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Employer-Employee Matching and Complementary Assets: The Role of Cross-Organization Collaborations

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ABSTRACT

Building on human capital theory and social capital theory, we theorize that cross-organization collaborations generate a rich and distinct source of relational capital that enhances employer-employee matches when complementary assets are important in the production process. We test our theory in the context of academic scientists where collaborations within and across organizations are common ways to access complementary assets. We find that cross-organizational collaborations are positively related to an individual's decision to move towards their previous co-authors. Additionally, moving to an organization where an individual had a direct collaboration is positively related to post-mobility performance. This suggests that prior collaboration facilitates better employer-employee matches. We unpack this finding and show that the post-mobility performance increase is not driven only by increased productivity with the prior co-authors, it is also driven by novel collaborations with new colleagues. Together, our findings suggest that cross-organization collaborations facilitate hiring employees that can integrate well with the complementary assets of the entire unit.

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Keywords: employee mobility, complementary assets, human capital, knowledge flow, knowledge workers.

INTRODUCTION

The productivity of employees is shaped by the complementary assets with which they work (Weller, 2019). As a result, complementary assets drive differences in employee productivity across organizations (Campbell, Coff, and Kryscynski, 2012a), which allows firms to generate and capture human capital rents (Chadwick, 2017). However, they also present a challenge to the employee mobility and hiring process. Since employee productivity and utility within an organization can only be observed after the job match actually occurs (Jovanovic, 1979), hiring firms and potential employees have limited *a priori* information on the ability of a worker to be productive (and to receive utility) when matched to the assets of the new organization (Coff, 1997; Oyer and Schaefer, 2011). In contexts where complementary assets are highly important to the production process, this information gap is particularly severe (Elfenbein and Sterling, 2018).

However, the organization of work (especially knowledge work) has been evolving towards increased incidence of employee coordination across organizational boundaries (Cramton, 2001; Cummings, 2004; Gibson and Gibbs, 2006; Lakhani, Kuruvilla, and Avgar, 2013). Under this productive model, firms and individuals can gain insight into the quality of their potential match through the personal connections of collaborators. This relational capital provides direct insight on the fit of an employee with the complementary assets at an alternative employer which allows knowledge workers and their employers to mitigate the informational asymmetries highlighted above. Thus, such collaborators facilitate the creation of more productive matches (Weller *et al.*, 2019). While this process is consistent with insights from the social/relational capital literature more broadly (Bian, 1997; Granovetter, 1973; Marsden and Gorman, 2001), we extend on this foundational literature to address the distinct challenges that occur when complementary assets are important to individual productivity (Brymer, Molloy, and Gilbert, 2014).

We thus contribute to the employer-employee matching literature by unpacking how collaborations that cross organizational boundaries can facilitate initial matches between employees and firms' complementary assets. We draw on strategic human capital theory and social capital theory to argue that cross-organization collaborations generate a rich and distinct source of relational capital that enhances employer-employee matches when complementary assets are important in the production process. Empirically, we explore the implications of our theory in the context of individual-level academic research activities. Specifically, we draw on data from a sample of academics employed at life science departments of universities in the United Kingdom. We focus on the academic context because collaborations across multiple individuals are a critical input for academic organizations (Adams *et al.*, 2005; Levin and Stephan, 1997) and thus complementarities across individuals are of high strategic relevance.

Given the complexity of the phenomenon of interest, we draw on novel quantitative data on co-authorship patterns, research productivity, and mobility collected from researchers' CVs and publication records. We find that cross-organization collaborations (i.e. co-authorship across organizational boundaries) are positively related to an individual's decision to move towards their previous co-authors. Additionally, we find that conditional on mobility, moving to an organization with which an individual had a direct collaboration is positively related to post-mobility performance. This suggests that prior collaboration with an institution facilitates better employer-employee matches. We then unpack this finding to examine to what extent this positive matching effect is associated with co-location with the previous co-authors versus access to new complementary colleagues. We find that the post-mobility performance increase is not only driven by increased productivity with the prior co-authors, it is also driven by novel collaborative relationships with new colleagues. Together, our findings suggest that cross-organization collaborations facilitate hiring employees that can integrate well within the entire unit – and not just with previous collaborators.

THEORETICAL FRAMEWORK AND HYPOTHESES

Complementary assets and employer-employee matches

The extant matching literature has focused on how varying degrees of employee-employer matches may result in different levels of productivity (Lazear and Oyer, 2004) as well as different levels of job satisfaction and employee utility (Kristof, 1996; Kristof-Brown, Zimmerman, and Johnson, 2005). The core framing underpinning this literature is that individuals bring a variety of heterogeneous skills and preferences to heterogeneous employers (Jovanovic, 1979). Through the lens of matching, these differences in underlying resources play an important role in the employer-employee relationship as they drive different organizational outcomes (Barney, 1991; Wright, Dunford, and Snell, 2001). When firms possess differential resources, even identical employees will demonstrate differential outcomes across firms. Moreover, when heterogeneous firm resources are combined with heterogeneous individuals, the resulting differences across outcomes are magnified. While such match-driven outcomes cover a variety of possible dimensions (such as employee utility and satisfaction), we focus on individual productivity as the outcome of interest.

