0.000	0.000***	0.000**	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Team affiliation prestige	0.078***	0.076***	0.078***	0.076***
	[0.001]	[0.001]	[0.001]	[0.001]
General journal	0.096***	0.096***	0.096***	0.096***
	[0.000]	[0.000]	[0.000]	[0.000]
Impact factor	0.000	0.000	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]
Constant	-0.008***	0.296***	0.234***	0.061***
	[0.001]	[0.001]	[0.001]	[0.001]
Year FE	Yes	Yes	Yes	Yes
Discipline FE	Yes	Yes	Yes	Yes
N	18,785,667	18,732,027	18,785,667	18,732,027
Log Likelihood	-30,050,000	-29,950,000	-30,040,000	-29,950,000
LR Chi Square	10,310,754.78	10,280,049.83	10,313,870.58	10,284,016.63
AIC	60,092,717	59,905,202	60,089,604	59,901,237
BIC	60,093,647	59,906,131	60,090,548	59,902,181
Ln alpha	-0.113***	-0.112***	-0.113***	-0.112***

Notes:
Results of negative binomial estimations are reported. Robust standard errors in parentheses. The DV is research impact (i.e., yearly count of citations for a given paper). + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All significance tests are based on two-tailed tests.

Table 8. Alternative proxies for internationality: research prestige

Variables	Model 21	Model 22	Model 23	Model 24
Team size	**0.283*** **	**0.270*** **	**0.289*** **	**0.287*** **
	[0.010]	**[0.010]**	**[0.011]**	**[0.011]**
Team size sq.	**-0.036*** **	**-0.034*** **	**-0.037*** **	**-0.038*** **
	[0.002]	**[0.002]**	**[0.002]**	**[0.002]**
Team cultural diversity	0.074***		0.297***	
	[0.016]		[0.108]	
Team geographic diversity		0.239***		0.345***
		[0.018]		[0.126]
Team size * Team cultural diversity			**-0.137*** **	
			[0.067]	
Team size sq. * Team cultural diversity			**0.018+**	
			[0.010]	
Team size * Team geographic diversity				**-0.130+**
				[0.078]
Team size sq. * Team geographic diversity				**0.031*** **
				[0.011]
Team tenure	0.011***	0.011***	0.011***	0.011***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research impact	0.000***	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Team research experience	-0.005***	-0.005***	-0.005***	-0.005***
	[0.000]	[0.000]	[0.000]	[0.000]
Team affiliation prestige	0.420***	0.413***	0.420***	0.412***
	[0.009]	[0.009]	[0.009]	[0.009]
General journal	1.500***	1.496***	1.500***	1.495***
	[0.012]	[0.012]	[0.012]	[0.012]
Impact factor	0.227***	0.227***	0.227***	0.227***
	[0.001]	[0.001]	[0.001]	[0.001]
Constant	-2.740***	-2.732***	-2.747***	-2.747***
	[0.026]	[0.026]	[0.026]	[0.026]
Year FE	Yes	Yes	Yes	Yes
Discipline FE	Yes	Yes	Yes	Yes
N	1,345,805	1,351,352	1,345,805	1,351,352
Log Likelihood	-99,501	-99,664	-99,501	-99,655
LR Chi Square	160,410	160,850	160,412	160,869
AIC	199,113	199,439	199,115	199,424
BIC	199,779	200,105	199,806	200,115

Notes:
Results of probit estimations are reported. Robust standard errors in parentheses. The DV is whether the focal paper has been published in a top (ABS 4*) journal. + p < 0.10, ** p < 0.05, *** p < 0.01. All significance tests are based on two-tailed tests.

Table 9. Instrumental variable estimations: research prestige

Variables / Instruments	Model 11	Model 12	Model 13
	(ref. & pag.)	(ref. & title)	(pag. & title)
Team size	0.008**	0.111***	0.321***
	[0.004]	[0.021]	[0.023]
Team size sq.	-0.005***	-0.073***	-0.057***
	[0.001]	[0.009]	[0.004]
Team tenure	0.000***	0.006***	-0.001***
	[0.000]	[0.001]	[0.000]
Team research impact	0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]
Team research experience	-0.000***	0.000***	0.000***
	[0.000]	[0.000]	[0.000]
Team affiliation prestige	0.037***	0.052***	0.016***
	[0.001]	[0.002]	[0.002]
General journal	0.109***	0.058***	0.108***
	[0.000]	[0.006]	[0.001]
Impact factor	0.020***	0.037***	0.022***
	[0.000]	[0.002]	[0.000]
Constant	0.101***	0.123***	-0.253***
	[0.006]	[0.019]	[0.028]
Year FE	Yes	Yes	Yes
Discipline FE	Yes	Yes	Yes
N	1,719,784	1,633,245	1,633,245
Log Likelihood	840,783.35	-1,169,863.01	94,195.38
LR Chi Square	177,881.11	366,282.69	110,548.36
Anderson Rubin Chi2(2)	5936.02***	2141.85***	4179.46***
Kleibergen-Paap LM†	987.12	5.813	5.226
Kleibergen-Paap Wald F	3976.94***	121.85***	1239.74***

Notes:
Each model uses a combination of two exogenous variables to instrument both team and team size squared. ref.-number of references listed in a paper; pag- number of journal pages of a paper; title-number of words (space separated) of a publication. Robust standard errors are reported. † Critical value is 7.03 (for 10 percent maximal bias) and 4.58 for 15 percent).

