

Stars in Their Constellations: Great Person or Great Team?

Denisa Mindruta,^{a,*} Janet Bercovitz,^b Vlad Mares,^c Maryann Feldman^d

^aStrategy and Business Policy, HEC Paris, 78350 Jouy-en-Josas, France; ^bLeeds School of Business, University of Colorado Boulder, Boulder, Colorado 80309; ^cINSEAD Europe Campus, Boulevard de Constance, F-77305 Fontainebleau Cedex, France; ^dASU School of Public Affairs, Phoenix, Arizona 85004

*Corresponding author

Contact: mindruta@hec.fr,  <https://orcid.org/0000-0001-5366-6058> (DM); janet.bercovitz@colorado.edu (JB); vladimir.mares@insead.edu (VM); maryann.feldman@asu.edu (MF)

Received: June 15, 2021

Revised: February 10, 2023;

September 29, 2023

Accepted: October 3, 2023

Published Online in Articles in Advance:
May 30, 2024

<https://doi.org/10.1287/mnsc.2021.01969>

Copyright: © 2024 INFORMS

Abstract. Although much attention is accorded to star performers, this paper considers the extent to which stars, themselves, benefit from the contribution of their collaborators (the constellation). By considering stars, constellations, and the synergies between them, we address a key question: To what extent is collaboration performance driven by the great individual or by great constellations? We introduce a novel approach that uses a matching model to uncover the complementarities driving collaboration formation. We use formal value-capture theory to estimate the relative contribution of stars and constellations to joint value creation. Analyzing a sample of academic research collaborations, we document that stars' relative contribution exceeds that of their constellations in less than 15% of collaborations, although constellations provide a greater relative contribution in 9%. In most collaborations, neither party dominates: Innovation is a collective endeavor driven equally by the star and the constellation. Joint value creation and relative contribution are explained by the subtle interplay between complementarities in joint work and the substitutability of collaborative parties in the market. Joint value creation increases with the strength of complementarities between parties in a match. Relative value creation, and hence dominance, increases with the substitutability of one's collaborative partner. Interestingly, joint value creation is greatest in collaborations where both stars and constellations offer bundles of rare attributes and where neither the star nor the constellation dominates.

History: Accepted by Olav Sorenson, organizations.

Funding: D. Mindruta gratefully acknowledges funding from the HEC Foundation and from the French National Research Agency (ANR) "Investissements d'Avenir" (LabEx Ecodec/ANR-11-LABX-0047). J. Bercovitz and M. Feldman gratefully acknowledge funding from the Science of Science Approach to Analyzing and Innovating the Biomedical Research Enterprise (SCISIPBIO) program of the U.S. National Science Foundation (NSF) [Grant 1934875].

Supplemental Material: The online appendices and data files are available at <https://doi.org/10.1287/mnsc.2021.01969>.

Keywords: teams • star scientists • matching • complementarities • value-creation • value-capture

1. Introduction

A fundamental inquiry in management is how to achieve the best possible organizational performance. The configuration of human capital in collaborative teams is a central part of this value-creation conversation. Relatedly, a key inquiry in this stream of research focuses on assessing the relative contributions of individuals (and subgroups) to team productivity. This topic has been studied in multiple contexts. In the management literature, researchers aim to isolate chief executive officer (CEO) or manager contribution to firm performance from firm attributes (Tervio 2008, Mollick 2012, Jarosiewicz and Ross 2023). In the human capital and innovation literature, a recurrent theme involves assessing the relative productivity of individuals and teams in project, innovation, or research collaborations (Groysberg and Lee 2008, Groysberg et al. 2008,

Bhaskarabhatla et al. 2021, Campbell et al. 2021) and the subsequent credit and financial allocation. Questions of individual versus team productivity have also been investigated in the context of professional sports and entertainment (DeVany and Walls 1999, Elberse 2007, Arcidiacono et al. 2017). Much attention has been given to the superior contribution by top performers with high human capital such as successful CEOs, star athletes, prominent analysts, or prize-winning scientists. Less studied, but equally important, is how the performance of these stars is influenced by their collaboration teams (Groysberg and Lee 2008).

These questions are central in the study of scientific research teams, where "star" scientists are often viewed as an important, if not the most important, form of human capital. Stars are recognized to publish more than their peers, produce papers that have greater

impact, and to actively participate in commercialization efforts: reporting inventions, patenting, licensing, and start-up formation (Zucker et al. 1998). However, scientists, particularly those in the medical and life sciences fields, rarely work alone (Wuchty et al. 2007, Jones et al. 2008): The average number of coauthors in the medical field is greater than four and trending higher over time (Adams et al. 2005). These publication collaborations transfer over to the intellectual property and commercialization domain as academic invention disclosures correspondingly involve multiple inventors: Bercovitz and Feldman (2011) find that more than 60% of invention disclosure involved two or more individuals. Although collaborations including stars have been shown to have, on average, higher performance, both in terms of academic papers and commercialization outputs, than collaborations that are unable to tap into such star resources, the mechanisms that drive this superior performance have not been holistically evaluated in prior research. An overemphasis on the contribution of the star to the detriment of the contributions of the other scientists in the collaboration, those who form the *constellations*, is common.¹ In this study, we examine collaborative productivity and relative value contribution in the context scientific research collaborations. Our goal is to understand to what extent and under which circumstances collaboration performance is driven by the contributions of the great individuals (star scientists) or great constellations.

The challenge in parsing the relative contribution comes from a need to simultaneously consider the two key elements at play in value creation: synergies between collaborative partners and the matching process bringing these partners together. First, at the collaboration level, higher performance (value creation) occurs with the increase in synergies between collaborative partners. Furthermore, given that partners bring bundles of attributes to the collaboration, multidimensionality must be considered to accurately capture these synergies. Second, scientific research teams are voluntary collaborations formed around mutual scientific interests and knowledge complementarities; as such, the selection of partners is not random. Crucially, the anticipation of synergies is an integral driver of how parties match and the subsequent assortative structure of the matching market.

The relative contribution of parties in a collaboration is typically assessed by examining the division of joint output among parties, via an analysis of value capture. Such an analysis becomes more complicated when collaborator multidimensionality, synergies at the collaboration level, and sorting at the market level contribute to value creation and therefore must be accounted for in the assessment of value capture. Furthermore, in these situations, relative contribution rests on how irreplaceable a party is in the matching market, which in turn depends in a non-trivial way on how the multidimensionality of synergies dictates the sorting outcomes and the resultant ordering

distance or “gaps” between agents in the market. Stars’ contribution may surpass the contribution of the constellation, but such dominance is contingent on a lack of close substitutes for the star in the collaboration space. Similarly, the constellation’s contribution has the potential to equal or surpass stars’ contribution but there is a risk that this contribution is undervalued when synergy and sorting effects are not fully accounted for.

Tackling this complexity with existing methodological tools is challenging. Prior work has resorted to either ignoring multidimensionality of synergies or discounting sorting issues. In addition, when investigating the contribution of stars, rarity of the stars’ attributes is commonly assumed but not explicitly examined. In this paper, we introduce a novel structural methodology that integrates the collaboration selection process of researchers, some of them star scientists, and their constellation of collaborators. Our method yields predictions about how they match and provides a means to estimate the contribution of each party to the value created jointly. The key players in our model are (1) the principal investigator (PI) researcher, either a star or nonstar; (2) the constellation (C), that is, the set of researchers the PI matches with, operationalized as a static bundle of attributes; and (3) the collaboration, the PI-constellation combination. We ground our methodological approach on formal models of matching and value-based theory (Brandenburger and Stuart 1996, MacDonald and Ryall 2004, Fox 2010, Gans and Ryall 2017). In doing so, we draw upon the general principle that the relative contribution (i.e., marginal productivity) of a party to the joint output is reflected in the value that this party anticipates capturing by being part of a collaborative effort (Tervio 2008). Within this approach, a party’s value capture lies in an interval: it is bounded by a maximum and a minimum value. Estimating this interval requires creating counterfactual collaboration configurations, which we do under some fairly basic assumptions about matching preferences and the boundaries of collaboration markets. To complete the analysis, we show that the uniqueness of the star’s and constellation’s bundle of attributes and the availability of viable alternative matches for collaboration determine which party’s value contribution dominates.

We apply our model to research activities at a prominent (R1) university with a top medical school. We compiled a data set of all 555 collaborations that resulted in an invention disclosure as recorded by the Technology Transfer Office during an 11-year period. In line with prior work (Rothaermel and Hess 2007, Azoulay et al. 2010, Oettl 2012), we defined stars as scientists in the higher echelons of the publication citation distribution.

Attending to the multidimensionality of synergies, we find that value creation is driven by the complementarities between PIs and constellations in terms of research quality, knowledge similarity, collaboration

experience, and research profile similarity with respect to the application domains of their research. The presence of these complementarities leads to assortative matching: Stars attract stronger constellations and stronger constellations attract stronger PIs, indicative of a resource attraction-based effect. Taken together, these synergy and sorting patterns not only inform value creation, but also provide a foundation for determining relative contribution via value capture. We document that stars' relative contribution rarely surpasses that of their constellations, occurring only in 14.3% of collaborations; similarly, constellations who dominate are also infrequent, accounting for only 9.5% of collaborations involving a star PI. In most collaborations, neither party dominates: Innovation is a collective endeavor.

Delving deeper, our analysis of the relative value contribution illustrates the subtle interplay between the role of complementarities and the rarity of parties in the market, where rarity is characterized by larger gaps between agents on each side of the market as ordered by bundles of attributes they offer. Rarity can be interpreted as a low degree of substitutability between agents in the market. We find that joint value creation, although increasing with the magnitude of complementarities, is greatest when both parties in the dyad offer bundles of attributes that are rare in the market. In these cases (77%), none of the players dominate and innovation is truly a collaborative product driven equally by the star and constellation. This is indicative of a bidirectional spillover effect within the dyad where each party enhances the capabilities of their collaborator so that the whole is greater than the sum of the parts. In the few instances when one party dominates, it is because they work with more substitutable partners, but this has an adverse effect on total value being created. Dominating players, who are better positioned to claim a larger slice of the value created in their collaborations, may effectively lose out as this slice is cut from a smaller pie.

Although we focus on scientific knowledge creation, our study applies more broadly to diverse collaboration contexts. We contribute to the literature on collaboration in three ways. First, we offer a novel methodology that provides an addition to the strategists' toolkit. In non-random collaborations where parties self-select into projects based on expected synergies between their strengths, the challenge is to parse the relative contribution of each party on performance, given endogenous team formation. The methodology we introduce enables the examination of the relative contributions of parties to joint outcomes without having to rely on dramatic shocks, such as the death of a collaborator, and fully takes the endogeneity into account. Second, with an eye to the role of top performers, we account for both sorting effects and bilateral, multidimensional, synergy effects. Prior work has typically focused on either sorting or complementarities in isolation. Third,

although the literature has accorded much attention to complementarities that raise the value of collaboration, there has been little consideration to how uniqueness, or rarity in the market, drives value creation and value capture dynamics. We highlight these dynamics by examining complementarities in the dyad and the rarity of each counterparty in the broader matching market to parse relative contribution. In addition to these methodological and theoretical contributions, our study has multiple practical implications for collaborative performance. Our findings inform questions of how to cultivate human capital investments and collaboration synergies, how to assess credit allocation biases, and how to improve the recruiting and socializing of personnel to the benefit of inventive activities and other collaborative organizational tasks.

The paper proceeds as follows. In Section 2, we briefly review the relevant literature on team science and star scientists to set the foundation for our investigation of relative contribution to joint outcomes. Section 3 provides an overview of our novel two-step methodological approach and the study context. Section 4 details our approach to modeling and estimating complementarities underlying PI-constellation matching (Step 1). We explain the theoretical foundations for the matching factors, variable operationalization, and results. Section 5 provides our methodological approach for assessing relative contribution (Step 2) and discusses our findings. We offer concluding thoughts in Section 6.

2. Role of Star Scientists in the Context of a Team: Knowledge Production and Innovation

In collaboration activities, the participation of a "star scientist," an individual whose past activities place him/her in the upper stratum of research achievements, is linked to higher collaboration-level performance (Zucker and Darby 1996, Zucker et al. 2002, Bercovitz and Feldman 2011). Two key mechanisms by which this "star-related" value is created are an attraction effect and a synergy-spawned spillover effect (Merton 1968, Azoulay et al. 2010, Higgins et al. 2011, Oettl 2012, Agrawal et al. 2017). The existing literature tends to focus, somewhat independently, on one or the other. We argue that these two mechanisms should be considered simultaneously.

