**Detrimental Collaborations in Creative Work: Evidence from Economics**

Keyvan Vakili*

Strategy and Entrepreneurship Department

London Business School

kvakili@london.edu

Florenta Teodoridis

Marshall School of Business

University of Southern California

florenta.teodoridis@marshall.usc.edu

Michaël Bikard

Strategy Department

INSEAD

michael.bikard@insead.edu

**Keywords:** collaboration, innovation, creativity, credit allocation, scientific credit, credit premium

**Acknowledgements:** For helpful comments and suggestions, we would like to thank seminar participants at Bocconi, ESADE, Imperial Business School, INSEAD, the Leeds School of Business at University of Colorado Boulder, London Business School, the Fisher College at Ohio State University, the Tuck school of Business at Dartmouth College, and Warwick Business School. We also thank Associate Editor PK Toh and anonymous reviewers for their valuable and constructive feedback on the paper. This study was supported by funding from INSEAD and the London Business School.

***** Author order is random. All authors contributed equally

# Detrimental Collaborations in Creative Work: Evidence from Economics

**Abstract:** Prior research on collaboration and creativity often assumes that individuals choose to collaborate to improve the quality of their output. Given the growing role of collaboration and autonomous teams in creative work, the validity of this assumption has important implications for organizations. We argue that in the presence of a collaboration credit premium—when the sum of fractional credit allocated to each collaborator exceeds 100%— individuals may choose to work together even when the project output is of low quality or when its prospects are diminished by collaborating. We test our argument on a sample of economists in academia using the norm of alphabetical ordering of authors' surnames on academic articles as an instrument for selection into collaboration. This norm means that economists whose family name begins with a letter from the beginning of the alphabet receive systematically more credit for collaborative work than economists whose family name begins with a letter from the end of the alphabet. We show that, in the presence of a credit premium, individuals may choose to collaborate even if this choice decreases output quality. Thus, collaboration can create a misalignment between the incentives of creative workers and the prospects of the project.

## INTRODUCTION

Collaboration has become ubiquitous in creative work. It enables recombination across increasingly narrow areas of specialization (Jones 2009; Toh and Polidoro 2013) and enhances the communication of new ideas (Fleming, Mingo, and Chen 2007). Prior research has been generally optimistic about this new normal, converging on the idea that individuals choose to collaborate because their collaboration, despite its costs, on average increases output quality (Wuchty et al. 2007; Singh and Fleming 2010; Taylor and Greve, 2006). This argument, however, hinges on the implicit assumption that individuals prioritize output quality when deciding whether to collaborate. This assumption's validity has important implications for organizations, particularly given the growing interest in non-hierarchical structures with autonomous teams and the increasing prevalence of open innovation (Adler, Kwon, and Heckscher 2008; Faraj, Jarvenpaa, and Majchrzak 2011). In essence, this assumption entails that organizations can rely on individuals to self-assemble into teams to maximize outcome quality, a win-win for both individuals and organizations.

However, in deciding whether to collaborate, creative workers consider not only the quality of the output but also the amount of credit that they will receive for that output (Merton 1968). In this paper, we argue that these two objectives might not always align. The goals of maximizing output quality on the one hand, and gaining individual credit on the other, may diverge if the credit given is not tightly linked to contribution. When individuals work alone, their contribution is observable and the allocation of credit is straightforward. Conversely, collaboration can obfuscate individual contributions, potentially leading to the emergence of a collaboration credit premium—that is, a situation in which the share of credit for collaborative output sums to more than 100% (Bikard, Murray, and Gans 2015; Kay, Proudfoot, and Larrick 2018). In the presence of a credit premium, each collaborator, on average, receives credit that is greater than their contribution.

Building on this core insight, we posit that individuals may sometimes rationally choose to collaborate on a project even if the project is of low quality or if the collaboration diminishes the project's prospects, as long as the expected benefits from the collaboration credit premium compensate for the loss in output quality. Collaboration can, therefore, cause a decoupling between individual incentives to maximize credit and the goal of maximizing output quality. Thus, when accounting for the collaboration decision-making process, there are conditions under which collaboration can, in fact, reduce output quality, not enhance it, as documented in other studies.

Testing this argument empirically is challenging. Individuals do not randomly choose to collaborate. It is therefore difficult to estimate how much of the association between collaboration and output quality might be driven by selection rather than treatment mechanisms. Moreover, we are interested in estimating the causal impact of a specific subset of collaborations: those formed as a result of the pull exerted by the collaboration credit premium.

We address these challenges using a sample of academic scientists in the field of economics. Specifically, we exploit a norm among researchers in this field - the alphabetical ordering of authors' names on collaborative publications – as an instrumental variable that attempts to get closer to random assignment to collaboration. Because of this norm, economists whose family name begins with a letter toward the end of the alphabet engage less in collaboration because they receive less credit for their collaborative publications. Indeed, these individuals are less likely to be promoted in their first academic job or to win prestigious awards than individuals whose family name begins with a letter toward the beginning of the alphabet (Einav and Yariv 2006). This norm essentially creates an exogenous variance in the gap between contribution and credit for collaborative work, and hence in individuals' collaborative behavior, such that individuals with family names toward the end of the alphabet collaborate less frequently than those with family names toward the beginning of the alphabet. Importantly, the instrument captures the variance in propensity to collaborate that is driven by the variance in the level of credit premium that individuals receive from their collaborations, thus allowing us to get closer to capturing the causal impact of credit-premium driven collaboration on output quality.

Our results first confirm that alphabetical ordering has a sizable effect on economists' propensity to collaborate. Individuals whose family names begin with letters that come later in the alphabet are significantly less likely to collaborate on their publications than their colleagues whose family names begin with letters that come earlier. Next, using the alphabetical ranking of names as an instrument for the propensity to collaborate, we show that collaboration has a significant negative effect on the quality of certain publications in our sample. Our findings suggest that collaborations formed because of their associated credit premium have an average negative effect on output quality.

Our study makes three main contributions. First, we highlight a new channel through which collaboration can negatively affect creative output quality. Research on the cost of collaboration has focused on the frictions embedded within the collaboration process, producing a rich literature that has highlighted a variety of mechanisms such as free-riding (Levine and Prietula 2013), coordination costs (Mell, Jang, and Chai 2020), conflict (Hinds and Bailey 2003), or groupthink (Godart, Shipilov, and Claes 2013). Rather than examining the process of collaboration, we show that the decision to engage in collaboration in the first place can be influenced by the misalignment of individual- and output-level incentives.

Second, our findings caution against overly optimistic interpretations of the well-documented positive correlation between collaboration and output quality (Wuchty, Jones, and Uzzi 2007; Singh and Fleming 2010). While indeed likely to often boost output quality, we underline that collaboration is often a choice. Workers have a strong incentive to cluster around the most promising projects, and this “pull” towards collaboration is likely further amplified in the presence of collaboration credit premium. Thus, some of the observed positive correlation between collaboration and output quality conceals a selection mechanism. We highlight conditions under which collaboration leads to lower output quality. When collaborators’ contributions are difficult to assess and collaborators expect a credit premium, individuals may choose to collaborate on a project even if this leads to lower quality output.

Third, our study highlights a hitherto understudied challenge associated with autonomy in creative work. The benefits of autonomy for innovation are large and have been well-studied (Bailyn 1985; Sauermann and Cohen 2010; Criscuolo, Salter, and Ter Wal 2013; Biancani, McFarland, and Dahlander 2014; Gambardella, Khashabi, and Panico 2020). We focus on autonomy in the context of collaboration and investigate one of this literature’s key implicit assumption—i.e., that what is good for the individual worker is generally good for the project, and vice versa. Our results highlight that autonomy in the decision to collaborate can induce tensions for individual workers who might have to choose between doing what is best from a project quality standpoint and what is best for their careers.

## COLLABORATION AND THE CREDIT PREMIUM

### Collaboration as a Choice

In many organizations, including in academia, individuals involved in creative tasks are free to decide whether to collaborate or not. This decision involves a number of important trade-offs (Taylor and Greve 2006; Bikard, Murray, and Gans 2015; Deichmann and Jensen 2018).

The benefits of collaboration are considerable. By bringing together individuals with different knowledge, opinions, skills, and resources, collaboration enables cross-fertilization and recombination of ideas (Hargadon and Sutton 1997; Toh and Polidoro 2013; Choudhury and Haas 2018; Kneeland, Schilling, and Aharonson 2020). It also enables specialization and a productive division of labor whereby individuals focus on what they can do best, thereby potentially increasing productivity for all (Jones 2009; Reagans, Miron-Spektor, and Argote 2016). Finally, collaboration can provide additional advantages such as learning (Liu, Mihm, and Sosa 2018), making it easier to identify and filter out bad ideas (Singh and Fleming 2010), increasing communication channels and the legitimacy of new ideas (Reagans and Zuckerman 2001; Cattani and Ferriani 2008), and providing a safe space to discuss original thoughts (Edmondson 1999).