Table 10. Propensity score matching descriptive statistics

	Panel A: 1 vs. 2			*Panel B: 2 vs. 3*		
Variables / Means	**Treated**	**Control**	**% Bias**	**Treated**	**Control**	**% Bias**
public. year	2005.9	2005.7	2.5	2008	2008	0.8
doc type	3.3452	3.2973	1.6	2.7354	2.6277	4.4
no. pages	14.696	15.143	-1.4	16.21	16.107	0.4
discipline	10.279	10.302	-0.3	9.9851	9.8889	1.6

	Panel C: 3 vs. 4			*Panel D: 4 vs. 5*		
Variables / Means	**Treated**	**Control**	**% Bias**	**Treated**	**Control**	**% Bias**
public. year	2010.5	2010.5	0.1	2011.6	2011.9	-4.6
doc type	2.6462	2.6183	1.2	2.578	2.4642	4.9
no. pages	14.642	13.391	1.4	15.211	15.248	-0.1
discipline	10.583	10.584	0.0	12.145	12.113	0.6

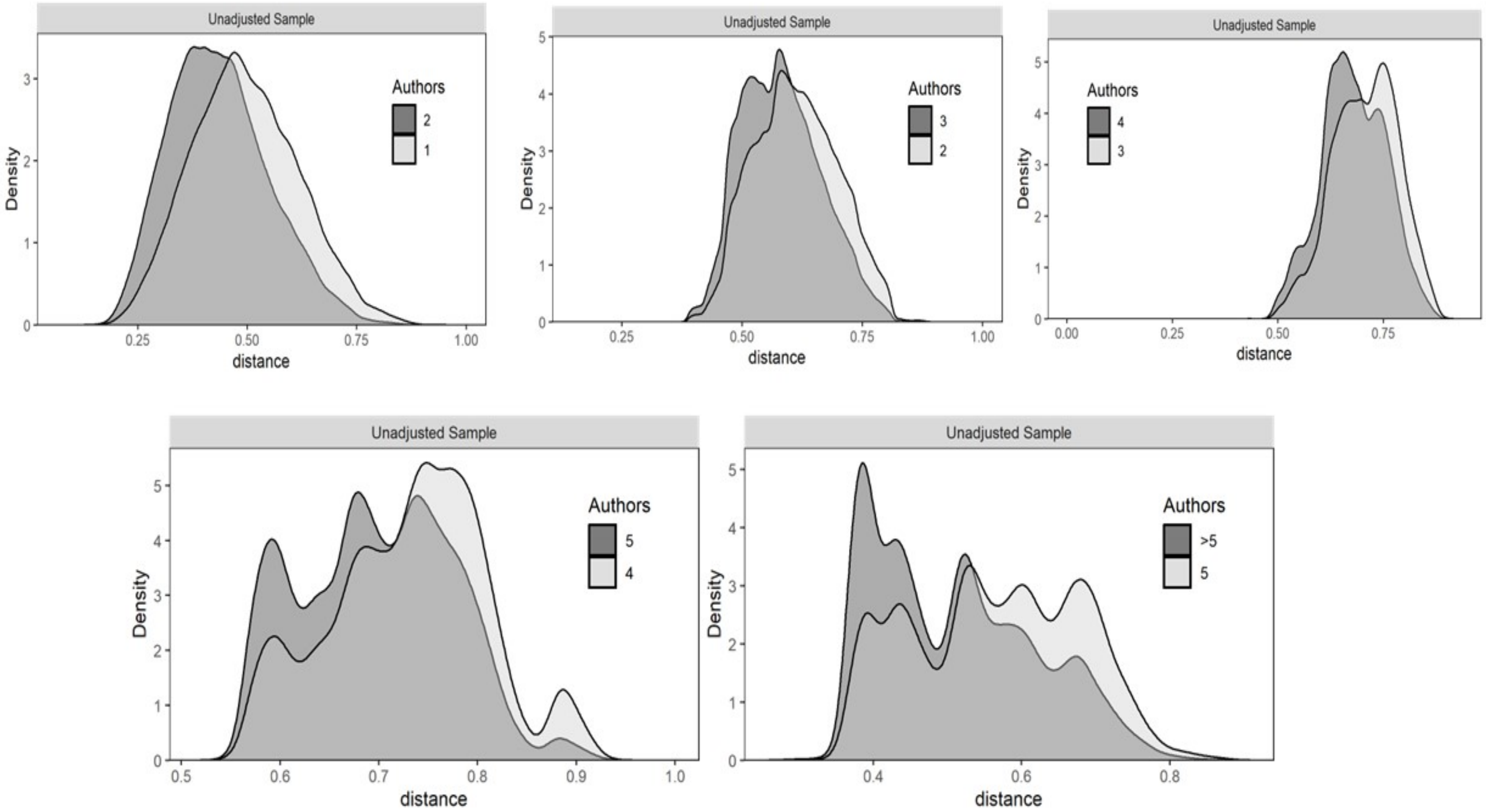
	Panel E: 5 vs. >5		
Variables / Means	**Treated**	**Control**	**% Bias**
public. year	2011.9	2012.1	-2.1
doc type	2.5878	2.4602	5.4
no. pages	13.637	12.954	1.7
discipline	14.017	13.942	1.4