Building on human capital theory and keeping individual productivity as the focus of our interest, we define a complementary asset as any resource that makes a focal employee more productive when working with it than in the absence of it. This characterization is consistent with the foundational definition of Milgrom and Roberts (1995) and is analogous to the terms "fit" and "congruence" as used in the strategy literature (Ennen and Richter, 2010). Strategic human capital theory has highlighted the importance of complementary assets to the ability of a firm to create and capture value from employees (Campbell *et al.*, 2012a). For example, Becker's insights on firm-specific human capital is fundamentally a story of workers being more productive when matched to a firm's complementary assets (Becker, 1964).

In contexts where complementary assets are important to the production process, the matching process is particularly challenging because social complexity and causal ambiguity lead to information problems (Coff, 1997). If complementary assets are unimportant, then assessing matches between individuals and firms is a low dimensionality problem: employees assess the value that a firm provides *per se*, firms assess the value that an individual provides *per se*, and there are no complex interactions between the two. However, when complementary assets are important, employer-employee matches reflect a high dimensionality problem where individual characteristics combine with firm characteristics in rich and complex ways to shape the outcomes of the employer-employee relationship.

As such, the complexity due to complementary assets plays a critical role in both the selection mechanism of the employer-employee match process and in the subsequent adaptation mechanism (Weller *et al.*, 2019). Focusing first on the selection mechanism, when a firm hires externally, both the firm and potential job candidates seek to select into matches that maximize the joint utilization of the individual's skills and the firm's resources to create the most value (Raffiee and Byun, 2020). After an employee is hired and the employer-employee match has occurred, the adaptation mechanism potentially enters into play, as the individual and/or firm adapt to better utilize the firm's resources and the individual's skills. These mechanisms are closely interrelated, as firms and individuals may seek to select into matches that provide a high potential for future positive adaptation.

In both mechanisms above, greater complexity increases a variety of frictions employees and employers must overcome when engaging in the joint matching process. In our study, we focus primarily on the frictions created because of limited information and transaction costs (Mahoney and Qian, 2013). These frictions are key factors that constrain both the selection and the adaptation of matches between individuals and firms' complementary resources.

Regarding limited information, firms and individuals face challenges with assessing the productivity of the individual within a new organization (Mawdsley and Somaya, 2016). Employee productivity within an organization is not known with accuracy until after a match occurs (Jovanovic, 1979). Similarly, employee utility is not known until the employee actually experiences the position in their new organization. As such, firms and employees must make inferences about the match of the employee to the organization's complementary assets based on very limited information on important factors including fungibility of the individual's skills, the match with existing complementary assets, the utility value of person-organization fit, and the potential for future adaptation. Thus, the selection process is noisy and can lead to poor matches. This is particularly true for knowledge workers where team interactions (Wright *et al.*, 2018) and access to complementary resources (Teece, 1986) are important contributors to individual productivity.

Further, transaction costs, such as search costs and adaptation costs, create challenges in the employer-employee matching process (Brymer *et al.*, 2014). As employees' search costs increase, employee mobility decreases because employees and employers may choose to not engage in the external labor market (van der Berg, 1992; Jovanovic, 1979). If individuals and/or firms do not engage in the labor market, then employer-employee matches cannot occur. Second, the process through which employees and employers adapt to each other is not costless. The process of co-specializing requires, among other things, the development of new skills and routines and the investment in new technologies, all of which are costly activities (Wang, He, and Mahoney, 2009). Thus, when search costs and adaptation costs are high, the employer-employee match process is constrained -- which limits the value creation potential of the matches.

Cross-organization collaboration and employer-employee matches

Given the importance (and challenges) of assessing employer-employee match prior to actual experience with the organization, firms and employees have strong incentives to collect additional information that would help them better forecast the quality of the employer-employee match *a priori*. Direct information exchange between employers and employees where both sides reveal their characteristics in order to accurately assess the match potential between the two parties is potentially unreliable as both sides have incentives to misrepresent their actual attributes in order to capture more value from the relationship (Bangerter, Roulin, and König, 2012). However, relational capital facilitates more accurate (but broad) information about job openings, potential candidates, and their underlying attributes - (Bian and Ang, 1997; Chua, 2011; Fernandez, Castilla, and Moore, 2000; Granovetter, 1995; Marin, 2013; Marsden and Gorman, 2001; Mouw, 2003). While purely social ties may facilitate these high-level knowledge flows that reduce search costs, they do not necessarily provide direct and precise information that reduce information asymmetry on other important attributes of the employee-employer match, such as the potential complementarities between employees and employers.