Beyond the benefits, scholars have also uncovered several costs associated with collaboration. A prominent research stream in psychology has shown that collaboration can lead to social loafing and free-riding (Latané, Williams, and Harkins 1979; Albanese and Van Fleet 1985). Moreover, an increase in the number of individuals involved in a project naturally increases the number of communication linkages among individuals nonlinearly. This, in turn, might increase the amount of time and effort it takes to keep all members informed of the project’s status and expand the variety of interpretations based on the same information. As a consequence, the time spent on the project might increase to accommodate the need to reconcile and integrate information at the team level (Lawrence and Lorsch 1967; Dougherty 1992; Perlow 1999; Heath and Staudenmayer 2000; Porac et al. 2004; Cummings and Kiesler 2007). Collaboration also introduces the possibility of conflict among collaborators, which can potentially harm team productivity (O'Dell 1968; Brewer and Kramer 1986; Cattani et al. 2013; Goncalo et al. 2015). Finally, studies on groupthink show that collaborators may engage in dysfunctional or irrational decision-making to minimize conflicts and maintain coherence in the team (Janis 1971).

In balancing the benefits and drawbacks, creative workers are likely to consider not only what is best from a project standpoint but also what is in their personal interest. This is important because collaborators are not always rewarded equally for joint work. Merton (1968), for example, argues that, independent of their contribution, high-status individuals on scientific teams are likely to accrue more credit for their paper than their lesser-known co-authors. Conversely, lower-status individuals or those belonging to minority populations may receive relatively low recognition even if their actual contribution is considerable (e.g., Heilman and Haynes 2005; Lissoni, Montobbio, and Zirulia 2020). Recognition for collaborative work does not always reflect one's effective contribution. The net benefit from collaboration appears very different for different people—even those working on the same project.

Considering the trade-offs, one may wonder whether the benefits of collaboration exceed the costs on average. The growth of collaboration among creative workers (de Solla Price 1965; Wuchty, Jones, and Uzzi 2007; Leahey 2016) might be interpreted as evidence of a net positive effect. Wuchty, Jones, and Uzzi (2007) examine 19.9 million scientific publications over five decades as well as 2.1 million patents and document a large-scale shift towards collective work across fields ranging from the social sciences to engineering, including patenting. Furthermore, collaborative work seems to be of higher quality, on average, than solo work (see also Singh and Fleming 2010). These results indicate that creative workers increasingly find value in collaboration. They do not mean, however, that collaboration always has a positive impact on output quality. Indeed, we argue that collaboration can sometimes benefit collaborators while hurting output quality.

## Individuals versus Projects

Although prior studies have explored the implications of collaboration from a project and from an individual standpoint respectively, they have not examined the relationship between the two. This omission would be inconsequential if the goals of the project and those of the individuals were always aligned. However, it could be significant if collaboration can be simultaneously good for the individual but bad for the project, or vice versa. In this scenario, the decoupling of individual- and project-level incentives may lead individuals to choose to collaborate (or to work alone) when it is not optimal from a project standpoint.

The validity of this assumption is crucial for organizations that rely on self-assembling collaborative teams to solve problems, which is an increasingly pervasive phenomenon (Adler, Kwon, and Heckscher 2008; Faraj, Jarvenpaa, and Majchrzak 2011; Contractor 2013). For example, organizations such as 3M, Google, and Valve allow employees to self-organize and choose the ideas they want to work on both within their daily responsibilities and also as a mechanism to encourage innovation (Foss 2003; Biancani, McFarland, and Dahlander 2014). Scholars have suggested that such autonomy leads to more optimal matches of skills within teams, increases motivation, and helps to attract and retain talent (Sauermann and Cohen 2010; Criscuolo, Salter, and Ter Wal 2013; Gambardella, Khashabi, and Panico 2020).

In this paper, we posit that individual- and project-level incentives in creative work are not always aligned. We build our argument on three premises. First, credit received for collaborative work is generally disconnected from the actual contribution of each collaborator. This results from the fact that each person’s contribution is difficult to observe and evaluate. Even collaborators themselves—who can presumably observe their own contribution—misjudge its significance systematically. A large body of work in psychology has shown that individuals tend to overestimate their contribution to collaborative work in various settings, from married couples sharing housework to co-workers in firms and athletes on sports teams (e.g., Ross and Sicoly 1979; Schroeder, Caruso, and Epley 2016). If the individuals themselves routinely misjudge their own contributions, evaluations from outsiders are likely to be less exact, since they generally have much less information about each person's work. Contribution obfuscation alone, however, does not necessarily lead to detrimental collaborations. As long as the gap between one's perceived contribution and actual contribution is random, we should expect individuals to collaborate only when the expected gains from collaboration appear superior to its expected cost[1].

Second, the individual shares of credit allocated for collective work can sum to more than 100%. Kay, Proudfoot, and Larrick (2018) show that observers systematically overestimate the creative skills of individuals in firms when their teammates are not visible and the actual contribution of each collaborator is hard to assess. In line with this finding, Bikard, Murray, and Gans (2015) study of collaboration choices and credit allocation among MIT scientists found evidence for the existence of a collaboration credit premium—each scientist receives on average more than their fractional share of credit for their joint work (see also Freeman, Ganguli, and Murciano-Goroff (2014)). Taken together, these studies suggest that incentives to collaborate may be particularly strong especially when different collaborators are evaluated by different people who may not know every team member.

Third, each individual can choose to collaborate or work alone, and that choice will depend in part on the amount of credit they expect from the audience. Clearly, taste for collaboration varies from one person to the next, as does their skill at working collaboratively with others. On average, however, we assume that creative workers will decide to collaborate more when all collaborators anticipate receiving more credit for joint work than working alone. Note that this assumption is consistent with

[1] In a setting where an individual is frequently rewarded more than their contribution and another is frequently rewarded less than their contribution, we do not expect to see a persistent collaboration between the two, assuming both can choose whether or not to collaborate.

prior studies where individuals have autonomy in deciding whether to collaborate or not, not only in science (Bikard, Murray, and Gans 2015) but also in firms (Lee and Puranam 2017; Deichmann and Jensen 2018).

These three premises suggest that individuals may choose to collaborate even when not desirable from the project standpoint. When individuals know that they will be rewarded above and beyond their contribution to a project, they are likely to seek collaboration even where the project is not promising or when the cost of joint work exceeds the benefits to the project. In other words, individuals might decide to collaborate even in cases where collaboration worsens the output quality.

To illustrate how such detrimental collaborations can occur, consider a situation where two R&D workers in a biotech company face a choice of whether to work independently or together. They will both be rewarded for their work by their respective managers, who do not know the other the partner. For the sake of argument, assume that both employees are equally capable but that working together leads to lower output quality. This could happen because there is little overlap in the type of projects on which the two R&D workers can collaborate, leading to a choice of a relatively lower quality project for the collaboration, or because coordination costs and disagreements erode output quality—compared with what they could accomplish separately. Thus, from a project standpoint, it would be better not to collaborate. However, if each person knows that they will receive more than 50% of the credit for the joint work, they may still decide to work together as long as the collaboration credit premium compensates for the expected loss in output quality.

We do not suggest that all collaborations have a detrimental effect on output quality. Rather, we argue that this might occur because individuals could get more credit for their work when they collaborate than when they work alone.