In early work on the social structure of science, Merton (1968) draws attention to the *Matthew effect*, noting that prominent scientists receive disproportionate recognition and resources. In simple terms, there is a "rich get richer" dynamic as initial advantages beget further advantages (Cole and Cole 1973, Simcoe and Waguespack 2011). Thus, collaborations involving star scientists may perform at a high level, in part, because of stars' ability to attract stronger collaborators due to a sorting effect (Allison and Stewart 1974). Merton's 1968

essay, “The Matthew Effect in Science,” which remains central in current theoretical conversations, identifies two elements, one perceptual and one tangible, that catalyze feedback loops resulting in accumulated advantage.² The first, recognition, functions via status signals that disproportionally draw attention and give attribution to the work of prominent researchers compared with their less prominent peers.³ A number of empirical studies provide support for this status-based aspect (Podolny 1993, Podolny and Phillips 1996). For example, Azoulay et al. (2014) exploit the “shock” of receiving a coveted appointment as a Howard Hughes Medical Institute investigator and documents a modest postaward citation boost, with the effect increasing under conditions of uncertainty about product (article) or awardee (relatively low preaward status) quality.

The second element supporting the “Matthew effect” functions via adoption of resource attraction mechanisms that over-reward past achievements in the allocation of scientific inputs, including human capital, for new projects. This resource-based feedback loop notes that status can have an effect on quality levels by generating preferential access to valuable scientific inputs. Key resources for academic knowledge production include research funding, quality graduate students, engaged and stimulating colleagues, laboratory facilities and equipment, and protected research time. Several recent studies have found evidence of a prestige-related “resource attraction effect.” For example, Agrawal et al. (2017) show that departments that add star scientists benefit from an ability to subsequently induce other high-quality researchers to join the department. Higgins et al. (2011) provide evidence of positive recruiting externalities for young biotechnology firms whose Scientific Advisory Boards are populated with prominent researchers. Groysberg and coauthors show that top performers can reduce the penalties associated with switching firms if they move with teammates rather than making solo moves (Groysberg and Lee 2008, Groysberg et al. 2008). If prestige attracts resources, then stars may be advantageously positioned to attract, and then benefit from, stronger constellations. Likewise, strong constellations may be advantageously positioned to attract, and then benefit from, star players.

In a related stream, a star-constellation spillover effect posits that the superior performance of research teams including eminent scientists may be driven by positive externalities generated by the star that rebound to the benefit of the constellation. Both Azoulay et al. (2010) and Oettl (2012) take advantage of a rare, yet disruptive, event, the unexpected death of star scientists, to sidestep endogeneity issues and investigate how such losses affect the subsequent performance of coauthors. Identifying stars based on cumulative scientific achievement, Azoulay et al. (2010) observe a 5%–10% lasting decrease in coauthor quality-adjusted publications following the

death of a superstar collaborator and this decrease is credited to “the loss of [an] irreplaceable source of ideas” (Azoulay et al. 2010, p. 552).⁴ Oettl (2012) broadens the definition of stars to include both productivity and helpfulness and finds that the output quality of surviving coauthors decrease between 14% and 16% when a star collaborator dies compared with when a nonstar collaborator dies. In a similar vein, several papers have taken advantage of immigration shocks (Waldinger 2012, Borjas and Duran 2015), noting the decline in productivity of collaborators left behind when superstars exit. These studies, however, are silent on the caliber of the team attracted by the star. Furthermore, the coauthors-to-star spillovers are rarely considered, which may lead to an overestimation of the contribution of the star to joint performance.

Although the current literature on star scientists has theorized about these key mechanisms, they have been analyzed independently and one-sidedly, leading to an incomplete understanding of when stars or constellations contribute more to joint performance outcomes. This gap in our understanding of relative contribution rests, to a great extent, on limited methodological options available to study the reinforcing aspects of complementarities and sorting. Simply put, it is important to address complementarity-driven collaboration matching and contribution endogeneity issues. Consideration of market context is also needed as relative contribution is shaped by the uniqueness of the stars and constellations and availability of viable alternatives for collaboration. We turn to these challenges now.

3. Overview of Methodological Design and Study Context

3.1. Overview of Methodological Design

The standard identifying assumption for assessing the contribution of a party to team performance entails observing a random assignment of different types of star PIs to otherwise similar constellations (respectively, a random assignment of constellations of various characteristics to similar stars). Under a random assignment, one could regress the joint output on the characteristics of PIs and constellations and estimate how the output changes with the type of individuals involved (for a more detailed discussion, see Lazear et al. (2015), who study a context in which the boss is assigned exogenously to the team). In academia, parties self-select for collaboration instead of being assigned into PI-constellations pairs and observed collaborations do not satisfy the random assignment condition. Performance is thus endogenous to team formation. A common way to deal with an endogeneity problem entails finding instrumental variables that explain collaboration formation and do not affect team performance. The difficulty is that individuals’ preferences over whom to

collaborate with are intrinsically related to the expectation that some collaborations are more productive than others. Thus, considerations leading to partner choice typically affect the subsequent collaboration performance, which restricts the range of valid instruments.

Given the limitations of the standard econometric methods, and in the absence of experimental data, several studies have used a quasi-experimental research design in which stars or constellations are added or removed from collaborations due to exogenous circumstances such as (premature) death (Azoulay et al. 2010, Oettl 2012) or (forced) emigration (Waldinger 2012, Borjas and Duran 2015). This approach estimates one-sided average effects of one party's contribution to joint performance but does not simultaneously parse out and compare both parties' contributions in nonrandom collaboration. Using this research design may overestimate the removed party's contribution, as it does not consider that some of the value attributed to the missing party results from synergies created with their partner.

Another empirical approach to identify the contribution of star performers separately from that of their teams, peers, or organizations leverages mobility events and builds on the fixed effects estimation of Abowd et al. (1999) (AKM). The challenge in this stream of work is that the standard AKM model also relies on strong assumptions, such as a random mobility of players across collaborations.⁵ Abowd et al. (2019) show that fixed effects estimates are highly sensitive to the exogeneity assumption and obtain different estimates under endogenous mobility. There has been great interest in recent empirical work to address this endogeneity challenge (Archidiacono et al. 2017, Black 2019, Bhaskarabhatla et al. 2021). However, in any variant of the fixed effects approach, the decomposition of a party's contribution to output relies fundamentally on estimating individual and match fixed effects. Thus, by design, these estimation techniques are unable to deal with the multidimensionality of complementarities that bring matched entities together, an issue that we will show to have greater importance than previously thought.

Our methodological precedent is the study of Tervio (2008) of CEOs.⁶ The author studies the matching of CEOs and firms and estimates the relative extent to which CEO talent and firm size contribute to the observed levels of economic surplus as captured by CEO pay and firm market value. Notably, he finds that differences in managerial ability are small and lead to little difference in economic surplus, whereas differences in firm size account for the largest effect.

Similar to Tervio (2008), we tackle the endogeneity problem of nonrandom selection in star-constellation pairing by using a structural, matching assignment model that integrates the selection process of parties for collaboration and yields predictions about how they match. We develop a deliberately stylized model in

which the focus is on the matching of PIs and constellations, with the underlying complementarities between their respective bundles of attributes driving their joint productivity.⁷ Relative to Tervio (2008), our approach has two distinctive features: (a) we estimate a richer multidimensional matching model, whereas Tervio considers only one attribute on each side of the market (in his model, firms are characterized only by size and CEOs only by ability), and (b) our methodology allows us to consider discrete characteristics of agents instead of assuming a continuous distribution of firm and CEO attributes. Although assuming a continuum of agents is attractive from a computational perspective, it is less appropriate for exploring "smaller" markets where "gaps" between agents on either side of the market are more relevant.

We use the identification technique developed by Fox (2010, 2018) to estimate the function describing the joint value that PIs and constellations expect to create by being matched. We detail this estimation process in Step 1. Three key assumptions underlie our matching approach. Assumption 1 states that the overarching objective of collaboration is knowledge creation. Parties in a match seek to maximize joint value (knowledge creation) under the expectation that more value will be created through collaboration relative to working independently. In practice, various outcomes such as inventions, publications, grants and influence are associated with knowledge creation. In our model, we treat the value creation function as a broad umbrella term without distinguishing between these outcomes. With the assumption of a common objective of knowledge creation, the matching criteria are held to be consistent across collaborations. We discuss the factors theory has suggested drives matching in support of knowledge creation and the construction of variables that guide our empirical approach in Section 4.1.

Assumption 2 stipulates that constellations are static and preformed. We envision the constellation as a bundle of observable attributes. We abstract away from modeling individual choice in constellation formation as our focus is not on the individual decision to join a team. Nor is our focus on the process of how the PI assembles the constellation. As such, we sidestep all issues of bargaining in constellation formation. The concept of "constellation" captures the often overlooked "one-to-many" structure of collaboration. In this structure, a collaboration is not the summation of independent dyads but rather, from the perspective of the star, a one-to-many relationship, in which the "many" elements form an inseparable bundle of attributes. Our approach is in line with Tervio (2008) who studies matching between CEOs and firms, where firms are a distinct entity.

Assumption 3, which is grounded in the game theoretic perspective, asserts that observed collaborations

reflect the revealed preferences of participants and that the configuration of observed matches is pairwise stable. Pairwise stability stipulates that no two parties among those not currently matched to each other would both find a match among themselves more attractive than their respective current match. The stability condition is a standard assumption of matching equilibrium (dating back to Shapley and Shubik (1971)), and the empirical estimator we are using (Fox 2010, 2018) is built on this assumption. Taken together, these three assumptions allow us to use the observed collaborations to infer back on the relative importance of complementarities driving the match, that is, to estimate the value creation function of the collaboration.

The novelty of this paper comes in the subsequent step (Step 2: Contribution) in which we extend the matching model to calculate the contribution to joint value creation for each party (PI and constellation) involved in a collaboration. This is detailed in Section 5. The contribution of each side is given by a value-capture interval: That is, the contribution is bounded by the *maximum* and the *minimum value* that principal investigators and their constellations expect to capture by pairing up. From a theoretical standpoint, these notions have been advanced by MacDonald and Ryall (2004) and Brandenburger and Stuart (1996) and are central to an understanding of value capture. We use the estimates of the value creation function obtained in the first step as parameters in the model of value capture. In Online Appendix 2 we provide the proofs. Our unique empirical approach consists in creating counterfactual pairings where ‘stars’ are rematched with the best available constellation under a scenario in which their observed constellation is absent from the market. The intuition is that the estimation of an agent’s contribution to a relationship requires building counterfactual scenarios that take into account the value creation alternatives available to that agent, because these alternatives influence the agent’s value capture potential. We do the rematching under the assumption that the drivers of value creation (i.e., the patterns of preferences for partners observed in this empirical context) are those revealed by the estimates of complementarities obtained in the first step. The counterfactual pairing keeps the bundle of attributes of each constellation unchanged.

3.2. Context

Knowledge generation activities are increasingly shifting from being an individual effort to a team-based endeavor. We examine collaborative knowledge production in the context of academic research. The size of scientific research teams has been growing steadily with the number of authors per paper and/or inventors per patent rising at rates of 15%–20% per decade since the mid-1950s (Adams et al. 2005, Wuchty et al. 2007). In

2005, more than 80% of science and engineering publications and close to two-thirds of all patents were products of multiple authors or inventors (Jones 2011). Furthermore, the evidence suggests a performance differential between solo and team-based efforts, with teams increasingly emerging as the source of higher-impact work (Wuchty et al. 2007; Jones 2009, 2011; Singh and Fleming 2010; Bikard et al. 2015). In sum, teams have become pervasive and essential players in scientific knowledge production and innovation, yet we have limited understanding of the matching process underlying collaboration and the relative contribution in the collaborative dyad.

Our sample of collaborations comes from the Technology Transfer Office (TTO) at one prominent (R1) U.S. research university with a renowned Medical School.⁸ Complementarities that support knowledge creation should be consistent regardless of the ultimate packaging of this knowledge—if the product is an invention or a publication. We use invention disclosures in our study as invention data give us more accurate information regarding members who contributed to knowledge/value creation in a collaborative effort. Given the legal standards associated with intellectual property claims underlying invention disclosure, the attributions in invention disclosure sidestep the social noise (favors, gifts, norms) that the literature has shown affects publications (Haeussler and Sauermann 2013). We have detailed data on the composition of 555 invention collaborations from this university for years 1988 to 1999. This constitutes the entire population of collaborative projects that have disclosed an invention to the TTO.⁹ Filing an invention disclosure is the initiating step in the commercialization of academic research. However, there is significant variation in the potential of disclosures received as there are no objective standards that faculty discoveries must meet to warrant filing (Jensen et al. 2003). Faculty may disclose low-value findings to remain in compliance with the requirement of funding sources or due to overoptimistic evaluation of their own research contributions.