Table 11. Full sample vs matched sample results (treatment by team size group): research prestige

Dummy	Full sample	Matched sample
1 vs 2	-0.252***	-0.292***
2 vs 3	-0.127***	-0.152***
3 vs 4	0.031***	0.059+
4 vs 5	0.005+	0.055+
5 vs >5	0.065+	0.028

Note: All models include the full batch of controls plus year and discipline FE similar to the main models reported in Tables 4 and 5. We report here only the coefficients of these dummies for comparisons. Thus, through these dummies we test whether similar papers from each of these groups matched on the above characteristics (single authored vs. 2 authors; 2 vs. 3; 3 vs. 4, etc) are significantly more/less likely to get published in a top journal.

Figure 7. Balance diagnostics before matching



APPENDIX B. ADDITIONAL DETAILS ON DATA COLLECTION PROCESS AND THE COMPUTED VARIABLES

In this study we make use of a large dataset on journals, papers, authors, affiliations, and citations collected from various sources. As a starting point, we employ the Academic Journal Guide by the Chartered Association of Business Schools (CABS) which identifies the most relevant journals in Business and Management. The CABS 2021 list includes 1,698 journals, of which 1,539 unique journals are available on Scopus. The journals excluded from the study since they were not indexed by Scopus are predominantly very low tier – i.e., ABS level 1 journals (81.6%)- with a few ABS 2 (15.8%) and ABS 3 (2.5%). With this as the basis for selection, we used Scopus to collect data on all papers published in the CABS journals between 1990-2020 (over 1.7 million papers).

We have recorded the affiliations of the authors for each paper. In most cases, the affiliation was specified with the name and address of the university or department. However, in some instances, these details were not clearly specified, thus impeding a harmonized data collection. To tackle these cases, we have created a score-based classifier, matching the given affiliation against recognized names of countries, based on the ISO3166 specification[24]. In addition, we have implemented some manually defined rules to handle cases such as the US states "New Mexico" or "Georgia" (which should not be classified as Mexico, or Republic of Georgia) and commonly used abbreviations (e.g., USA or UK). After a first round, remaining affiliations were classified based on the decided classes of other paper-level affiliations to the same university, where the affiliation has been stated in full. This was only used where there was full agreement among the classified instances of the university. Using this classifier, we were able to identify the country of affiliation for 99.7% of the cases. For authors with more than one affiliation listed for a paper, we have used their first affiliation to assign their institutional nationality. Evidently, author nationality is here based on the location of their affiliation and does not address the personal background.

For robustness checks, we also compute geographical distances within the author team, using the location of each country as retrieved from the Nominatim API[25]. The resulting point (longitude-latitude) represents the central point of the country. Given that we are interested in international diversity, our measure does not distinguish within-country distances between authors in the same country. The geographical distances within an author team are calculated as the root mean squared dyadic geodesic distance between each pair of authors.

To measure cultural diversity, we use Hofstede's six-dimensional representation of national culture[26]. This data was available for 118 countries and matched with the country of each affiliation per paper and author. Team diversity was calculated as the root mean squared dyadic Euclidian distance. Some countries do not have measurements for all 6 dimensions, and for these we used the dimensions that are available for both countries in the dyadic calculation. For all team diversity measures, single-authored papers have considered to have no (i.e., zero) international, geographic, or cultural diversity. Finally, we apply min-max normalization to both the geographical and cultural diversity variables to get comparable results to our international diversity measure (based on Jaccard index). The resulting variables (ranging from 0 to 1) are used in our subsequent robustness checks regressions.

[24] https://www.iso.org/glossary-for-iso-3166.html
[25] https://nominatim.org
[26] https://www.hofstede-insights.com/country-comparison/

For indicators of research prestige, i.e., whether a paper was published in a top-journal, we used the most current ranking list at the time of the publication. For the CABS-list, papers published before 2010 (first edition of CABS that distinguishes "4*" as the highest category) are coded according to the 2010-list. For the ABDC-list, papers published before 2008 (first edition) are coded according to the 2008-list. For the UTD-list, all papers are coded according to the list from 2022.

The variables computed from authors' publication history, including previous citations, are limited to papers in the Scopus database, but not solely the journals covered by the CABS list. The subsample for which we retrieved and calculated the word-count is inevitably limited to the publishers and journals from which we could access, and machine process the full-text. The word-count was done using the word tokenizer in NLTK (v3.7) on sections considered to be the body text, i.e., excluding list of references, author biographies, and declarations of funding etc.