## METHODS

### Empirical Strategy

We test our predictions by examining the collaborative choices of economists in academia. This context provides several important advantages. First, we can observe both the evolution of collaborative choices and the quality of collaborative output using publication data. The authors listed on each paper helps us identify the set of collaborators on each project. The number of citations to each publication provides a convenient—though imperfect—proxy for output quality. Both measures have been used extensively in prior studies. Assuming academics care primarily about maximizing their credit on the portfolio of their publications (Rahmandad and Vakili, 2019) , it is then possible to impute the level of credit premium by observing the combination of their collaboration choices and the quality of their publications. This is at the core of the method used by Bikard et al. (2015) to estimate the level of collaboration credit premium among a population of members of the science and engineering faculty at MIT. We use a similar approach, explained in more detail below, to confirm the presence of a credit premium in our sample as a prerequisite to testing our prediction.[2]

Second, in the field of economics, the norm of alphabetical ordering of the authors on publications enables us to get closer to estimating the causal impact of collaborations formed as a result of credit premium on output quality. Estimating the causal effect of collaboration is rife with endogeneity challenges. Specifically, individuals' collaboration decisions are a result of many factors, some of which are empirically unobservable. For example, a positive association between collaboration and output quality might stem from the fact that promising projects attract more collaborators than less-

[2] Credit in science can take a number of forms ranging from public acknowledgements, citations, publications, awards, and tenure. Without credit, scientists will find it difficult not only to get a job, but also to do science, as they might not be able to attract the resources that they need. While scientists routinely strive to quantify credit by counting publications, citations and awards, it is important to remember that those are only imperfect measures. In the paper, we do not assume that scientists need a specific number of publications or citations to e.g., get tenure. Rather, we assume that they strive to maximize credit and hence the number of citations to their works overall. Credit maximization, in turn, is likely to affect collaboration choices.

promising ones. Also, such a positive association might be the result of the unobserved superior ability of collaborators to promote the project.

To address these concerns, we use an instrumental variable method. The approach is meant to get closer to the gold standard of random assignment to treatment, in this case, random assignment to collaboration decisions driven by credit premium. This empirical strategy targets the selection into collaboration issue by engaging an instrument variable that is correlated with the resulting project quality but only through its impact on the propensity to collaborate. Our choice of instrument is directly informed by research showing that economists whose family names begin with letters toward the end of the alphabet receive less credit for their collaborative papers than their peers whose family names begin with letters toward the beginning of the alphabet. Therefore, we expect that researchers with less-favorable alphabetical ranking will collaborate less frequently at the margin. Conversely, individuals with more-favorable alphabetical ranks may engage in more collaborations because of the levels of credit premium they receive from collaborating.

For our instrumental variable approach to be valid, our instrument needs to satisfy the three criteria of relevance, independence, and exclusion restriction. As shown below, alphabetical ranking of last names has a meaningful causal effect on economists' propensity to engage in collaboration, hence satisfying the relevance criterion. Moreover, we can safely assume that people do not systematically select their last names in expectation of benefiting from a career as researchers in economics. Therefore, alphabetical rank is as good as randomly assigned to individuals, thus satisfying the independence criterion. Finally, alphabetical rank does not affect individuals' output quality through any channels other than their propensity to engage in collaboration. Thus, alphabetical rank also satisfies the exclusion restriction.

As we have discussed in the theory section, we expect the collaboration credit premium to lead to lower output quality through two different mechanisms. It is possible that the credit premium drives individuals to select lower quality projects to collaborate on to begin with. At the same time, individuals may choose to collaborate even when they expect the collaboration to lower the output quality, as long as the decline in quality is more than compensated by the collaboration credit premium. Although we cannot fully disentangle these two mechanisms, both are at odds with the positive correlation between collaboration and output quality shown in previous studies (e.g., Wuchty et al 2007; Singh & Fleming 2010; Bikard et al. 2015) and both occur through the same channel – collaboration behavior – thus not affecting the validity of our instrument.

The alphabetical ranking as an instrument for individuals' collaboration choice enables us to extract the local average treatment effect (LATE), i.e., the impact of collaborations formed because of credit premium on the output quality of projects on which these collaborations have happened. In other words, our empirical strategy compares a treatment group composed of collaborations by economists from the top of the alphabet with a control group composed of collaborations by economists from the bottom of the alphabet, controlling for individuals' productivity.

While the academic field of economics meets all the criteria for testing our theory, our empirical focus on this setting does not mean that detrimental collaborations driven by a collaboration credit premium do not occur in other settings. The decoupling between contribution and credit is inevitable in any creative context such as firm R&D, artistic production, or consulting. In these contexts, individual contributions are hard to measure. The creative process is usually iterative, and the value of one's input is not necessarily correlated with the amount of effort exerted. Moreover, in many non-academic settings, just as in academia, collaborators are evaluated by different audiences, increasing the chance that evaluators do not know all the team members, therefore leading to the emergence of a collaboration credit premium (Bikard, Murray, and Gans 2015; Kay, Proudfoot, and Larrick 2018). For example, R&D teams may include individuals from different divisions or regional offices that are evaluated by their respective managers. Collaborating artists often receive individual reputational awards from dispersed audiences. Even collaborating firms can be recognized and rewarded differently by their stakeholders for the same output. In these and similar contexts, the independent evaluation of collaborators based on their collaborative output give rise to a collaboration credit premium and, hence, create an incentive to engage in detrimental collaborations.

**Sample**

We build our sample by first collecting the full list of 21,905 PhD graduates from 12 top economics departments in the United States between 1990 and 2015 from the ProQuest Dissertation & Theses database. We then construct the career history of each individual since graduation using online resources such as university websites, LinkedIn, and company pages. Next, we exclude all individuals who did not pursue a career in academia. For each remaining individual, we specifically focus on the period before tenure. We do so because the amount of credit attributed to pre-tenure academics by their audience is an important input in the tenure decision, one of the most important career steps in academia. In contrast, we expect tenured faculty to be relatively less concerned with credit given their lifetime appointment. Note also that a sample of tenured faculty is likely to suffer from selection bias because collaboration choices affect whether individuals receive tenure. In other words, we are concerned that a sample that includes tenured individuals would capture researchers who advanced in their career because they took advantage of the credit premium phenomenon. The presence of this group would downward-bias the effects we are interested in evaluating.

Our final sample includes 1,164 pre-tenure economists in academia. Next, we extract the full record of each individual's publication portfolio from Scopus, a comprehensive bibliographic database maintained by Elsevier that documents worldwide academic publications across a variety of domains. We also collect key information about the institutions and departments at which these individuals worked during each year in our observation window, since the beginning of their PhD program.

Figure 1 shows the distribution of individuals across the institutions from which they graduated and the years of their graduation, the distribution of their publication rates per year, the alphabetical distribution of their family names, and the distribution of the number of authors on all papers in our sample. Table 1 shows summary statistics for the key variables in our sample. On average, individuals in our sample graduated from their PhD program in 2004; published 0.42 papers per year, of which 61% involved collaborators; and received 14 citations per year. Twenty-five percent of the individuals in our sample are women. Note that while the majority of researchers in our sample work in an economics department, some work in departments that cover a mix of economics and other fields such as health economics, law and economics, and economics and policy. In our empirical analysis, we control for the type of department in which each researcher works. Table A2 in the online appendix shows the correlation between our main variables. The VIFs of all main variables are below the conventional threshold of 10. We also observe higher correlation values only where expected, such as between the number of collaborative papers and that of published articles.

**—Figure 1 and Table 1 about here—**

## Evidence of a Collaboration Credit Premium

To establish the basis for our instrumental variable analysis, we first provide evidence for the presence of a credit premium in our sample and, second, confirm that individuals whose family names begin with a letter toward the beginning of the alphabet experience higher levels of credit premium than their peers whose family names begin with letters toward the end of the alphabet.

It is difficult to estimate the level of credit allocation for each instance of collaboration in our sample, since the individual contribution of collaborators and the amount of credit attributed to each by their respective audiences are unobservable. To circumvent these challenges, we use an indirect method of estimating the collaboration credit premium developed by Bikard et al. (2015). The method assumes that (1) researchers, on average, choose a level of collaboration that is expected to maximize their allocated credit; and (2) the credit allocated to each author on a paper amounts to a fraction of the citations to that paper. The latter assumption simply suggests that the credit for the paper must be shared among collaborators, albeit in a way that might sum up to more or less than 100%. The intuition behind the method is that individuals will increase their collaboration rate if they think it will increase their fractional credit. Conversely, they will reduce their collaboration rate if they believe that doing so will increase the fractional credit allocated to their papers. Therefore, at the population level, we should see neither a positive nor a negative relationship between the average fractional credit allocated to individuals and their collaboration rate. Any significant positive or negative relationship suggests that individuals can still increase their allocated credit by increasing or decreasing their collaboration rates. Based on this idea, one can examine a range of hypothetical levels of credit premium and identify the latent level of credit premium for which the relationship between the fractional credit and the collaboration rate becomes zero. The online appendix explains the method in more detail and provides all the estimations conducted to uncover the level of credit premium in our sample.

Our estimates suggest that for a team of two authors on a paper in our sample, each author receives on average 79% of the citations to the paper as individual credit, 29 more percentage points of credit than in the no-premium scenario.[3] The magnitude of the effect is slightly larger than that reported in Bikard et al. (2015) for their sample of MIT science and engineering faculty members.