Team formation in the academic research context is internally managed rather than externally assigned. Broadly, the PI sets forth a research agenda, solicits funds to pursue this agenda, and then partners with a constellation, either within their laboratory group or across laboratory groups, to explore specific research questions. Team formation is a two-sided selection process. The PI seeks to draw skilled students and colleagues to the PI’s projects, whereas these same individuals evaluate multiple opportunities seeking to align themselves with most promising projects and investigators. As new constellations are formed around specific research questions, it is not unusual to see a particular PI concurrently working with multiple unique constellations. Although at times PIs may work with their entire laboratory, PIs tend to work with multiple constellations that are subsets of their labs (Conti and Liu

2015). It is also not uncommon to see collaborations that span labs and departments, involve multiple full professors, and include researchers from external institutions.¹⁰

The 555 collaborations in the data involve a total of 1003 unique scientists, of which 248 serve as PIs. To designate stars, we defined a group of 30 highly productive scientists in terms of publications and external recognition through citations using the Web of Science. Specifically, we identified stars as the scientists in the top 5% of the distribution of Web of Science citations received by individuals in our sample during the five-year window prior to the collaboration year. The distribution of citations considers the differences in citation propensity across fields by grouping scientists in three broad areas, basic life sciences, clinical life sciences, and engineering and physical sciences, per their departmental affiliation.

During the entire period studied, the 30 star PIs in our sample were involved in 105 collaborations. Half of the stars had more than one collaboration per year but only one star PI reached the maximum of five collaborations in a year (with three others having four collaborations in their most active year). Among the 218 nonstar PIs, only 13.2% had more than one collaboration per year, and those who did were either “rising stars” (in the sense that these individuals would eventually become stars toward the end of the time period studied here) or individuals whose citations were close to the cutoff threshold for being considered a star. To construct the human capital in the collaboration (PI and constellation), we hand-collected information on scientists’ publication records from ISI/Web of Science, vitae, and bios.

As an example, consider the collaborations of one of the prominent star scientists in our data set. This professor, Professor A, a Howard Hughes Medical Investigator, participated in multiple collaborations. In 1988, Professor A had a citation count of 19,185 and collaborated with a constellation of three consisting of an associate professor and two postdoctoral students, who together amassed 15,264 citations. In 1992 Professor A, who at that time had a citation count of 23,228, worked with a constellation of four, who also had high impact as represented by their combined citation count of 20,539. This constellation was diverse in terms of academic rank, including a full, an associate, and an assistant professor, as well as a postdoctoral student. These constellations differed in terms of their experience working together, with the first having a deeper collaboration record than the second. However, the second constellation showed a stronger commonality with the PI in terms of research subject areas. The PI was highly focused on basic science research and constellations shared that focus and published in journals that specialized in such research. In both these cases, the constellation included some individuals who worked in Professor A’s laboratory, some individuals from

different labs at the same university, and some individuals from outside research institutions, including one in Europe. One of the team members subsequently became a star and formed multiple collaborations as a PI that did not include Professor A.

4. Step 1: Matching Estimation

4.1. Drivers of Matching

Numerous factors that may drive matching have been discussed in the literature. These factors fall within four main categories: (1) quality, (2) size, (3) knowledge, and (4) experience. We turn now to discuss the logic for including these factors in our matching model and then we detail their operationalization.

4.1.1. Quality. A fundamental attribute of teams believed to underlie performance is member “quality.” Simply, a collection of high-performing researchers is more likely to coalesce into a high-performing team than is a collection of low-performing researchers. In general, a positive assortative matching on research quality between PI and constellation is expected, as each party will strive to work with the best available counterparty. This aspect of matching was noted by Kremer (1993) who provides a more general justification of assortativeness in the skills of agents collaborating in knowledge production. We measured quality and prominence (PI: *Research Impact*, C: *Research Impact*) as the number of citations received by a scientist during a six-year window prior to (and including) the collaboration year.¹¹ Although an imperfect measure of ability, past research achievements (proxied by publication counts and citation rates) shape scientific reputations and are often interpreted as a signal of researcher quality (Stern et al. 2014). We focused on a limited time window prior to collaboration to capture the extent to which a scientist’s research has received recent recognition by the academic community in the years preceding collaboration. We included citations and articles published during the collaboration year to account for publication lag. Because the distribution of this variable is skewed across fields and scientists, we applied a log transformation and we checked the robustness of results to this transformation.

4.1.2. Size. Team size has been argued to have both positive and negative influences on team performance. On the positive side, larger teams can signal the presence of greater resources. The sheer fact that a large team has been assembled for a research effort reflects a substantial commitment in personnel, facilities, and research materials. Furthermore, as each individual team member brings their own set of human and social capital to the collaboration, larger teams can benefit from greater aggregate capital levels and the subsequent

effort of a greater number of individuals (Reagans and Zuckerman 2001). On the negative side, performance may suffer given the increasing coordination challenges, free-riding hazards, and credit-sharing concerns that accompany expansion of team membership (Holmstrom 1982, Jin et al. 2019). In our sample, the size of the constellation ranges from 1 to 14 individuals and is skewed toward lower values. Because of these reasons, we measure size (*C Size*) as the square root of the count of individuals in the constellation. Size alone, however, is a blunt indicator of collaboration capabilities and/or internal dynamics. Understanding the level of benefits or costs accruing to a research team of any particular size requires digging into their unique knowledge-related attributes and their experience-based relationships.

4.1.3. Knowledge. One oft-cited benefit of knowledge production teams is the potential to support individual specialization while exploiting the complementarities between the individual team members (Adams et al. 2005). The advantage of such division of labor is typically argued to accrue from success in managing the rapidly expanding “burden of knowledge” needed to operate at the technological frontier in an innovative field (Jones 2009). Through collaboration, a scientific team can both benefit from, as well as overcome the limitations of, the deep yet narrow knowledge of individual members (Jones 2011, Bikard et al. 2015). Relatedly, teams can bring together scientists holding diverse knowledge (across-technological fields) leading to both search and combinational advantages. Specifically, scientists grounded in different disciplines will approach research challenges from different perspectives and are likely to search for solutions in different technological domains. This broader search can give rise to novel insights and new research trajectories (Reagans et al. 2005). In addition, the diverse knowledge of team members allows for greater experimentation and the generation of a greater set of domain-based combinational alternatives. It is these unique combinations that underlie discovery and spawn innovation (Taylor and Greve 2006, Fleming et al. 2007). Although scope (diversity) is necessary, scope alone is not sufficient to prompt recombinatorial innovative activity. If the knowledge held by the different team members is distant and nonoverlapping, the challenge to integration will be high. The PI and constellation benefit from some overlap of knowledge elements as such overlap provides a common ground from which to build on as they incorporate less familiar (or new to one partner) knowledge. However, the value that can be created is expected to decrease if the knowledge portfolios of the constellation and the PI are too similar given redundancies in knowledge.

We include two dyadic terms to measure knowledge similarity between the PI and the constellation in terms

of scientific expertise, or knowledge portfolios: *PI-C Knowledge Similarity* and *PI-C Knowledge Similarity (Squared)*. To build these variables, we first pooled together all publications of all individuals in the constellation. We calculated the knowledge vector for both PIs and constellations as the frequency of publications in the multidimensional space formed by the subject categories in which they published. The *PI-C Knowledge Similarity* is a proximity measure defined by the cosine similarity between PI’s knowledge vector and the constellation’s knowledge vector. To identify the subject categories of a publication, we relied on the standardized categories reported by ISI Web of Science. *PI-C Knowledge Similarity* ranges from zero to one, with higher values indicating greater similarity in the knowledge expertise shared. Given that theory predicts that high similarity may benefit collaborations by reducing communication costs but that too much similarity may be detrimental to innovation, we include *PI-C Knowledge Similarity (Squared)* to allow for a potential diminishing effect of knowledge proximity.

Beyond scientific disciplines, cohort membership (or professional age) can contribute to the knowledge diversity of collaborations. There is significant evidence of a “vintage effect” in science, where academics trained in different periods anchor to different reference points in the field and hold different research, innovation, and commercialization norms. These cohort differences can simultaneously influence question selection, investigative process, and scientific productivity (Levin and Stephan 1991, Bercovitz and Feldman 2008). Cohort-based diversity is expected to increase the range of search and the variation of knowledge domains drawn upon leading to the development of more innovative solutions (Guimera et al. 2005). The rank diversity variable (*C Rank Diversity*) captures constellation’s diversity in terms of six academic rank levels: 1, staff; 2, student; 3, postdoc; 4, assistant professor; 5, associate professor; 6, full professor. Following Reagans and Zuckerman (2001), we measured this variable as the mean of the absolute difference in rank levels between any two individuals.

Collaborations can be further characterized by how their research efforts are distributed across basic, translational, and applied domains. Recent studies have documented significant heterogeneity in academic researchers’ “taste for science” (Roach and Sauermann 2010). Although some investigators follow traditional academic norms and show a marked preference for focusing their inquiries on upstream basic science, other researchers are partial to pursuing downstream applied questions that are perceived to have direct clinical or industrial implications (Sauermann and Stephan 2013). Such variation in research profiles, ranging from a strong “taste for science” to a high “affinity for application,” has implications for collaboration dynamics. Whereas some degree of diversity in subject area

knowledge is desired, similarity in research profiles may be advantageous as conflict within a team is expected to be lower when collaborators approach research from a common perspective and with common motivations. Broadly, as the nature of the work (basic, translational, or applied) has implications for the framing of studies, the organization of project activities, the expected pace of work, and the choice of when, how, with whom, and to what degree the collaboration will engage with the larger scientific/innovation community, working with other's holding a similar research profile is logical. (Dasgupta and David 1994, Tijssen 2010, Sauermann and Stephan 2013, Cohen et al. 2020).

The PI-constellation similarity in research profile (*PI-C Research Profile Similarity*) is a dyadic variable. We first built the vectors of PIs' and constellations' frequency of publications in research application domains as revealed by the journal types in which scientists have published. We rely on the application domains identified by Tijssen (2010). The application orientation classification extends the dichotomy between basic and applied research by capturing the organizational environment in which research activities are conducted. Using an extensive bibliometric analysis of the affiliation of authors publishing in all journals indexed by the Web of Science database, Tijssen (2010) identified the following six sets of journal application domain categories: (1) academic, (2) industry relevant (with some contributions from corporate authors), (3) industry practice (with many contributions from corporate authors), (4) clinical relevant (with some contributions from authors affiliated with hospitals and medical centers), (5) clinical practice (with many contributions from authors affiliated with hospitals and medical centers), and (6) industry-clinical relevant (with some contributions from both industry and hospitals/medical centers). To build the application domain profile of PIs and constellations, we calculated the percentage of publications that PIs and constellations had in each journal category, as classified by Tijssen (2010). The *PI-C Research Profile Similarity* is the cosine similarity of the research profile of a PI-constellation pair, calculated in the observed and counterfactual collaborations.

4.1.4. Experience. Communication and coordination are pervasive challenges in teamwork (Zenger and Lawrence 1989, Reagans and Zuckerman 2001). Discipline-specific languages and methods can impede the development of common understanding and hinder knowledge transfer (Simonin 1999). These communication difficulties, in turn, can exacerbate coordination challenges as key interdependencies in the research process may not be recognized, conveyed, or addressed in a timely and efficient manner (Porac et al. 2004, Cummings and Kiesler 2005). Taken together, such communication and coordination hurdles can slow, or even derail,

scientific advancement. One type of experience that can lower these hurdles is the experience the members of the constellation have had with each other (Reagans et al. 2005). Through past interactions, team members gain familiarity with the field-specific scientific jargon and the training-ingrained perspectives of their cross-disciplinary peers. Via experience, research constellations establish a baseline level of common understanding that enables knowledge sharing and joint knowledge production. Moreover, informational social influence, a byproduct of familiarity, can engender a melding of research perspectives and lead to a collective research identity within the constellation (Katz 1982). In addition to better communication, prior experience working together enables the constellation to map out standardized practices and develop routines (Huckman and Pisano 2006). These routines can streamline the research process and effectively reduce the coordination costs of leveraging the diverse knowledge that is distributed across the constellation (Taylor and Greve 2006). The variable *C Experience* captures the experience of individuals in the constellation via the number of coauthored articles by any members of the constellation. We excluded publications coauthored with the PI from the count. We scaled the team experience count from zero to one. We coded the experience of constellations of one individual as one, under the assumption that there are no communication or coordination frictions within a team of one.