Next, we confirm that individuals whose family names begin with a letter toward the beginning of the alphabet experience higher levels of credit premium than their peers whose family names begin with letters toward the end of the alphabet. Our instrumental variable method relies on this assumption. To test it, we repeat our estimation of credit premium separately for individuals whose family names begin with letters toward the first half of the alphabet (A to M) and for those whose family names begin with letters toward the second half of the alphabet (N to Z) (see the online appendix for more details).[4] Our estimations suggest that the former group receives on average 82% of the citations to their papers

[3] Note that the level of collaboration credit premium varies with the number of collaborators. In the appendix, we estimate the level of credit premium as a function of the number of collaborators on each paper. The reported level of credit premium here is for the median number of collaborators in our sample, which is two.

[4] The median first letter of alphabet in our sample is L. The results are very similar if we define the first half of alphabet as A to L and the bottom half as M to Z.

as individual credit, whereas the latter group receives only about 68% of the citations to their papers, a markedly lower level of credit premium.

**Instrumental Variable Analysis**

We perform our instrumental variable analysis at the individual-year level, even though we are ultimately interested in the effect of collaboration choice on the quality of output at the paper level. There are two main reasons for our choice. First, our instrument is at the individual level. At the paper level, it is unclear how the instrumental variable approach should be operationalized given that multiple individuals are listed on any collaborative paper. At the individual level, however, we can observe and use the aggregated collaboration choices of each individual in our sample in any given time period. Moreover, the choice of individual-year allows us to keep the input (i.e., time) constant by controlling for individual productivity. Given that the collaboration choice influences individual productivity as well as output quality, it is important to control for the productivity channel in our estimations. Throughout our analysis we only compare individuals that have produced the same number of papers each year. Our instrumental variable approach then captures how, for a given number of papers, an increase in the number of collaborations driven exogenously by individuals' alphabetical ranking would change the number of citations they receive. At the paper level, we do not have access to an appropriate control for individual productivity.

We use a 2SLS model for our estimations. In the first stage, we estimate the effect of alphabetical rank on individual's collaboration rate using the following equation:

$$(1)\ collaboration\ rate_{it} = \alpha_0 + \alpha_1 alphabetical\ rank_i + \theta_{it} + \delta_i + \gamma_t + \epsilon_{it}$$

In the second stage, we estimate the effect of the fitted values of $collaboration\ rate_{it}$ from the first stage on the number of yearly citations an individual receives using the following equation:

$$(2)\ \ln(citations_{it} + 1) = \beta_0 + \beta_1 \widehat{collaboration}\ rate_{it} + \theta_{it} + \delta_i + \gamma_t + \varepsilon_{it}$$

$collaboration\ rate_{it}$ is the number of collaborative papers published by individual $i$ in year $t$ and $citations_{it}$ is the total number of citations to those papers at the time of our data collection efforts in 2019. We log normalize the number of citations to account for its skewed distribution. Year fixed effects ($\gamma_t$) ensure that all comparisons happen between papers published in the same year. Because our instrument—alphabetical rank—is fixed at the individual level, we cannot include individual fixed effects in our estimations. Instead, we control for a wide range of time-variant ($\theta_{it}$) and time-invariant ($\delta_i$) individual characteristics. We include a set of fixed effects for the total number of papers produced by each individual in a given year to ensure that the impact of collaboration on citations is not driven by changes in productivity. Further, researchers with stronger records may care less about the credit attributed to them, and hence their collaboration choice may be less sensitive to alphabetical rank. Therefore, we control for researcher's publication record by including the cumulative number of papers produced by each researcher and the cumulative number of citations to those papers by $t - 1$. We also control for individuals' log normalized number of past collaborative papers to capture their idiosyncratic preference for collaboration, the size of their prior collaboration network, and their collaboration skills.

Moreover, research suggests that women receive less credit for their work, on average, than men (Sarsons 2017). Thus, we also control for researcher's gender. We further control for the starting and finishing years of individual's PhD program, the institution from which they graduated, the institution at which they worked at time *t,* and the type of department at which they worked at time *t,* to ensure that the comparison is between individuals from the same cohort facing similar institutional norms and expectations.

One might also be concerned that the distribution of alphabetical rank may be systematically correlated with individuals' ethnicity, which may positively or negatively affect individuals' propensity to collaborate or the quality of their work. Indeed, in our sample, Asian family names are more likely to begin with letters from the second half of the alphabet. Thus, we also control for whether an individual has an Asian family name or not. We also control for the logged (1 plus the) number of individual's yearly papers for which the co-authors are not listed alphabetically, as well as the median rank of the individual in the list of authors on her publications in year t. Both variables represent how often the author's rank on a paper corresponds with the alphabetical rank of their family name. A negative association between these variables and an individual's alphabetical rank may signal collaboration with non-economists or publication in non-economics outlets, both of which may affect citation outcomes for the researcher. We use a dual clustering of standard errors at institution and year levels in both stages.

Some of our control variables are endogenous to our instrumental variable choice. More specifically, our instrument affects various control variables in our model including past and present productivity i.e., number of papers produced, cumulative number of citations and collaborative papers by $t-1$, and the number of papers breaking the alphabetical norm. While the majority of these controls are unlikely to directly affect the outcome of interest (i.e., the number of citations an individual receives on her papers published in year $t$), individual's productivity in year $t$, measured as the number of papers published in year t, could potentially expose our estimations to (collider stratification) bias because there could be an omitted factor that simultaneously affects productivity (conditioned on the instrument) and our outcome variable of interest. Following Angrist and Pischke (2009), we recognize that, while not without limitations, our choice of controls as a proxy for omitted variables is preferred over not including these endogenous controls at all.

**RESULTS**

To demonstrate the necessity of employing our instrumental variable technique, we begin by replicating the effect documented in past research – that of a positive relationship between the number of collaborators on a publication or a patent and its quality (e.g., Wuchty, Jones, and Uzzi 2007; Singh and Fleming 2010). These correlations are useful to document noteworthy patterns and trends, but they do not separate selection and treatment effects. We replicate those results in our data at the level of the individual-year. To do so, we estimate the equation (2) above replacing the fitted values of collaboration rate ($\widehat{collaboration}\ rate_{it}$) with their actual values ($collaboration\ rate_{it}$). Like past studies, we find a significant positive relationship between collaboration and output quality in our sample (Table 2).

**—Table 2 about here—**

Next, we repeat this estimation using our instrumental variable strategy. Table 3 shows our first-stage results. Consistent with our expectation, the alphabetical rank of individuals has a statistically significant and economically meaningful effect on their choice of collaboration. The estimates suggest that one drop in alphabetical rank is equivalent to a 0.003-percentage-point drop in the yearly number of collaborative papers. Given that the average number of collaborative papers per year is 0.24, the estimate suggests that a one-standard-deviation decrease in alphabetical rank leads to an approximately 10% decline in one's propensity to collaborate. Because we cluster the standard errors, the first-stage F-statistic does not provide a reliable source for testing the weakness of our instrument. Instead, we report the Kleibergen-Paap Wald F-statistic. Comparing our Kleibergen-Paap Wald F-statistic of 20.347 with the critical values of the Stock-Yogo weak identification test suggests that the relative bias of our estimation is smaller than 5% for a 5%-level Wald test (Stock and Yogo 2005).

**—Table 3 about here—**

Table 4 shows the results for the second stage. In line with our hypothesis, the estimates suggest that the number of collaborative papers in a year has a significant negative effect on the number of citations received by an author in that year. More specifically, switching from a solo paper to a collaborative paper, driven by the collaboration credit premium, leads to an average 47% decline in the number of citations per year. Given that authors receive 14 citations per year on average, the effect is equivalent to a loss of approximately seven citations per year due to collaborations that were exogenously driven by the variance in the credit premium allocated to individuals.

The size of the effect is in line with the level of credit premium we have estimated in our sample. Our estimates suggest that the credit premium in our sample can be anywhere between 68% and 93% (within a 95% confidence interval), which is equivalent to a 26% to 86% increase in citations accrued to a collaborator. Meanwhile, the range for the estimated decline in citations because of detrimental collaborations is between 2% and 78% (again for a 95% confidence interval). The range for the two estimates map onto each other.

**—Table 4 about here—**

These results confirm our prediction that a collaboration credit premium can lead to the formation of collaborations that hurt output quality. Note that we cannot generalize our estimated effect to the whole sample or more broadly to the field of economics. In other words, we do not (and cannot) claim that all collaborations in the field of economics have a negative average effect on output quality. Rather, consistent with our hypothesis, our results show that the credit-premium-driven increase in collaboration levels in our sample has a negative treatment effect on output quality.