4.2. Matching Model and Estimation

Underlying our matching model of team formation is the idea that PIs and constellations match with the overarching objective of knowledge creation. The value created jointly, denoted by $v(PI, C)$, increases with the strength of synergies between the attributes of PIs and constellations. We model the joint value $v(PI, C)$ as a knowledge production function (or, equivalently stated, as a multidimensional matching function), whose inputs are the complementarities between PI and constellation attributes.

$$\begin{aligned} V(PI, C|\beta) = & \beta_0 \text{PI: Research Impact} * C: \text{Research Impact} \\ & + \beta_2 \text{PI-C Knowledge Similarity} \\ & + \beta_3 \text{PI-C Knowledge Similarity (Squared)} \\ & + \beta_4 \text{PI-C Similarity in Research Profile} \\ & + \beta_5 \text{PI: Research Impact} * C: \text{Rank Dispersion} \\ & + \beta_6 \text{PI: Research Impact} * C: \text{Experience} \\ & + \xi_{PI} + \xi_{CI} + \varepsilon_{PI|CI} \end{aligned} \quad (1)$$

where ξ_{PI} and ξ_{CI} are, respectively, PI and constellation fixed effects, and $\varepsilon_{PI|CI}$ are match-specific errors.

Equation (1) builds on the hypothesis that matching is driven by the expectation that PIs of a higher research impact create more value when collaborating with

constellations of higher research impact (β_0) and constellations of larger size (β_1). The term β_1 containing the constellation size also serves as a control variable for better isolating the effects of the other constellation attributes in the model.¹² Knowledge-related considerations suggest that higher value is created when PIs collaborate with constellations with a moderate degree in the expertise shared with the PI: thus, we expect β_2 to be positive and β_3 to be negative. A more similar research profile is also a potential source of synergy in collaboration, as individuals who share similar taste for science are less likely to have conflicts over project direction and goals. We test this hypothesis via β_4 . Additionally, we expect complementarity between PI's research impact and the cohort diversity in the team (β_5) as strong PI are better positioned to attract both seasoned and novice researchers, who in turn benefit more from working with more prominent PIs. The experience-related considerations suggest complementarity between PIs of higher research impact and constellations with more experience of working together (β_6).

As a reminder, we assume that the matching criteria are consistent across collaborations, given the common knowledge creation objective. Experienced academic researchers arguably share a common understanding of what complementarities are central for knowledge creation. Because of variation in the bundle of attributes each party holds, however, this understanding does not imply a common ranking of partners on the other side of the market. We acknowledge that PIs or constellations could have some idiosyncratic preferences for whom to collaborate but assume that these preferences are not correlated with the revealed complementarities and, instead, are subsumed in the error term ε_{PIiCi} . This is Assumption 4.

To estimate the match value function $v(PI, C|\beta)$ we use a nonparametric method suitable for studying matching contexts known as the maximum score estimator (Fox 2010, 2018). As we discussed in Assumption 2, the estimator assumes and exploits the pairwise matching stability condition (Fox 2010). This condition translates into stating that the sum of the value created by any two observed collaborations in the data, say $v(PI_i, C_i|\beta)$ created by $\{PI_i$ and Constellation $C_i\}$ and $v(PI_j, C_j|\beta)$ created by $\{PI_j$ and Constellation $C_j\}$ is greater than the sum of value created by counterfactual collaborations obtained by switching partners (here, $\{PI_i$ and Constellation $C_j\}$ and $\{PI_j$ and Constellation $C_i\}$).¹³ Formally, this condition, commonly referred to as a “local maximization condition” (Fox 2010), is an inequality:

$$v(PI_i, C_i|\beta) + v(PI_j, C_j|\beta) > v(PI_i, C_j|\beta) + v(PI_j, C_i|\beta). \quad (2)$$

Equation (1) can be estimated under fairly standard econometric assumptions regarding the unobservable

terms and standard errors. Following Fox (2018) we assume that the unobserved agent-specific fixed effects ξ_{PIi} and ξ_{Ci} are not correlated with the observable characteristics of PIs and constellations included in the model. When Inequality (2) is written for the match value v described in Equation (1), fixed effects ξ_{PIi} and ξ_{Ci} cancel out. Intuitively, this reflects the idea that only the “interacted” attributes of the entities on the two sides of a matching market matter in the matching process. The estimator does not impose a distribution on the match-specific errors ε_{PIiCi} . It allows heteroskedasticity, and the distribution of unobservables does not have to be the same across markets either (Fox 2010). Conditional on the observable covariates in the model, error terms are assumed to be independently distributed and uncorrelated with the unobservable terms.

Coefficient estimates are obtained by maximizing the number of satisfied inequalities. Let h be a market index, which takes values from 1 to 33, and three distinct markets (basic life sciences, clinical life sciences, and engineering and physical sciences, which we describe in more detail below) over 11 years. Let N_h be the total number of collaborations in a market h . The estimates $\hat{\beta}$ are obtained by numerically computing the global maxima of the function that counts the number of correctly predicted inequalities for all combinations of realized and counterfactual collaborations within all 33 markets:

$$Q(\beta) = ((N(N-1))^{-1} \sum_h \sum_{1 \leq i \neq j \leq N_h} 1[v(PI_i, C_i|\beta) + v(PI_j, C_j|\beta) > v(PI_i, C_j|\beta) + v(PI_j, C_i|\beta)]) \quad (3)$$

where $N = \sum_h N_h$ and $1[\cdot]$ is an indicator with a value of one if the inequality in the parenthesis is true and zero otherwise.

An attractive feature of the estimator is its ability to deal with the nonrandom feature of collaboration formation and accommodate the constraints a party could have in securing a collaboration with the most desirable individual(s). The matching Equation (1) incorporates (through the interaction terms) the mutual preferences of PIs and constellations when deciding whom to collaborate with for a research project. Inequality (2) accounts for the constraints that PI and constellations have when picking collaborators who may have more valuable partnering alternatives.¹⁴

Writing Inequalities (2) requires defining the boundaries of “matching markets” within which partner switching among collaborations was plausible within our context. We consider that relevant exchanges could have taken place within the same scientific field as the one of the principal investigators and within the same academic year (Assumption 5). By adopting this convention, we define 33 “matching markets” corresponding to three academic fields (basic life sciences, clinical life sciences,

and engineering and physical sciences) and the 11 academic years in the sample.¹⁵ Counterfactual PI-constellation dyads are built within the boundaries of each market. Around 34% of the 555 collaborations observed in the sample occurred in basic life sciences with representative departments including genetics, immunology, neurobiology, and pharmacology; 45% of the collaborations in clinical life sciences with departments such as anesthesiology, OB-GYN, pediatrics, and surgery; and 21% of the collaborations in engineering and physical sciences with departments such as biophysics, biomedical engineering, and chemistry.

The empirical matching function (1) contains three sets of covariates: the attributes of the PIs; the attributes of the constellation of individuals collaborating with the PI; and dyadic variables that measure similarity between a PIs and a constellation, calculated for both the observed 555 collaborations and, as required by the estimation, the counterfactual ones. The values taken by the covariates vary highly in scale, across years, and across specialization area. To make the range of covariates more comparable to each other, we rescaled them to take values from zero to one, with zero representing the lowest value in the sample and one being the highest value taken by that covariate in a market. This rescaling does not change the nature of complementarities between the corresponding attributes, and we account for it in the interpretation of results.

4.3. Descriptive Statistics and Matching Results

Table 1 shows the descriptive statistics. The maximum value of research impact is 28,748 citations in the case of principal investigators and 33,681 in the case of constellations. On average, principal investigators received 3,557 citations and constellations roughly half of that (1,874 citations). The correlation between the two sides' *Research Impact* is 0.505, which is already an indication of assortative matching on research impact (see also Ahmadpoor and Jones (2019) for recent evidence on positive assortative matching on citations of coauthorship constellations). This is the strongest correlation across

the two sides' attributes. In general, the variable *PI Research Impact* correlates positively with all constellation variables with which it interacts in the matching equation (size, rank dispersion, and experience variables). There is important variation in the sample on all dimensions.

Because the value creation function that describes matching does not have a natural scale, the maximum score estimator requires a scale normalization. For this purpose, we set up the coefficient β_0 , which measures the complementarity between PI and constellation research impact, to be equal to one. The interpretation of this positive relationship is that the higher the research impact of a principal investigator, the higher the returns from collaborating with constellations of higher research impact and vice versa. The magnitude of all other coefficients will be evaluated relative to this baseline coefficient. Table 2, Panel A, describes the results. We report the coefficient estimates and the 95% confidence intervals.

In line with the theoretical logic, we find evidence that knowledge-related and experience-related attributes are central in the matching process and a key source of complementarities. Some knowledge similarity between the PI and the team has a positive effect on matching ($\beta_2 = 5.779$), suggesting a perceived value of common perspectives and common language for innovation pursuits. However, similarity squared has a negative effect on matching ($\beta_3 = -2.646$), indicative of the potential penalties associated with knowledge redundancies and reduced opportunities for innovation through novel recombination. Another knowledge-related synergy arises from similarity in the research profile. We find strong evidence that PIs and constellations match on considerations related to their application orientation, whether it be similarity in a taste for basic science or similarity in a taste for appliedness ($\beta_4 = 3.390$). Furthermore, knowledge-related considerations stemming from complementarities between PI's research impact and constellation rank diversity are also a significant matching driver ($\beta_5 = 1.620$). The positive

Table 1. Descriptive Statistics

Variable	Mean	Standard deviation	Minimum	Maximum	1	2	3	4	5	6	7	8
1. PI: Research Impact	3,556.728	4,885.78	2	28,748	1							
2. PI-C Knowledge Similarity	0.513	0.258	0	1	0.073	1						
3. PI-C Knowledge Similarity (squared)	0.330	0.271	0	1	0.019	0.965	1					
4. PI-C Similarity in Research Profile	0.712	0.293	0	1	0.283	0.267	0.227	1				
5. C: Research Impact	1,699	3,652.102	0	33,681	0.556	0.014	-0.025	0.169	1			
6. C: Size	2.043	1.460	1	14	0.273	-0.031	-0.081	0.02	0.440	1		
7. C: Rank Diversity	0.164	0.232	0	1	0.121	-0.128	-0.162	0.033	0.268	0.454	1	
8. C: Experience	0.185	0.274	0	1	0.166	-0.008	-0.008	0.160	0.192	0.009	-0.157	1

Notes. Descriptive statistics are shown for the observed 555 collaborations. PI refers to the Principal Investigator; C to the constellation; PI-C denotes attributes specific to the collaboration between the PI and the constellation.

Table 2. Matching Model Estimates

Panel A: Estimates of the (matching) value creation function					
Coefficient	Relationship	Point estimate	95% confidence interval		
β_0	PI: Research Impact $\times$ C: Research Impact	1	Superconsistent		
β_1	PI: Research Impact $\times$ C: Size	0.865	{−0.202, 1.932}		
β_2	PI-C Knowledge Similarity	5.779	{2.842, 8.716}		
β_3	PI-C Knowledge Similarity Squared	−2.646	{−4.835, −0.456}		
β_4	PI-C Research Profile Similarity	3.390	{1.792, 4.989}		
β_5	PI: Research Impact $\times$ C: Rank Dispersion	1.620	{0.148, 3.092}		
β_6	PI: Research Impact $\times$ C: Experience	2.078	{0.795, 3.360}		
Panel B: Relative importance of matching drivers					
Coefficient	Covariate	Point estimate	Standard deviation of covariate	Point estimate $\times$ Standard deviation	Covariate's relative impact
$\hat{\beta}_0$	PI: Research Impact $\times$ C: Research Impact	1	0.278	0.278	1
$\hat{\beta}_1$	PI: Research Impact $\times$ C: Size	0.865	0.270	0.234	0.840
$\hat{\beta}_2$	PI-C Knowledge Similarity	5.779	0.259	1.497	5.384
$\hat{\beta}_3$	PI-C Knowledge Similarity Squared	−2.646	0.271	−0.717	−2.579
$\hat{\beta}_4$	PI-C Research Profile Similarity	3.390	0.293	0.993	3.573
$\hat{\beta}_5$	PI: Research Impact $\times$ C: Rank Dispersion	1.620	0.162	0.262	0.944
$\hat{\beta}_6$	PI: Research Impact $\times$ C: Experience	2.078	0.221	0.459	1.652

Notes. All variables are rescaled to take values between zero and one. The importance of a coefficient estimate is calculated as the impact on the match value of one standard deviation increase in the covariate (point estimate $\times$ standard deviation of the covariate). The table reports the impact of PI-C Average Knowledge Similarity separately for the direct and the quadratic term. The combined, net impact of this variable is equal to $\hat{\beta}_2 \times s.d. + 2 \hat{\beta}_3 \times s.d. \times x$, where x ($0 \leq x \leq 1$) stands for PI-C Average Knowledge Similarity and $s.d.$ is the standard deviation of this variable (0.259). The net impact ranges from 0.126 to 1.497 and the relative impact from 0.453 to 5.384. The relative impact of PI-C Knowledge Similarity on the match value is greater than the impact of the baseline relationship for all values of PI-C Average Knowledge Similarity below 0.888.

sign of $\beta_6 = 2.078$ coefficient suggests complementarities between research quality on the PI side and higher experience of the constellation side. *Ceteris paribus*, we do not find evidence of synergies between research prominence and sheer constellation size (β_1 is small and nonsignificant).