As a robustness test, in Table A3 in the appendix, we report the first-stage results for the tenured researchers in our sample. As expected, the estimated effect of alphabetical rank is positive, very close to zero, and nonsignificant at the 10% level (p-value = 0.979). This suggests that tenured faculty in our sample are less sensitive to the skewed allocation of a credit premium in collaborative efforts. In Table A4, we repeat our estimations with dual clustering at the individual and year levels. The results are similar to those reported above. In Tables A5 and A6, we report the second-stage results based on a two-stage generalized method of moments (GMM) estimation and on a limited-information maximum likelihood method. All results remain robust to the effect reported in our main estimation models.

## DISCUSSION AND CONCLUSION

Creative workers in firms and in academia can often choose whether to collaborate or to work alone. The choice is an important one, not only because it influences the quality of the work output but also because it affects the credit they receive. Prior research has implicitly assumed that these two goals, project quality and personal credit, are aligned—in other words, that what is good from a project standpoint is good for the individual, and vice versa. We challenge this assumption, arguing that collaborative work can lead to a decoupling of individual- and project-level incentives.

Our argument rests on the idea that credit allocation in collaborative work is difficult because individual contributions are generally unobservable. Team members may share credit in a way that sums to more than 100%, especially when individuals are evaluated by different audiences (Bikard et al. 2015; Kay et al. 2018). This collaboration credit premium is likely to create a strong pull toward collaboration. Under these circumstances, individuals might choose to collaborate even if it leads to lower output quality, as long as the credit premium more than offsets this negative impact.

We theorized and found empirical support for the proposition that, to gain extra credit, researchers in economics decide to collaborate even when collaboration is detrimental to output quality. We focused on economics because its norm of alphabetical ordering provides an opportunity to address the usual endogeneity concerns with estimating the causal effect of collaboration on the quality of output. However, our theoretical claims apply to other creative settings where individual contributions to collaborative work are difficult to observe, where individuals can choose whether or not to collaborate, and where one can expect the existence of a collaboration credit premium.

While the case of economists in academia provides a useful setting in which to test our theoretical predictions, some limitations remain, and our results should therefore be interpreted with caution. First, although economics is a prominent academic discipline, we study only one setting and are unable to assess how the phenomenon of detrimental collaboration varies from one setting to the next. Our goal is therefore to show the existence of the phenomenon, not to examine its prevalence or to make generalizable claims about the magnitude of its effect. Because the same empirical strategy cannot be used to examine this phenomenon in other settings, future studies need to devise other strategies to estimate the causal impact of credit premium driven collaborations on project quality in other settings. Also, it is possible that economists react more strongly to credit-related incentives than individuals in other creative fields. After all, economists are known to be more sensitive to economic incentives than the rest of the population (Marwell and Ames 1981; Carter and Irons 1991).

Second, our study is limited by the fact that our measures of credit allocation are indirect. Our empirical strategy relies on individuals at the end of the alphabet differing from people from the beginning of the alphabet by the fact that they receive less credit for collaborative work but are being otherwise comparable in other dimensions (at least, those that are not orthogonal to output quality). Yet it is possible that those two groups differ in ways that are unobservable to us. For example, one could imagine that economists toward the end of the alphabet are more likely to leave the field since they know they are being discriminated against. We investigated this potential selection process by comparing the distribution of alphabetical ordering at the PhD and at the faculty level and found no meaningful differences. Still, some economists might act strategically to avoid alphabetical discrimination, for example by changing their last name or by leaving the field.

Third, our findings raise a range of interesting questions that we are unable to answer using our dataset. For example, and as discussed in the theory section, detrimental collaboration can be explained by two different mechanisms. The credit premium may compel creative workers to choose to collaborate on lower quality projects to begin with, or in situations where the collaboration is expected to lower output quality, rather than help. Future research might productively attempt to separate the two. In addition, our findings also raise the question of how creative workers might act in situations where measures of quality change overtime. In the field of economics, evaluators might consider that journal impact factor is a good measure of quality early on, but that citations become a more relevant measure after a few years. This change in measure opens the door to strategic behaviour and potential trade-offs between short- and long-term performance. This tension might also constitute a promising avenue for further research.

Our study makes several contributions. First, we highlight a novel mechanism through which collaboration negatively affects output quality in creative work—incentive misalignment. Prior studies of the cost of collaboration have hitherto focused on challenges associated with the process of collaboration. They have emphasized costs stemming from coordination difficulties (Mell, Jang, and Chai 2020), free-riding (Levine and Prietula 2013), groupthink (Godart, Shipilov, and Claes 2013) or conflict (Hinds and Bailey 2003). Instead, we highlight a challenge that is not associated with the process of collaboration but with selection into collaboration in the first place.

Second, our study contributes to our understanding of the well-documented positive correlation between collaboration and output quality (e.g., Wuchty, Jones, and Uzzi 2007; Singh and Fleming 2010). Our results indicate that those positive correlations might be driven in part by individuals collaborating on more-promising ideas rather than collaboration improving outcomes. In our data, we replicate the finding that articles written by collaborating individuals tend to be of better quality on average. However, when we use alphabetical name ordering to identify the treatment effect of collaboration, we find that the latter is negative among collaborations formed because of variances in credit premium. Our findings therefore suggest that prior studies' optimism regarding the causal impact of collaboration on output quality may be overstated because of lack of attention to selection biases.

Third, our findings are also relevant to a growing literature that has described the benefits of autonomy in creative work in general and in R&D activities in particular. Those studies have shown that autonomy can increase workers' motivation and efficiency (Bailyn 1985; Sauermann and Cohen 2010; Agarwal and Ohyama 2013; Criscuolo, Salter, and Ter Wal 2013; Gambardella, Khashabi, and Panico 2020). One important downside, however, is loss of control whereby employees undertake projects that might have little short-term value from a firm standpoint (Gittelman and Kogut 2003; Stern 2004). Here we focus on autonomy with regards to collaboration and highlight another potential downside of autonomy in creative work, namely that it creates tensions for creative workers who might have to prioritize between personal rewards and output quality.

Firms that ignore these challenges may not only fail to reward individuals who contribute a lot but may end up rewarding individuals who chose to organize their work in a way that benefits themselves more than the project. In particular, our findings highlight the risks of over-rewarding collaborative work. While it might not be easy to eliminate detrimental collaborations driven by the credit premium, closer attention to the division of labor and to each person's incentives can help companies better monitor the performance of individual team members and potentially intervene to mitigate this cost of collaboration to the extent possible.

We do not suggest that all collaborations have a negative impact on output quality or that all creative workers exhibit opportunistic behavior when engaging in collaboration. There is extensive evidence on the benefit of and need for collaboration, as discussed earlier in this paper. In other words, the take-away must not be to impose blanket policies that deter or excessively police collaboration behavior. Rather, we hope that our findings inspire a more nuanced evaluation of collaboration incentives, ensuring that workers are rewarded fairly, whether or not they choose to collaborate.

This paper is a first step in exploring the relationship between individual- and project-level incentives in collaborative creative work. In particular, we show that individuals can sometimes benefit from collaborating even when it reduces the quality of their creative output. The importance of furthering this line of research should not be understated. As an organization of work, autonomous collaborations are becoming more and more prevalent, and there is no sign that this trend is slowing. By highlighting the fact that collaboration can create a gap between what benefits a project and what benefits the individuals working on that project, we hope that our study enhances our understanding of the drivers of creative performance as a collective enterprise.

## REFERENCES


Adler, Paul S., Seok-Woo Kwon, and Charles Heckscher. 2008. 'Perspective--Professional Work: The Emergence of Collaborative Community'. *Organization Science* 19 (2): 359–76.

Agarwal, Rajshree, and Atsushi Ohyama. 2013. 'Industry or Academia, Basic or Applied? Career Choices and Earnings Trajectories of Scientists'. *Management Science* 59 (4): 950–70.

Albanese, Robert, and David D. Van Fleet. 1985. 'The Free Riding Tendency in Organizations'. *Scandinavian Journal of Management Studies* 2 (2): 121–36.

Bailyn, Lotte. 1985. 'Autonomy in the Industrial R&D Lab.' *Human Resource Management* 24 (2): 129–46.

Biancani, Susan, Daniel A. McFarland, and Linus Dahlander. 2014. 'The Semiformal Organization'. *Organization Science* 25 (5): 1306–24.

Bikard, Michaël, Fiona Murray, and Joshua Gans. 2015. 'Exploring Tradeoffs in the Organization of Scientific Work: Collaboration and Scientific Reward'. *Management Science* 61 (7): 1473–95.

Brewer, Marilynn B., and Roderick M. Kramer. 1986. 'Choice Behavior in Social Dilemmas: Effects of Social Identity, Group Size, and Decision Framing.' *Journal of Personality and Social Psychology* 50 (3): 543.

Carter, John R., and Michael D. Irons. 1991. 'Are Economists Different, and If So, Why?' *Journal of Economic Perspectives* 5 (2): 171–77.

Cattani, Gino, and Simone Ferriani. 2008. 'A Core/Periphery Perspective on Individual Creative Performance: Social Networks and Cinematic Achievements in the Hollywood Film Industry'. *Organization Science* 19 (6): 824–44.

Cattani, Gino, Simone Ferriani, Marcello M. Mariani, and Stefano Mengoli. 2013. 'Tackling the "Galácticos" Effect: Team Familiarity and the Performance of Star-Studded Projects'. *Industrial and Corporate Change* 22 (6): 1629–62.

Choudhury, Prithwiraj, and Martine R. Haas. 2018. 'Scope versus Speed: Team Diversity, Leader Experience, and Patenting Outcomes for Firms'. *Strategic Management Journal* 39 (4): 977–1002.

Contractor, Noshir. 2013. 'Some Assembly Required: Leveraging Web Science to Understand and Enable Team Assembly'. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 371 (1987): 20120385.

Criscuolo, Paola, Ammon Salter, and Anne L. J. Ter Wal. 2013. 'Going Underground: Bootlegging and Individual Innovative Performance'. *Organization Science* 25 (5): 1287–1305.

Cummings, Jonathon N., and Sara Kiesler. 2007. 'Coordination Costs and Project Outcomes in Multi-University Collaborations'. *Research Policy* 36 (10): 1620–34.

Deichmann, Dirk, and Michael Jensen. 2018. 'I Can Do That Alone…or Not? How Idea Generators Juggle between the Pros and Cons of Teamwork'. *Strategic Management Journal* 39 (2): 458–75.

Dougherty, Deborah. 1992. 'Interpretive Barriers to Successful Product Innovation in Large Firms'. *Organization Science* 3 (2): 179–202.

Edmondson, Amy. 1999. 'Psychological Safety and Learning Behavior in Work Teams'. *Administrative Science Quarterly* 44 (2): 350–83.

Einav, Liran, and Leeat Yariv. 2006. 'What's in a Surname? The Effects of Surname Initials on Academic Success'. *Journal of Economic Perspectives* 20 (1): 175–87.

Faraj, Samer, Sirkka L. Jarvenpaa, and Ann Majchrzak. 2011. 'Knowledge Collaboration in Online Communities'. *Organization Science* 22 (5): 1224–39.

Fleming, Lee, Santiago Mingo, and David Chen. 2007. 'Collaborative Brokerage, Generative Creativity, and Creative Success.' *Administrative Science Quarterly* 52 (3): 443–75.

Foss, Nicolai J. 2003. 'Selective Intervention and Internal Hybrids: Interpreting and Learning from the Rise and Decline of the Oticon Spaghetti Organization'. *Organization Science* 14 (3): 331–49.

Freeman, Richard B., Ina Ganguli, and Raviv Murciano-Goroff. 2014. 'Why and Wherefore of Increased Scientific Collaboration'. *The Changing Frontier: Rethinking Science and Innovation Policy*, August, 17–48.

Gambardella, Alfonso, Pooyan Khashabi, and Claudio Panico. 2020. 'Managing Autonomy in Industrial Research and Development: A Project-Level Investigation'. *Organization Science* 31 (1): 165–81.

Gittelman, Michelle, and Bruce Kogut. 2003. 'Does Good Science Lead to Valuable Knowledge? Biotechnology Firms and the Evolutionary Logic of Citation Patterns'. *Management Science* 49 (4): 366–82.

Godart, Frédéric C., Andrew V. Shipilov, and Kim Claes. 2013. 'Making the Most of the Revolving Door: The Impact of Outward Personnel Mobility Networks on Organizational Creativity'. *Organization Science* 25 (2): 377–400.

Goncalo, Jack A., Jennifer A. Chatman, Michelle M. Duguid, and Jessica A. Kennedy. 2015. 'Creativity from Constraint? How the Political Correctness Norm Influences Creativity in Mixed-Sex Work Groups'. *Administrative Science Quarterly* 60 (1): 1–30.

Hargadon, Andrew, and Robert Sutton. 1997. 'Technology Brokering and Innovation in a Product Development Firm'. *Administrative Science Quarterly* 42 (4): 716–49.

Heath, Chip, and Nancy Staudenmayer. 2000. 'Coordination Neglect: How Lay Theories of Organizing Complicate Coordination in Organizations'. *Research in Organizational Behavior* 22 (January): 153–91.

Heilman, Madeline, and Michelle Haynes. 2005. 'No Credit Where Credit Is Due'. *Journal of Applied Psychology* 90 (5): 905–16.

Hinds, Pamela J., and Diane E. Bailey. 2003. 'Out of Sight, Out of Sync: Understanding Conflict in Distributed Teams'. *Organization Science* 14 (6): 615–32.

Janis, Irving L. 1971. 'Groupthink'. *Psychology Today* 5 (6): 43–46.

Jones, Benjamin. 2009. 'The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?' *Review of Economic Studies* 76 (1): 283–317.

Karau, S. J, and K. D Williams. 1993. 'Social Loafing: A Meta-Analytic Review and Theoretical Integration'. *Journal of Personality and Social Psychology* 65: 681–681.

Kay, Min B., Devon Proudfoot, and Richard P. Larrick. 2018. 'There's No Team in I: How Observers Perceive Individual Creativity in a Team Setting'. *Journal of Applied Psychology* 103 (4): 432–42.

Kneeland, Madeline K., Melissa A. Schilling, and Barak S. Aharonson. 2020. 'Exploring Uncharted Territory: Knowledge Search Processes in the Origination of Outlier Innovation'. *Organization Science* 31 (3): 535–57.

Latané, Bibb, Kipling Williams, and Stephen Harkins. 1979. 'Many Hands Make Light the Work: The Causes and Consequences of Social Loafing'. *Journal of Personality and Social Psychology* 37 (6): 822–32.

Lawrence, Paul R., and Jay W. Lorsch. 1967. 'Differentiation and Integration in Complex Organizations'. *Administrative Science Quarterly* 12 (1): 1–47.

Leahey, Erin. 2016. 'From Sole Investigator to Team Scientist: Trends in the Practice and Study of Research Collaboration'. *Annual Review of Sociology* 42 (1): 81–100.

Lee, Sunkee, and Phanish Puranam. 2017. 'Incentive Redesign and Collaboration in Organizations: Evidence from a Natural Experiment'. *Strategic Management Journal* 38 (12): 2333–52.

Levine, Sheen S., and Michael J. Prietula. 2013. 'Open Collaboration for Innovation: Principles and Performance'. *Organization Science* 25 (5): 1414–33.

Lissoni, Francesco, Fabio Montobbio, and Lorenzo Zirulia. 2020. 'Misallocation of Scientific Credit: The Role of Hierarchy and Preferences. An Extension of Lissoni et al.(2013)'. *Industrial and Corporate Change*.

Liu, Haibo, Jürgen Mihm, and Manuel E. Sosa. 2018. 'Where Do Stars Come From? The Role of Star vs. Nonstar Collaborators in Creative Settings'. *Organization Science* 29 (6): 1149–69.

Marwell, Gerald, and Ruth E. Ames. 1981. 'Economists Free Ride, Does Anyone Else?: Experiments on the Provision of Public Goods, IV'. *Journal of Public Economics* 15 (3): 295–310.

Mell, Julija N., Sujin Jang, and Sen Chai. 2020. 'Bridging Temporal Divides: Temporal Brokerage in Global Teams and Its Impact on Individual Performance'. *Organization Science*, November.

Merton, Robert K. 1968. 'The Matthew Effect in Science The Reward and Communication Systems of Science Are Considered'. *Science* 159 (3810): 56.

O'Dell, Jerry W. 1968. 'Group Size and Emotional Interaction'. *Journal of Personality and Social Psychology* 8 (1, Pt.1): 75–78. https://doi.org/10.1037/h0025326.

Perlow, Leslie A. 1999. 'The Time Famine: Toward a Sociology of Work Time'. *Administrative Science Quarterly* 44 (1): 57–81.