To aid interpretation, Table 2, Panel B, shows the relative importance of each complementarity in the matching process. Because the predicted match value lacks a natural metric, we focus on the impact on the match value of a one standard deviation increase in each complementarity measure. For the knowledge similarity covariate, we report the combined effect of the simple and squared term. Consider the baseline covariate, which measures the complementarity between PI and constellation research impact (PI: Research Impact $\times$ C: Research Impact). A one-standard-deviation change in the baseline covariate corresponds to a change in the match value equal to 0.278, which in percentage terms, represents on average a 5% percentage increase in the match value v when the other covariates are left unchanged. Reverting back to the original scale of research impact measured as the number of citations, a back-of-the-envelope calculation shows that a one-standard-deviation increase in the baseline is equivalent to each party increasing their citations by roughly 1,400 each year. This is a big gap to overcome by those PI and constellations who start from zero or a low number of citations.

The last column in Table 2, Panel B, reports the relative impact or importance of the other significant complementarities on the match value compared with the baseline effect of the complementarity in research prominence. Because the variable PI-C Knowledge Similarity enters in the equation both as a simple and a squared term, its impact varies with the level of knowledge similarity between the PI and the constellation (see the table legend in Table 2, Panel B), and it is greater than the baseline effect as long as PI-C Knowledge Similarity scores lower than 0.888 (on a scale from 0 to 1), which happens in 90% of collaborations. The impact of similarity in the research profile of the PI and their constellation on the expected match value is 3.5 times higher than the baseline effect. The impact of the synergy between PI: Research Impact and C: Experience on the match value is roughly 1.5-fold higher and the impact of the synergy between PI: Research Impact and C: Rank Diversity is similar to the baseline effect.

These findings can be further interpreted with reference to the work by Becker (1973), who showed that complementarities lead to top-down sorting of the matching partners along the compatible matching attributes. In our context, this top-down sorting reveals that prominent PIs are advantaged not only because they match with constellations assortatively by research impact, but also because they have access to, and are preferred by, constellations with whom they share similar expertise and taste for science, constellations that

have greater experience working together, and constellations built around a higher diversity of rank which bring varying perspectives and roles in project execution. Complementarities not only explain the rationale behind how PIs and constellations sort for collaboration but also describe the value they expect to create through joint interaction (Mindruta et al. 2016).

As a validity check of the payoffs calculated and the ordering of value creation by collaborations, we tapped licensing data attained from the technology transfer office of the university studied. Our post hoc analysis of the correlation between predicted payoffs of formed collaborations and actual licensing data (both probability of licensing and amount of royalties generated) is in-line with predictions and indicates that our assumption of positive matching is reasonable. The correlation between estimated payoff values and the likelihood of licensing is 0.14 ($p = 0.0007$) and the correlation between estimated payoff values and licensing revenues is 0.16 ($p = 0.0001$). To further illustrate this relationship, we calculated the percentage of inventions licensed and licensing revenues for each quintile of payoffs. We find that for inventions in the top quintile of estimated payoffs, 48% are licensed and the average value of licensing revenues for this quintile is \$52,555. For the bottom quintile of estimated payoffs, only 28% of the inventions are licensed and the revenues generated by these licenses are much lower, averaging \$2,578. These data, shown in Figures 1 and 2, provide external validation of our methodological approach.

5. Step 2: Calculation of Contribution Intervals

5.1. Methodological Approach

A long-standing economic principle stipulates that an agent's contribution to output is proportional to that agent's payoff. In standard competitive models, the payoff is reflected in the agent's marginal productivity (i.e., the increase in output associated with one unit increase in input). Calculating the marginal productivity in a matching context is more complex as an agent with an improved set of attributes (i.e. a "better input") will assortatively match with a stronger counterparty. Thus, both changes in input quality and subsequent changes

Figure 1. Licensing Revenue by Payoff Quintile

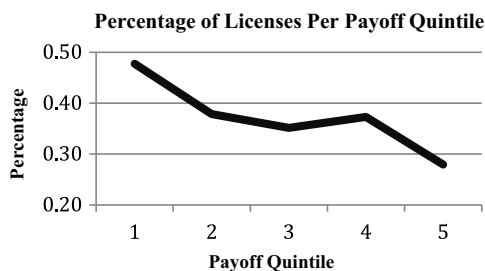
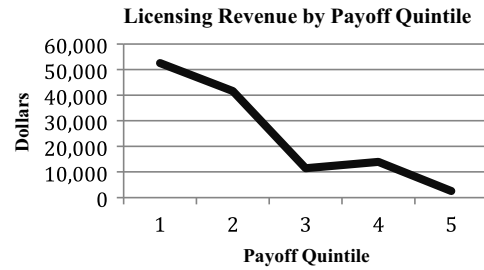


Figure 2. Percentage of Licenses per Payoff Quintile



in matching configurations need to be simultaneously considered to calculate payoffs and hence contributions. The works by MacDonald and Ryall (2004) and Brandenburger and Stuart (1996) on value-capture theory provide the foundation to calculate the contribution of an agent to a relationship in a bargaining free model, where an agent's contribution to a relationship accounts for the value creation alternatives available to that agent. The contribution takes the form of an interval, whose boundaries are given by the *maximum* and the *minimum value* that agents expect to capture by pairing up. We build on this work to provide a pathway for estimating the contribution of PIs and constellations. Although a general analytic solution does not exist, the formal proofs in Online Appendix 2 establish a closed form expression for the computation of the value-capture interval in a matching context.

At the core of this approach is the creation of counterfactual collaborations where stars and respectively, their constellations are rematched with the best available partner under a scenario in which their actual partner is absent from the market. Our procedure for rematching the remaining participants in the market after each removal is based on two conditions: (a) the general underlying preferences driving the matching of PIs and constellations (the estimates of the value creation function Equation (1)) remain unchanged, and (b) the new matching configuration at the market level is stable and optimal: It maximizes the sum of the aggregate value created by all pairings in the market. Both conditions are aligned with our analytical solution for calculating the value capture interval. Condition (a) allows us to focus on the plausible value-creation alternatives available to the participants in the market instead of suggesting unsubstantiated alternative value-creation objectives or preferences. Condition (b) allow us to follow the linear programming solution of Shapley and Shubik (1971) to calculate a stable configuration of matches.¹⁶

We begin by removing star scientists from the sample one at a time. After each removal, we rematch the constellations and the remaining PIs (including the other stars) by applying conditions (a) and (b) described previously. After the new matching configuration was

obtained, we calculated the total value created in a market (i.e., the sum of the estimated joint value of all PI-constellation matches in the market) both with and without the star scientist in the sample. The difference represents the upper bound of the star's contribution. The upper bound is commonly referred to as the "marginal product" or the "added value" of a player in a strategic interaction (MacDonald and Ryall 2004, p. 1326):

$$\text{MaxPI}_j = \sum_j v(\text{PI}_j, C_j | \beta) - \sum_j v(\text{PI}_j^{-i}, C_j | \beta) \quad (4)$$

where PI_j^{-i} indicates that we are indexing across all principal investigators j , less the star i .¹⁷

We repeat the procedure for all constellations matched with the stars in our sample (the "star constellations"). We remove each of the star constellations from the sample one at a time and rematch all PIs in the market with the remaining constellations. Like before, we recalculated the total value of all pairings in the market with and without a star constellation in the sample. This value loss created in the market represents the upper bound of the constellation's contribution:

$$\text{MaxC}_j = \sum_j v(\text{PI}_j, C_j | \beta) - \sum_j v(\text{PI}_j, C_j^{-i} | \beta) \quad (5)$$

where C_j^{-i} indicates that we are indexing across all constellations j , less the constellation that was initially paired with the star i .

The first two steps allowed us to calculate the *upper* bound of a star's and a constellation's contribution. The

lower bound of the star's contribution (referred to by MacDonald and Ryall (2004) as the minimum residual) is the difference between the value created jointly by the star-and-constellation pair and the maximum contribution of the constellation with whom the star collaborates in the sample:

$$\text{MinPI}_j = v(\text{PI}_j, C_j | \beta) - \text{MaxC}_j. \quad (6)$$

Similarly, the *lower* bound of the constellation's contribution is the difference between the value created jointly by the star and the constellation and the maximum contribution of the star with whom the constellation collaborates in the real data.

$$\text{MinC}_j = v(\text{PI}_j, C_j | \beta) - \text{MaxPI}_j \quad (7)$$

5.2. Empirical Findings

The results of this second-stage analysis are presented in Table 3. On average, star scientists have higher contribution than constellations, both in the upper and the lower bound (see Panel A). However, a closer look at the contribution intervals indicates that the averages do not tell the full story. In only a subset of the star-constellation matches is there an unequivocal dominance in contribution by the star scientist. In 15 star PI-constellation matches (or 14.3% of the 105 collaborations involving a star PI observed in the sample), the star PI is the dominant contributor, meaning that the star's lower bound is higher than the corresponding constellation's higher bound. This is clearly the subset driving the positive average differentials found and represents, in turn, the collaborations which prior work

Table 3. Contribution Intervals: Empirical Findings

Panel A: Summary of star PIs and star-constellations' contribution interval				
Player	Average	Standard deviation	Minimum	Maximum
Stars' contribution interval				
Maximum bound	9.640	6.353	1.746	27.035
Minimum bound	2.113	1.084	0.000	4.174
Constellations' contribution interval				
Maximum bound	5.020	1.607	1.358	9.087
Minimum bound	1.123	1.535	0.000	5.507
No. of observations (collaborations)		105		
Panel B: Summary of non-star PIs and non-star-constellations' contribution interval				
Player	Average	Standard deviation	Minimum	Maximum
Non-star PIs' contribution interval				
Maximum bound	4.735	3.674	0	21.001
Minimum bound	1.362	1.026	0	4.848
Non-star-constellations' contribution interval				
Maximum bound	3.606	1.682	0	7.842
Minimum bound	1.280	1.265	0	6.435
No. of observations (collaborations)		450		

Notes. Values are expressed in a conventional unit of collaboration output. This conventional unit represents the additional value created when both the PIs and the constellation's research impact (citations) increase by 1%.

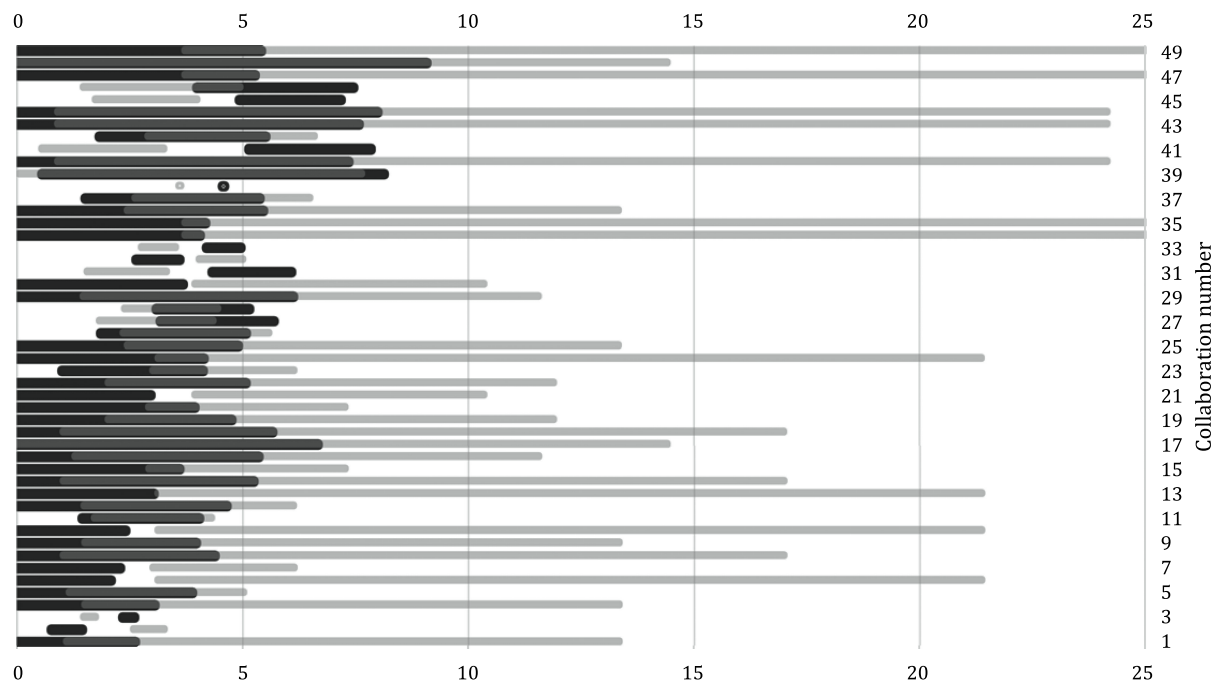
has characterized as indicative of star-to-constellation spillovers. Importantly, we also observe 10 collaborations (9.5%) in which the value capture interval of the constellation is higher than that of the star-PI. Furthermore, there is substantive overlap in contribution intervals for the remaining star-constellation matches. In these cases, one cannot unambiguously assert a dominant contributor position and conclude that “success is in the stars” or that “it takes a village.” Rather, the data indicate that a minority of stars bring value that is irreplaceable while most constellations provide sufficient value to the market and to their collaboration to merit “recognition” either via IP credits or financial rents. As an illustration, Figure 3 plots the contribution intervals for stars and star-constellations in the basic science domain.

We conducted a similar analysis of relative added value for the nonstar PIs and their constellations (Table 3, Panel B). Compared with the average contribution intervals of star PIs, nonstar PIs, on average, have both a lower maximum value and a lower minimum contribution. In the nonstar team subset, there are 76 nonstar PIs with net contributions (14%) and 80 (14.8%) constellations with net contributions. Overlaps in contributions continue to make up a substantial proportion of the collaborations.

5.3. Post Hoc Analysis

This analysis reveals that, in contrast to conventional wisdom, dominating (or net contributing) stars or constellations are rare. Approximately 77% of the time, we find that the resultant value is created jointly by the stars and their constellations. Indeed, the attributes of these players are reinforcing with reciprocal spillovers creating strong complementarities in these PI-constellation collaborations. To fully understand our findings, we look further into the defining feature of those cases of dominating players. To do so, we estimate the joint value lost when players on one side of the market (PIs, respectively, constellations) are taken out of the market and, through rematching, replaced in the collaboration by their next best substitute.¹⁸ We start with an analysis of the 105 collaborations involving a star PI. We begin by calculating the loss in value that constellations experience when they rematch with their second-best option after the removal of the original star PI from the market. We find differential effects that depend on the status, dominating or nondominating, of the constellation. A dominating constellation working with an alternative PI suffers only 23% loss in joint value creation, whereas a nondominating constellation is severely impacted losing, on average, 40% in joint value. A similar pattern is revealed on the other side of the partnership when the

Figure 3. Contribution Intervals of Stars and Constellations in Basic Sciences Collaborations



Notes. The horizontal bars illustrate the contribution intervals of the star PIs (in very light gray) and their corresponding constellations (in black), for the 49 collaborations in our sample that occur in basic sciences. The overlapping contribution intervals are in gray. The length of the contribution intervals is expressed in value creation units. Collaborations are stacked from bottom up in increasing order of their joint value. The Stars' contributions dominate in eight collaborations, whereas the constellations' contributions dominate in six collaborations. Collaborations in which stars dominate predominantly appear among those ranked in the lowest half by the magnitude of joint value created.

constellation is replaced by its closest available substitute in the market. A dominating star PI faces lower costs, losing on average 20% when forced to switch constellations, whereas the nondominating PI loses on average 33.7% in joint value. In sum, we find that dominating players bring significant value to the collaboration but have matched with substitutable counterparties such that when these counterparties are unavailable the dominating player can easily tap the market for a replacement with little loss in value. Those who do not dominate also bring significant value to the collaboration; however, they are more tightly intertwined with their partners and the partners are less substitutable: There are few, if any, alternatives in the market that provide the similar desired bundle of attributes. These results suggest that uniqueness is a key determinant of value creation and value capture. It is important that such rarity be considered in addition to synergies between partners and their relative ranking (based on level of attributes) in the market to gain a nuanced understanding of relative contribution and overall performance in collaborative activities.¹⁹

To corroborate our findings that dominating players have more substitutable counterparties, we replicated our analysis for the 450 collaborations headed by non-star PIs. Indeed, we observe a similar pattern. Dominant PIs and dominant constellations are effectively immune to counterparty changes and do not experience a drop in value by working with their second-best partner. However, replacement is very costly for nondominating players matched with less substitutable partners. We show that moving to the second-best partner results in a 26.85% reduction in joint value creation for non-dominating constellations and 30% drop for non-dominating PIs.²⁰ These results are summarized in Figure 4, (a) and (b).

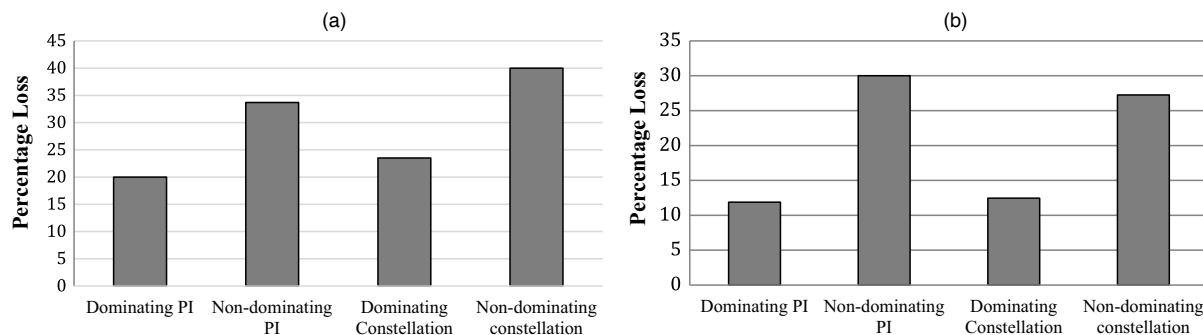
Although earlier we looked at change in value, it is also informative to consider the absolute level of value

created in these collaborations. As expected, we find that the average value created when there is a star involved in the collaboration is, on average, 43% greater than the value created by nonstar collaborations. This finding is consistent with the previous literature that has focused on the important role of stars. However, previous studies have not explicitly considered that stronger PIs can attract stronger constellations, the assortative matching effect, and hence may tend to give too much credit to the star for the joint value created by the collaboration. Additional insights can be gained by digging deeper into the differences between stars. In the 105 collaborations involving star PIs, it is the nondominating stars with their constellations that create the most value. Among these star-constellation matches, those involving dominating players are least likely to fall within the highest tranche in terms of value created. The highest third, ranked by value created, includes only one dominating star and four dominating constellations. In fact, collaborations involving dominating constellations reside mostly near the mean in value creation while the majority of those involving dominating stars fall to the bottom of the payoff distribution. It is the collaborations consisting of nondominating stars and non-dominating constellations in which both parties are codependent on each other that tend to rise to the top in terms of value (Table 4).

5.4. Robustness Checks

The main results provide the contribution intervals based on the point estimates of the matching production function. However, point estimates represent a summary statistic of unknown population parameters. This aspect introduces uncertainty regarding the magnitude of contribution intervals. To understand how the dominance patterns depend on the initial matching estimates, we took multiple draws from the distributions of matching estimates and recalculated the contribution intervals.

Figure 4. Post-hoc Comparative Analysis: Loss in Joint-Value from Pairing with a Second-Best Partner



Notes. (a) Average percentage loss in joint-value created when parties are paired with the counterfactual second-best partner (collaborations including a star). (b) Average percentage loss in joint-value created when parties are paired with the counterfactual second-best partner (collaborations without a star).

Table 4. Distribution of Dominant and Non-dominant Players Across Collaboration Payoff Levels

Payoffs	Dominating stars	Dominating constellations	Percentage nondominating agents within each payoff range
Highest third	6.66%	40.00%	37.5%
Middle third	33.33%	50.00%	31.5%
Lowest third	60.00%	10.00%	31.5%

The findings remain substantively consistent despite some variation across draws (see Online Appendix 1 for details).²¹

More generally, there are important questions as to what extent the dominance patterns are sensitive to our empirical choices. We addressed these concerns both conceptually and through robustness checks. Although the current model predicts 99% of inequalities, it is plausible that unobserved, idiosyncratic preferences driving matching (for example, laboratory equipment or project cospecialization) could be important in some markets. In such situations, our approach will underestimate the magnitude of interdependencies between agents in the match and hence, the cases of “no dominance.” Given that with the current model, we find that most collaborations are cases where neither party is dominant, such underestimation does not appear to have substantive implications for the interpretation of results. We conducted additional robustness checks including (1) covariate rescaling, (2) probing the relationship between market thickness and dominance results, and (3) conducting Step 2 of the analysis by removing PIs involved in multiple collaborations from one project at a time rather than from the market entirely. Results remain substantively the same. Finally, through analytical examples, we showed that there is no determinate relationship between the richness of the matching model specification and the dominance results.²²

6. Conclusion

Much in the literature has been written about the important role of star scientists in knowledge production, innovation, and commercialization. This study adds to this literature by investigating the role of star scientists in the context of their research collaborations. By considering the stars, the constellations, and synergies between the two, we provide insight into their relative value contribution. We investigate the role of star scientists in the context of their research teams by explicitly acknowledging the potential presence of both the Matthew effect and the spillover effect and note the bilateral nature of these mechanisms in driving matching and joint value creation. We probe the relative contribution of each party, star and constellation, on value creation under endogenous team formation conditions.

To address these issues, we estimated the underlying drivers of collaboration formation via a two-sided

matching model. Our emphasis was on complementarities between the PI and the constellation. We see evidence of a Matthew effect in the matching of star-PIs and their constellations. Star PIs attract stronger constellations in terms of quality, knowledge, and experience. Similarly, strong constellations attract stronger PIs. The strongest driver of matching is the similarity in research profile: an indication of commonality in “taste for science” or commonality in an “affinity for application” between the PI and the constellation. In line with existing theory, a moderate degree of common knowledge between PIs and constellations also emerges as an important driver of matching. In addition, PIs with higher research quality enjoy stronger complementarities by collaborating with constellations composed of researchers of varying ranks, an indication of diversity in knowledge vintage and perspective. We also find that collaboration performance is enhanced when the constellation has gained experience through a history of working together. Thus, we confirm the first principle of the Matthew effect, which is often overlooked in the literature on scientific teams that “to those that have much is given.”

The second step in our analysis took sorting into account and relied on the creation of counterfactual pairings to estimate the relative contribution of the collaboration parties. This allows us to contribute to the theoretical literature on collaboration in two ways. First, our approach is unique in that we capture bilateral influences of the PI-constellation synergy on joint value creation. Empirical studies that rely on shocks (e.g., death or immigration) identify the loss in joint performance when the star performer is missing, but do not isolate the importance of the constellation to performance of the star. As such, star effects may be overstated as synergy effects are attributed to the star. Our method allows us to avoid attributing the portion of the superior performance created by PI-constellation complementarity entirely to the individual star, or vice versa, to the constellation.

Second, although the literature has accorded much attention to complementarities that raise the value in collaborations, there has been little consideration to how uniqueness, or rarity in the market, drives value creation and value capture dynamics in joint efforts. Our results suggest that joint value creation is greater when star PIs match with nonsubstitutable constellations; that is, constellations that offer bundles of

attributes that are rare in the market (in addition to being synergetic with the attributes of the PI). We find a similar pattern when we consider the collaboration from the perspective of the constellation: Greater joint value is created when the “matched” star PI is less comparable to other PIs participating in the market. Overall, we document that joint value creation is greatest when neither the constellation nor the PI are dominant players: situations when both counterparties are relatively unique in the market. However, there is a tradeoff between value creation and value capture. Dominating players, although they generate synergies with their existing counterparties, can return to the market and easily recreate these synergies in a new match. As such, these dominating players are better positioned to claim a larger slice of the value created in their collaborations even if the relative level of value created (i.e., the size of the pie) is smaller. Elfenbein and Zenger (2017) highlight a similar tradeoff in value creation and value capture in their study of buyer-supplier relationships, showing evidence that buyers may trade off the enhanced value creation provided by repeated exchange for the opportunity to improve value capture by opting to engage with new suppliers.