Porac, Joseph F., James B. Wade, Harald M. Fischer, Joyce Brown, Alaina Kanfer, and Geoffrey Bowker. 2004. 'Human Capital Heterogeneity, Collaborative Relationships, and Publication Patterns in a Multidisciplinary Scientific Alliance: A Comparative Case Study of Two Scientific Teams'. *Research Policy* 33 (4): 661–78.

Rahmandad, Hazhir, and Keyvan Vakili. 2019. 'Explaining Heterogeneity in the Organization of Scientific Work'. *Organization Science* 30 (6): 1125–1393.

Reagans, Ray, and Ezra W. Zuckerman. 2001. ‘Networks, Diversity, and Productivity: The Social Capital of Corporate R&D Teams’. *Organization Science* 12 (4): 502–17.
Reagans, Ray, Ella Miron-Spektor, and Linda Argote. 2016. 'Knowledge Utilization, Coordination, and Team Performance'. *Organization Science* 27(5): 1108-1124.
Ross, Michael, and Fiore Sicoly. 1979. ‘Egocentric Biases in Availability and Attribution’. *Journal of Personality and Social Psychology* 37 (3): 322–36.
Sauermann, Henry, and Wesley Cohen. 2010. ‘What Makes Them Tick? Employee Motives and Firm Innovation’. *Management Science* 56 (12): 2134–53. https://doi.org/10.1287/mnsc.1100.1241.
Schroeder, Juliana, Eugene M. Caruso, and Nicholas Epley. 2016. ‘Many Hands Make Overlooked Work: Over-Claiming of Responsibility Increases with Group Size’. *Journal of Experimental Psychology: Applied* 22 (2): 238–46.
Singh, Jasjit, and Lee Fleming. 2010. ‘Lone Inventors as Sources of Breakthroughs: Myth or Reality?’ *Management Science* 56 (1): 41–56.
Solla Price, D. J. de. 1965. *Little Science, Big Science... and Beyond*. Columbia University Press.
Stern, Scott. 2004. ‘Do Scientists Pay to Be Scientists?’ *Management Science* 50 (6): 835–53.
Stock, James H., and Motohiro Yogo. 2005. ‘Testing for Weak Instruments in Linear IV Regression’. *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, 80.
Taylor, A., and H. R. Greve. 2006. ‘Superman or the Fantastic Four? Knowledge Combination and Experience in Innovative Teams’. *Academy of Management Journal* 49 (4): 723.
Toh, Puay Khoon, and Francisco Polidoro. 2013. ‘A Competition-Based Explanation of Collaborative Invention within the Firm’. *Strategic Management Journal* 34 (10): 1186–1208.
Whyte, Glen. 1989. ‘Groupthink Reconsidered’. *Academy of Management Review* 14 (1): 40–56.
Wuchty, Stefan, Benjamin Jones, and Brian Uzzi. 2007. ‘The Increasing Dominance of Teams in Production of Knowledge’. *Science* 316 (5827): 1036.