In addition to these theoretical contributions, we also add to the field’s methodological toolbox by developing and using a new technique for estimating the contribution interval of an agent in a strategic interaction. This technique resolves a longstanding challenge in the value-capture theory stream (Chatain and Mindruta 2017, Gans and Ryall 2017, Montez et al. 2018) by providing a means of empirically estimating the upper and lower bounds of value parties to a transaction can create and subsequently capture. The methodology presented here can be extended to other contexts where the strategic interactions depend on the matching between players. Importantly, the structural model employed here deals with the endogeneity of team formation and team performance and eliminates the need for heroic attempts to identify relevant natural experiments or viable instrumental variables for dealing with the problem of mutual selection leading to the sorting of transacting parties.

The deployment of skilled human capital is an important management concern for universities in our context, but also for firm inventive activity. Thus, our study has multiple practical implications. First, the study provides insights into how collaboration structure influences joint value creation. We show that combinations of nondominating players, which are characterized by codependence, typically generate more value than collaborations that involve a dominating player. For star performers, then, there are benefits to acknowledging the costs of dominance and to be willing to sacrifice value capture to enhance value creation. The specific investment made by sets of

nondominating constellations/nondominating PIs in a collaboration should not be evaluated solely with respect to hold up concerns but in terms of value creation that provides potentially greater (not less) value capture for the collaboration. Second, these findings remind us that too much laudatory focus on stars may be detrimental given that value is generated through complementarities between the collaborating entities. For the majority of collaborations, we find that constellations and PIs are equal contributors of value (i.e., the value creation intervals overlap). As such, it is important to acknowledge and address the common credit allocation biases stemming from the status-based Matthew effect: that stars are disproportionately credited for joint value creation achieved in collaborations (Merton 1968, Bikard et al. 2015). Constellations are deserving of more recognition than they typically receive. A need to re-evaluate credit assignment to avoid attributional biases is thus one relevant take-away of our study. Correcting these biases may lead to better incentive structures, healthier collaborations, and more efficient outcomes. In a minority of cases, however, we do document the occurrence of dominating constellations, a situation analogous to that of dominating stars, where the contribution of the constellation exceeds the contribution of the star PI in the joint value created by the collaboration. This finding is a reminder that stars themselves can be substitutable. Even an entity that is a leader in their field may find that they have a small set of peers of equal quality and capabilities. As highlighted in the entrepreneurial literature, there is the potential of reference group neglect (Camerer and Lovo 1999), where stars may overestimate the uniqueness of their skills, failing to realize that other stars may have similar capabilities to offer. To stars then, the message should be “Check your ego at the door.” Finally, our findings speak to additional factors universities and firms may want to consider in recruiting and socializing faculty and/or management. Consistent with the work of Groysberg and colleagues (2008) and Agrawal et al. (2017), our results suggest universities or firms should look to hire personnel with strong collaboration histories and adopt policies that allow for the hiring of entire teams. For universities specifically, continued support for cross-institution collaboration should be encouraged.

Despite these contributions, there are limitations that merit additional attention and invite future work. First, our data are based on one university. As such, further studies are needed to ensure the generalizability of our findings. In particular, it would be valuable to go beyond scientific research collaborations and investigate team formation and value contribution for other types of self-selecting constellations, such as management, project, or work constellations inside commercial organizations. Second, although the methodology used

is advantageous as it squarely focuses on complementarities in collaborative teams and how these complementarities create value, we are cognizant that complementarities may arise across numerous dimensions. We built on the established literature on scientific team performance and captured three key dimensions, knowledge, experience, and quality, that are highlighted in this literature. We found that complementarities in these dimensions have very high predictive power, but this may not always be the case. For example, considerations of affinity and demographic characteristics and associated complementarities may have a greater importance in other settings, such as artistic or leadership collaborations, and should be explored in future research. Furthermore, we assume an overarching common objective of knowledge creation for the collaborations in our study. As such, we also maintain that different attributes that drive the matching process will be consistently valued according to this overarching common objective. Although reasonable, this assertion of consistency merits further investigation as relative importance of factors may shift in contexts where there are many, possibly diverging, objectives or where there are multiple viable paths to achieving a common objective. For example, conducting our analysis using academic or theoretical breakthroughs, rather than invention disclosures to identify collaborations would be constructive. Third, our current analysis considers constellations as fixed bundles of attributes. Although the study looks at collaborations across multiple years, it does not track trajectories or roles of individuals as they move into and out of different teams. Studies that relax the assumption of indivisible, fixed constellations to explore the career paths of academic scientists could provide insight into how the ability of individual scientists to create and capture value changes over time. Notably, it would be interesting to investigate the laboratory context in more depth to illuminate how value creation is driven across levels within a laboratory group to better understand under what condition is value driven by PI, professional staff, postdocs, or graduate students. Furthermore, studies that focused more on the dynamics to investigate team contribution to the creation of stars and to understand patterns in PIs' choices between solo and collaborative work would be of interest.

In sum, our study highlights the importance of looking at highly qualified human capital in the context of their collaborations. Although star status contributes to the creation of value, that alone does not provide a complete picture. The value stars bring to the table rarely dominates the value contributed by the constellation. In fact, for a star, dominance can be detrimental as it occurs by matching with an easily replaceable team, lowering the joint value created (the star stands to capture a larger share of a lower value). Value creation is enhanced when stars and constellations mutually invest to create

interdependencies, although this limits each party's collaboration alternatives and reduces each party's value capture.

Like looking at the North Star, our academic gaze has been drawn to the study of star scientists; however, we are enriched if we broaden our view beyond the brilliance of that single star so we can observe the rest of the constellation and absorb the full beauty of the Little Dipper.

Acknowledgments

The authors thank Theodore Chronis and Panaghis Mavroukafalos for contributions to the Mathematica and R code used for the statistical analysis.

Endnotes

¹ We recognize that constellations are made up of several "stars." However, not all "stars" in a constellation burn equally bright. It is only when they are seen together as a unit that a new image is formed. Consider the North Star that burns brightly on its own, but together with other less bright stars, forms Ursa Minor: the Little Dipper.

² The article is based on a paper presentation given by Merton to the American Sociological Association in 1967.

³ Inspired by the Gospel According to Saint Matthew that reads, "For unto every one that shall be given, and he shall have in abundance; but from him that hath not shall be taken away even that which he hath." Merton (1968, p. 58) offers a simplified translation: "Put in less stately language, the Matthew effect consists in the accruing of greater increments of recognition for particular scientific contributions to scientists of considerable repute and the withholding of such recognition from scientists who have not yet made their mark."

⁴ Azoulay et al. (2010) found that most affected by the loss of a star were co-authors close in the intellectual space, whereas other co-authors were less affected and even experienced an increase in scientific output following the death of a superstar. In these latter collaborations, a substitution effect may occur, wherein the star's skills are replaced through new collaboration relationships. These findings suggest the need to examine the substitution effects more closely, which we do here.

⁵ In recent work re-evaluating the "CEO effects" with the AKM approach, Jarosiewicz and Ross (2023) find that estimating CEO contribution via fixed effects could also generate spurious coefficients because of some other intrinsic aspects of the method such as its reliance on a large number of fixed effects dummy variables.

⁶ We are grateful to the associate editor for the suggestion to highlight this methodological precedent to our study.

⁷ Modeling team formation as a coalition or a multisided matching game entails taking into consideration each participant's preferences for joining various configurations that could be formed by team members and endogenizing the team size together with the complementarities among team members. Notwithstanding the methodological challenges, such an approach would also depart from our research focus on the constellation viewed as a bundle of attributes that are synergetic with the bundle of PI attributes.

⁸ To achieve this top-tier R1 designation, a university must offer at least 20 doctoral degree granting programs and have at \$5 million in total research expenditures annually. For confidentiality reasons, we cannot reveal the name of this university.

⁹ There were also 230 solo disclosures during this period. More than 80% of the faculty that disclosed solo are also in our data set either as PI

(the majority) or constellation members. The subpopulations of faculty who disclosed solo and faculty who disclosed inventions in teams do not differ significantly in terms of citations. However, the probability of a solo invention being licensed less than half the probability of a team invention being licensed, which is in line with recent findings that collaborative efforts, on average, produce higher impact outcomes than solo efforts. We did not use information on solo disclosures for two reasons: (a) individuals capture all the value they are creating in solo disclosures, and (b) the matching methodology requires observation of collaborative efforts.

¹⁰ Of the 555 collaborations in the data, 52% span departments, 14% include at least an external team member (either another university or industry), and close to 15% of the collaborations include two or more full professors.

¹¹ We use PI to denote the attributes of the principal investigator, C to denote the attributes that characterize constellations, and PI-C the dyadic attributes that characterize combinations of PI-constellations pairs.

¹² The low number of women in our data did not allow us to include gender as a control. This lack of women is in line with recent work that shows that women become PIs at a lower rate (Lerchenmuller and Sorenson 2018).

¹³ As an example, consider two rock bands each having a lead singer and a “constellation” of musicians. The first (well-known) band is The Rolling Stones with Mick Jagger as the lead singer. The second band (less well-known but equally enthusiastic) is the High School Garage Band with your neighbor’s 16 year-old son, Junior, as lead singer and a number of his classmates on the instruments. Imagine that Mick initially joined the High School Garage Band (GB), giving your neighbor’s son the opportunity to front the Rolling Stones. Our estimation approach relies on the following inequality holding: $v(\text{Mick, Rolling Stones}|\beta) + v(\text{Jr., GB}|\beta) > v(\text{Mick, GB}|\beta) + v(\text{Jr., Rolling Stones}|\beta)$.

¹⁴ Some PIs participate in multiple collaborations in a year (i.e., up to four per year, but instances of three or more are very rare). This aspect is fully accommodated by the estimation. Consider a market with two PIs denoted $\{A, B\}$ and three constellations denoted $\{C1, C2, C3\}$. Assume the following matches: $\{A; C1\}$ and $\{B; C2, C3\}$. Inequality (1) involves exchanging C1 with C2 in one inequality (whereas C3 remains paired with “B”) and swapping C1 and C3 in another inequality (whereas C2 remains paired with “B”). Furthermore, we conducted a thorough examination to ensure that the multiple collaborations led by the same PI comprised distinct and independent projects. This allowed us to focus on PIs-constellation pairings, and we did not include modeling for potential complementarities at the PI-portfolio level (e.g. in the above example, synergies between C2 and C3).

¹⁵ To confirm the validity of market definition, we calculated knowledge similarity for pairings of PIs and constellations within markets and pairings that span markets. The average knowledge similarity is 0.48 for observed PI-constellations, it is 0.12 for counterfactuals that are created within markets, and 0.07 for counterfactual pairings that span markets. This difference in magnitude indicates that broadening markets further would be detrimental as it would introduce numerous nonplausible pairings (where knowledge similarity is effectively zero) into the analysis.

¹⁶ This is a standard method for generating stable matchings starting from a given set of preferences and distribution of agents’ attributes. Using random pairing as a benchmark would not take into account the constraints of partnership formation in a matching context, such an agent not being able to collaborate with the most desirable partner when the partner has better partnering alternatives and/or capacity constraints.

¹⁷ The existing work has used proxies of a player’s added value instead of estimating it directly (Chatain 2011, Obloj and Capron

2011), with the exception of Chatain and Mindruta (2017), who also used theoretically derived counterfactuals to measure added value. Montez et al. (2018) propose a theoretically different way to deriving the value-capture bounds. See also Ross (2018) for a discussion.

¹⁸ The ability to analyze the role of substitution is an advantage of our method over the AKM fixed effects approach.

¹⁹ Interval estimates provide further insights into the factors influencing potential value appropriation. As Gans and Ryall (2017) explain, the maximum value an agent can capture is determined by the competition the agent faces in attracting better partners, while the minimum value is determined by the competition for partnering with the agent. Within this interval, the net payoff reflects one’s persuasive ability.

²⁰ As these results indicate, star dominance is not an artifact of the star definition. Six of our dominating stars are in the top 1% in the citation distribution, and we find dominating PIs even among those who fall below 5% in terms of citations. Defining stars with a more stringent threshold would only reduce the number of net dominant stars found, without substantially altering our results.