**Figure 1.** The distributional characteristics of the final sample.

Figure 1a

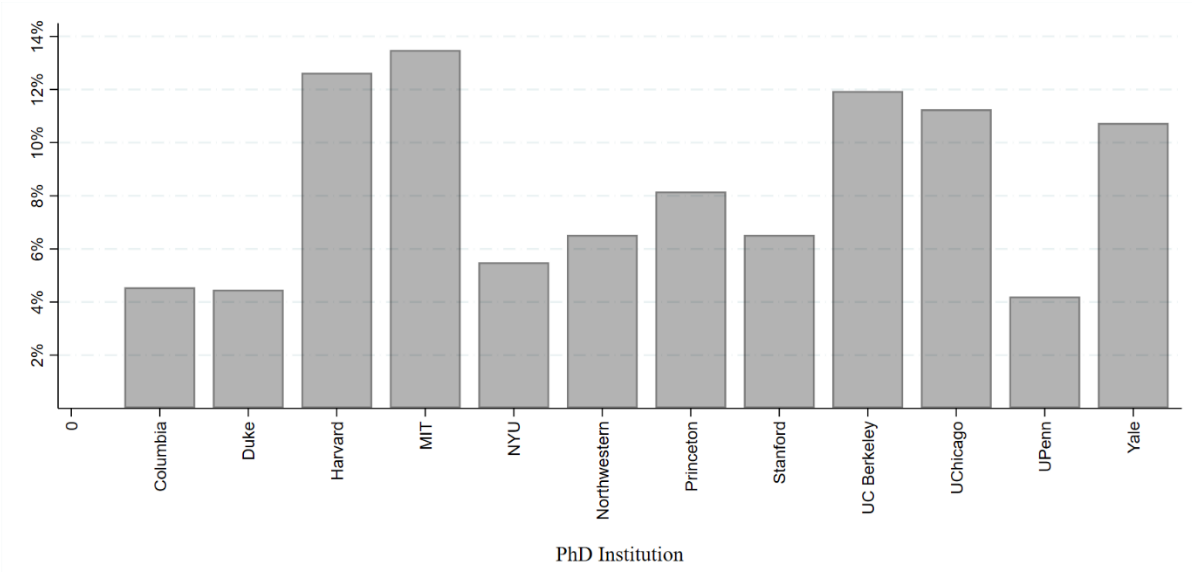



Figure 1b

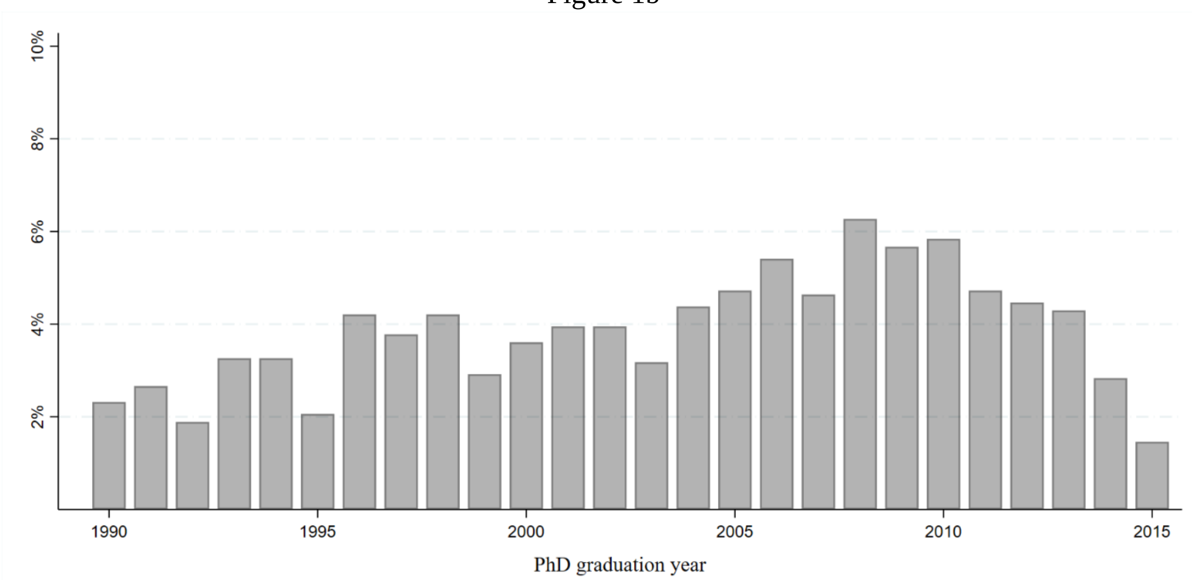


Figure 1c

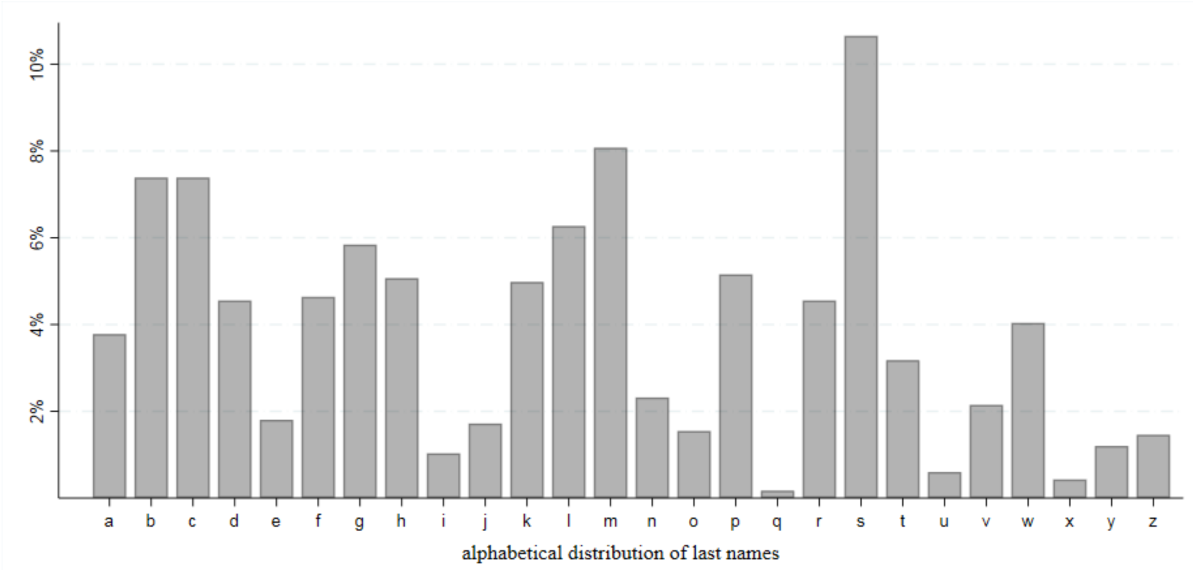



Figure 1d

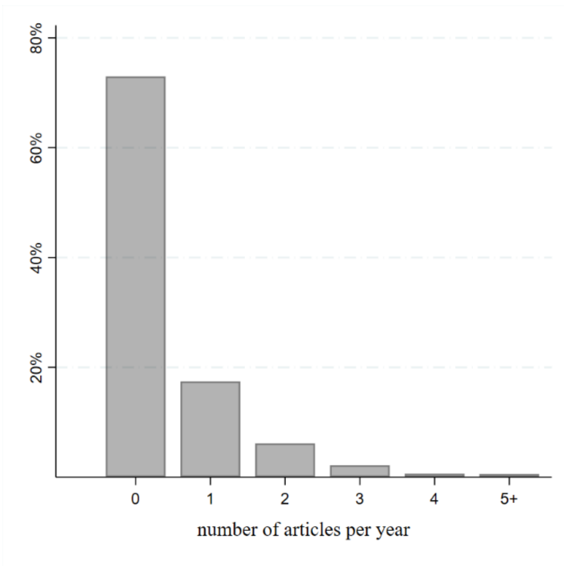
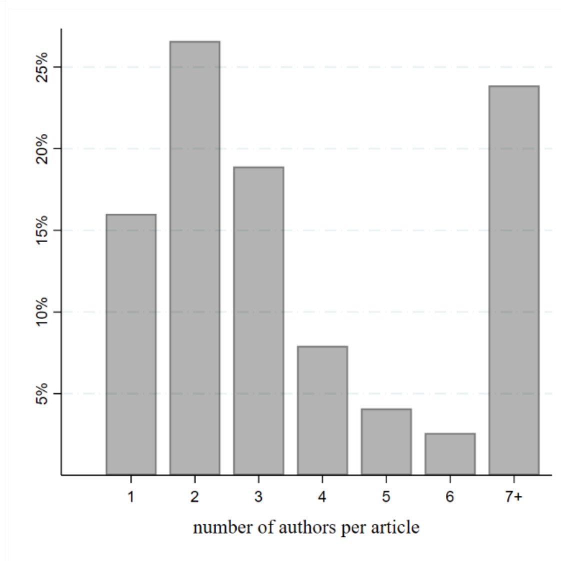



Figure 1e




*Note*. Figures 1a through 1e show the distribution of individuals across the institutions from which they graduated (N=1,164), the years of their graduation (N=1,164), the alphabetical distribution of their family names (N=1,164), their publication rates per year (N=16,260), and the distribution of the number of authors on all papers in our sample, respectively (N=16,260).

**Table 1.** Summary Statistics

| | Obs. | Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Alphabetical rank (individual level) | 1,164 | 11.588 | 6.991 | 0 | 26 |
| PhD graduation year (individual level) | 1,164 | 2003.556 | 6.846 | 1990 | 2015 |
| Female (individual level) | 1,164 | 0.250 | 0.433 | 0 | 1 |
| Asian family name (individual level) | 1,164 | 0.299 | 0.458 | 0 | 1 |
| Number of articles (individual-year level) | 16,260 | 0.425 | 0.888 | 0 | 14 |
| Collaborative articles (individual-year level) | 16,260 | 0.240 | 0.667 | 0 | 14 |
| Number of citations (individual-year level) | 16,260 | 14.030 | 73.030 | 0 | 2,715 |
| Cumulative count of articles (individual-year level) | 16,260 | 1.678 | 3.479 | 0 | 84 |
| Cumulative count of citations (individual-year level) | 16,260 | 61.700 | 228.971 | 0 | 6,236 |
| N. of articles not in alphabetical order (individual-year level) | 16,260 | 0.105 | 0.579 | 0 | 13 |
| Median author rank on publications (individual-year level) | 16,260 | 0.393 | 0.786 | 0 | 16 |

**Table 2.** The Relationship between Collaboration (Non-instrumented) and the Output Quality

| **Model:** | **OLS** |
|---|---|
| **DV:** | **ln(citations+1)** |
| Count of collaborative papers | 0.086** |
| | (0.037) |
| Ln(cumulative number of articles+1) | -0.443*** |
| | (0.057) |
| Ln(cumulative number of citations+1) | 0.190*** |
| | (0.019) |
| Female | -0.001 |
| | (0.018) |
| Asian family name | -0.019 |
| | (0.017) |
| Number of articles not in alphabetical order | -0.035 |
| | (0.040) |
| Median author rank on publications | 0.001 |
| | (0.032) |
| Additional controls: year dummies, number of articles dummies, current institution dummies, department type dummies, starting year of PhD dummies, finishing year of PhD dummies | Yes |
| Obs. | 16,260 |
| F-statistics | 26.22 |
| Adjusted R^2 | 0.725 |

*Notes.* The analysis is at the individual-year level. The estimation is based on OLS regression with robust standard errors dual-clustered at the institution and year levels.
*** p < 0.01, ** p < 0.05.

**Table 3.** The Effect of Alphabetical Rank of Scientists on Their Propensity to Collaborate (First-Stage Results of the Instrumental Variable Method)

| **Model:** | **OLS** |
|---|---|
| **DV:** | **Count of collaborative papers** |
| Alphabetical rank | -0.003*** |
| | (0.001) |
| Ln(cumulative number of articles+1) | 0.038*** |
| | (0.015) |
| Ln(cumulative number of citations+1) | -0.001 |
| | (0.004) |
| Female | -0.024*** |
| | (0.009) |
| Asian family name | 0.011* |
| | (0.006) |
| Number of articles not in alphabetical order | 0.263*** |
| | (0.035) |
| Median author rank on publications | 0.124*** |
| | (0.012) |
| Additional controls: year dummies, number of articles dummies, current institution dummies, department type dummies, starting year of PhD dummies, finishing year of PhD dummies | Yes |
| Obs. | 16,260 |
| F-statistics | 20.35 |
| Kleibergen-Paap Wald F-statistic | 20.347 |

*Notes.* The analysis is at the individual-year level. The estimation is based on OLS regression with robust standard errors dual-clustered at the institution and year levels. The critical value of the Stock-Yogo weak identification test for a bias smaller than 5% for a 5% level Wald test is 16.38.
*** $p < 0.01$.

**Table 4.** The Impact of Collaboration (Instrumented) on the Output Quality (Second-Stage Results of the Instrumental Variable Method)

| **Model:** | **OLS** |
|---|---|
| **DV:** | **ln(citations+1)** |
| Count of collaborative papers (instrumented) | -0.642**<br>(0.308) |
| Ln(cumulative number of articles+1) | -0.417***<br>(0.058) |
| Ln(cumulative number of citations+1) | 0.190***<br>(0.019) |
| Female | -0.018<br>(0.021) |
| Asian family name | -0.012<br>(0.019) |
| Number of articles not in alphabetical order | 0.156*<br>(0.090) |
| Median author rank on publications | 0.089**<br>(0.036) |
| Additional controls: year dummies, number of articles dummies, current institution dummies, department type dummies, starting year of PhD dummies, finishing year of PhD dummies | Yes |
| Obs. | 16,260 |
| F-statistics | 24.03 |

*Note.* The analysis is at the individual-year level. The estimation is based on OLS regression with robust standard errors dual-clustered at the institution and year levels.
*** $p < 0.01$, ** $p < 0.05$.