²¹ We are grateful to the department editor for suggesting this sensitivity analysis.

²² These examples and additional analyses are available upon request.

References

- Abowd JM, Kramarz F, Margolis DN (1999) High wage workers and high wage firms. *Econometrica* 67(2):251–333.
- Abowd JM, McKinney KL, Schmutte JM (2019) Modeling endogenous mobility in earnings determination. *J. Bus. Econom. Statist.* 37(3):405–418.
- Adams JD, Black GC, Clemmons JR, Stephan PE (2005) Scientific teams and institutional collaborations: Evidence from U.S. universities, 1981–1999. *Res. Policy* 34(3):259–285.
- Agrawal AK, McHale J, Oettl A (2017) How stars matter: Recruiting and peer effects in evolutionary biology. *Res. Policy* 47:853–867.
- Ahmadpoor M, Jones B (2019) Decoding team and individual impact in science and invention. *Proc. Natl. Acad. Sci. USA* 116(28):13885–13890.
- Allison PD, Stewart JA (1974) Productivity differences among scientists: Evidence for accumulative advantage. *Amer. Sociol. Rev.* 39(August):596–606.
- Arcidiacono P, Kinsler J, Price J (2017) Productivity spillovers in team production: Evidence from professional basketball. *J. Labor Econom.* 35(1):191–225.
- Azoulay P, Stuart T, Wang Y (2014) Matthew: Effect or fable? *Management Sci.* 60(1):92–109.
- Azoulay P, Zivin JSG, Wang J (2010) Superstar extinction. *Quart. J. Econom.* 125(2):549–589.
- Becker GS (1973) A theory of marriage: Part I. *J. Political Econom.* 81(4):813–846.
- Bercovitz J, Feldman M (2011) The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Res. Policy* 40(1):81–93.
- Bercovitz J, Feldman M (2008) Academic entrepreneurs: Organizational change at the individual level. *Organ. Sci.* 19(1):69–89.
- Bhaskarabhatla A, Cabral L, Hegde D, Peeters T (2021) Are inventors or firms the engines of innovation? *Management Sci.* 67(6):3899–3920.
- Bikard M, Murray F, Gans JS (2015) Exploring trade-offs in the organization of scientific work: Collaboration and scientific reward. *Management Sci.* 61(7):1473–1495.
- Black I (2019) *Better Together? CEO Identity and Firm Productivity* (Duke University).
- Borjas GJ, Duran KB (2015) Which peers matter? The relative impacts of collaborators, colleagues, and competitors. *Rev. Econom. Statist.* 97(5):1104–1117.

- Brandenburger A, Stuart G (1996) Value-based business strategy. *J. Econom. Management Strategy* 5:5–24.
- Camerer C, Lovoal D (1999) Overconfidence and excess entry: An experimental approach. *Amer. Econom. Rev.* 89(1):306–318.
- Campbell B, Di Lorenzo F, Tartari V (2021) Employer-employee matching and complementary assets: The role of cross-organization collaborations. *Acad. Management J.* 64(3):799–823.
- Chatain O (2011) Value creation, competition, and performance in buyer-supplier relationships. *Strategic Management J.* 32(1):76–102.
- Chatain O, Mindruta D (2017) Estimating value creation from revealed preferences: Application to value-based strategies. *Strategic Management J.* 38(10):1964–1985.
- Cohen WM, Sauermann H, Stephan P (2020) Not in the job description: The commercial activities of academic scientist and engineers. *Management Sci.* 66(9):4108–4117.
- Cole JR, Cole S (1973) *Social Stratification in Science* (University of Chicago Press, Chicago).
- Conti A, Liu CC (2015) Bringing the laboratory back in: Personnel composition and scientific output at the MIT Department of Biology. *Res. Policy* 44(9):1633–1644.
- Cummings JN, Kiesler S (2005) Collaborative research across disciplinary and organizational boundaries. *Soc. Stud. Sci.* 35(5):703–722.
- Dasgupta P, David PA (1994) Toward a new economics of science. *Res. Policy* 23(5):487–521.
- De Vany A, Walls D (1999) Uncertainty in the movies: Can star power reduce the terror of the box office? *J. Cultural Econom.* 23:285–318.
- Elberse A (2007) The power of stars: Do star actors drive the success of movies? *J. Marketing* 71(4):102–120.
- Elfenbein D, Zenger T (2017) Creating and capturing value in repeated exchange relationships: The second paradox of embeddedness. *Organ. Sci.* 28(5):894–914.
- Fleming L, Mingo S, Chen D (2007) Collaborative brokerage, generative creativity, and creative success. *Admin. Sci. Quart.* 52(3):443–475.
- Fox JT (2018) Estimating matching games with transfers. *Quant. Econom.* 9(1):1–38.
- Fox JT (2010) Identification in matching games. *Quant. Econom.* 1(2):203–254.
- Gans JS, Ryall MD (2017) Value capture theory: A strategic management review. *Strategic Management J.* 38:17–41.
- Groysberg B, Lee LE (2008) The effect of colleague quality on top performance: The case of security analysts. *J. Organ. Behav.* 29:1123–1144.
- Groysberg B, Lee LE, Nanda A (2008) Can they take it with them? The portability of star knowledge workers' performance. *Management Sci.* 54(7):1213–1230.
- Guimera R, Uzzi B, Spiro J, Amaral L, Nunes A (2005) Team assembly mechanisms determine collaboration network structure and team performance. *Science* 308(5722):697–702.
- Haeussler C, Sauermann H (2013) Credit where credit is due? The impact of project contributions and social factors on authorship and inventorship. *Res. Policy* 42(3):688–703.
- Higgins MJ, Stephan PE, Thursby JG (2011) Conveying quality and value in emerging industries: Star scientists and the role of signals in biotechnology. *Res. Policy* 40(4):605–617.
- Holmstrom B (1982) Moral hazard in teams. *Bell J. Econom.* 13(2):324–340.
- Huckman R, Pisano G (2006) The firm specificity of individual performance: Evidence from cardiac surgery. *Management Sci.* 52(4):473–488.
- Jarosiewicz VE, Ross DG (2023) Revisiting managerial "style": The replicability and falsifiability of manager fixed effects for firm policies. *Strategic Management J.* 44(3):858–886.
- Jensen R, Thursby JG, Thursby MC (2003) The disclosure and licensing of university inventions: Doing the best we can with the S**t we get to work with. *Internat. J. Industry Organ.* 21(9):1271–1300.
- Jin GZ, Jones B, Feng Lu S, Uzzi B (2019) The reverse Matthew effect: Consequences of retraction in scientific teams. *Rev. Econom. Statist.* 101(3):492–506.
- Jones BF (2009) The burden of knowledge and the death of the renaissance man: Is innovation getting harder? *Rev. Econom. Stud.* 76(1):283–317.
- Jones BF (2011) As science evolves, how can science policy? Lerner J, Stern S, eds. *NBER Innovation Policy and the Economy 11* (University of Chicago Press, Chicago), 103–131.
- Jones BF, Wutchy S, Uzzi B (2008) Multi-university research teams: Shifting impact, geography, and stratification in science. *Science* 322(5905):1259–1262.
- Katz R (1982) The effects of group longevity on project communication and performance. *Admin. Sci. Quart.* 27:81–104.
- Kremer M (1993) The O-ring theory of economic development. *Quart. J. Econom.* 108(3):551–575.
- Lazear E, Shaw K, Stanton C (2015) The value of bosses. *J. Labor Econom.* 33(4):823–861.
- Lerchenmuller M, Sorenson O (2018) The gender gap in early career transitions in the life sciences. *Res. Policy* 47(6):1007–1017.
- Levin SG, Stephan PE (1991) Research productivity over the life cycle: Evidence for academic scientists. *Amer. Econom. Rev.* 81(1):114–132.
- MacDonald G, Ryall MD (2004) How do value creation and competition determine whether a firm appropriates value? *Management Sci.* 50(10):1319–1333.
- Merton RK (1968) The Matthew Effect in science. *Science* 159(3810):56–63.
- Mindruta D, Moen M, Agarwal R (2016) A two-sided matching approach for partner selection and assessing complementarities in partners' attributes in inter-firm alliances. *Strategic Management J.* 37(1):206–231.
- Mollick E (2012) People and process, suits and innovators: The role of individuals in firm performance. *Strategic Management J.* 33(9):1001–1015.
- Montez J, Ruiz-Aliseda F, Ryall M (2018) Competitive intensity and its two-sided effect on the boundaries of firm performance. *Management Sci.* 64(6):2716–2733.
- Obloj T, Capron L (2011) Role of resource gap and value appropriation: Effect of reputation gap on price premium in online auctions. *Strategic Management J.* 32(4):447–456.
- Oettl A (2012) Reconceptualizing stars: Scientist helpfulness and peer performance. *Management Sci.* 58(6):1122–1140.
- Podolny JM (1993) A status model of market competition. *Amer. J. Sociol.* 98(4):829–872.
- Podolny J, Phillips D (1996) The dynamics of organizational status. *Industrial Corporate Change* 5(2):453–471.
- Porac JF, Wade JB, Fischer HM, Brown J, Kanfer A, Bowker G (2004) Human capital heterogeneity, collaborative relationships, and publication patterns in multidisciplinary scientific alliance: A comparative case study of two scientific teams. *Res. Policy* 33(4):661–678.
- Reagans R, Zuckerman EW (2001) Networks, diversity, and productivity: The social capital of corporate R&D teams. *Organ. Sci.* 12:502–517.
- Reagans R, Argote L, Brooks D (2005) Individual experience and experience working together: Predicting learning rates from knowing who knows what and knowing how to work together. *Management Sci.* 51(6):869–881.
- Roach M, Sauermann H (2010) A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry. *Res. Policy* 39(3):422–434.
- Ross DG (2018) Using cooperative game theory to contribute to strategy research. *Strategic Management J.* 39(11):2859–2876.

- Rothaermel F, Hess A (2007) Building dynamic capabilities: Innovation driven by individual-, firm-, and network-level effect. *Organ. Sci.* 18(6):898–921.
- Sauermann H, Stephan P (2013) Conflicting logics? A multidimensional view of industrial and academic science. *Organ. Sci.* 24(3):889–909.
- Shapley LS, Shubik M (1971) The assignment game I: The core. *Internat. J. Game Theory* 1(1):111–130.
- Simcoe TS, Waguespack DM (2011) Status, quality, and attention: What's in a (missing) name? *Management Sci.* 57(2):274–290.
- Simonin BL (1999) Ambiguity and the process of knowledge transfer in strategic alliances. *Strategic Management J.* 20(7):595–623.
- Singh J, Fleming L (2010) Lone inventors as sources of breakthroughs: Myth or reality? *Management Sci.* 56(1):41–56.
- Stern I, Dukerich JM, Zajac E (2014) Unmixed signals: How reputation and status affect alliance formation. *Strategic Management J.* 35(4):512–531.
- Taylor A, Greve HR (2006) Superman or the Fantastic Four? Knowledge combination and experience in innovative teams. *Acad. Management J.* 49(4):723–740.
- Tervio M (2008) The difference that CEOs make: An assignment model approach. *Amer. Econom. Rev.* 98(3):642–668.
- Tijssen RJW (2010) Discarding the 'basic science/applied science' dichotomy: A knowledge utilization triangle classification system of research journals. *J. Amer. Soc. Inform. Sci. Tech.* 61(9):1842–1852.
- Waldinger F (2012) Peer effects in science: Evidence from the dismissal of scientists in Nazi Germany. *Rev. Econom. Stud.* 79(2):838–861.
- Wuchty S, Jones BF, Uzzi B (2007) The increasing dominance of teams in the production of knowledge. *Science* 316(5827):1036–1039.
- Zenger TR, Lawrence BS (1989) Organizational demography: The differential effects of age and tenure distributions on technical communication. *Acad. Management J.* 32(2):353–376.
- Zucker L, Darby M (1996) Star scientists and institutional transformation: Patterns of invention and innovation in the formation of the biotechnology industry. *Proc. Natl. Acad. Sci. USA* 93(23):12709–12716.
- Zucker L, Darby M, Armstrong J (2002) Commercializing knowledge: University science, knowledge capture, and firm performance in biotechnology. *Management Sci.* 48(1):138–153.
- Zucker LG, Darby MR, Brewer MB (1998) Intellectual human capital and the birth of U.S. biotechnology enterprises. *Amer. Econom. Rev.* 88(1):290–306.