To overcome this limitation, firms and individuals can invest in cross-organization collaborations which support accurate insights on employee performance within the context of the new organization. We define cross-organization collaborations as team production events where contribution and output are shared and the relationships exist across an organization boundary. Cross-organization collaborations are thus an antecedent to relational capital. Specifically, they are an antecedent to a form of relational capital that can mitigate both the limited information and transaction costs that inhibit employer-employee matches. Drawing on this perspective and extending previous contributions, we explore how an individual's cross-organization collaborations affect employee mobility and post-mobility productivity when complementary assets are important.

While a rich body of research highlights that relational capital facilitates employee mobility in general (Granovetter, 1995; Mouw, 2003), we argue that this effect is strongest for relational capital that is generated when employees and employers share prior work collaborations. Above, we highlighted two important frictions that constrain employee-employer matches when complementary assets are important. We argue that such cross-organization collaborations allow firms and individuals to more effectively reduce those frictions.

First, instead of inferring broadly from an individual's previous experiences whether an employee's abilities might be fungible and thus valuable outside the employee's current organization, organizations that are directly connected to an employee through external collaborations can develop more accurate inferences on the fit of employees within the specific firm (Simon and Warner, 1992). Similarly, when employees at a firm engage in collaborations with a potential hire, the firm can directly observe how the external employee matches with a subset of their complementary assets (i.e. the internal collaborators) and can solicit evaluations and feedback from this current employees on the fit of the connected outsider (Glitz, 2017). This reduces asymmetric information for the collaborating organization and as a result, directly-connected employers have more accurate information on which they can select better matching potential employees (Bangerter *et al.*, 2012; Coff, 1997; Oyer and Schaefer, 2011). Further, collaborative relationships build trust, which enhances the flow of accurate information between collaborating individuals across organizations (Gulati and Nickerson, 2008; Kogut and Zander, 1992) and in turn facilitates matching individuals with firms with which they have direct collaborative experience. Therefore, collaborative experience allows firms to better assess both the underlying general human capital of a potential employee and the fit of the employee with the complementary assets embedded in the organization. Both mechanisms lead to selection of individuals who will be more productive in the new organization relative to individuals with whom the hiring firm does not have this channel of information.

Analogously, on the supply-side, employees are better able to forecast their productivity in an organization with which they have direct experience and knowledge and can thus select into better matches. Since jobs are experience-based goods where productivity relies on complementary assets that are potentially causally ambiguous (Coff, 1997; Jovanovic, 1979), it may be costly or impossible for a potential employee to accurately predict their individual performance until they have actually interacted with the new set of complementary assets. However, through cross-organization collaborations, an individual has access to trusted colleagues in the new organization who can provide testimonials about the current employer and who can assess and communicate the potential fit of the employee with the target employer. Moreover, employees can conduct a preview working with at least some of the complementary assets that the new employer possesses.

Similarly, such trusted collaborators within the new organization can provide information to the candidate on the elements of person-organization fit that impact employee utility beyond the implications for individual performance (Kristof, 1996; Kristof-Brown *et al.*, 2005). In other words, a trusted collaborator can observe the personality traits of a potential candidate and provide information both to the candidate and the employer regarding how much utility the candidate would reap in the organization. While the information would certainly not be perfect, if there is not a direct collaborator, each party would have very little information on this dimension.

Also, cross-organization collaboration can support more accurate evaluations of the potential for future adaptation of the employer-employee match. Given an internal collaborator's knowledge position as having insights on both the abilities and credibility of the firm to invest in co-specialization and the potential ability and willingness of the individual to do the same, the internal collaborator can more accurately predict future co-adaptation potential.

Finally, cross-organization collaborations reduce search costs on both sides of the employer-employee match. Through the collaborative relationship, job openings can be more easily disseminated to the connected candidates and an individual's candidacy can be more easily communicated to the potential employer.

Together, these mechanisms suggest that prior cross-organization collaborations between an employee and a focal organization reduce the frictions due to information gaps and search costs that constrain the employer-employee match process. In other words, hiring a candidate with whom the firm has engaged in cross-organization collaboration reduces uncertainty and the search process is less costly. So, for individuals with a larger set of cross-organization collaborators, the likelihood that one of their connected organizations would provide a match that dominates their current employer is greater than for an individual with a smaller set of co-authors. Thus:

H_1: Individuals with more cross-organization collaborations will be more likely to move to their previous collaborators than individuals with fewer cross-organization collaborations.

Mobility to collaborators and post-mobility performance

In line with the logic above, collaborative experience will enable both sides to have access to less costly and more accurate information regarding the other party and the general quality of each. In turn, this facilitates selection into more productive matches, so individuals who choose to move to organizations with which they had prior exposure should outperform employees who moved to organizations where they did not have prior collaborative experience (Raffiee and Byun, 2020). Additionally, an external collaborator has richer information on whether a potential employee's previous performance reflects their quality or reflects the match with their current organization's complementary assets. On the labor market, this is particularly salient for poor performers looking to exit (Trevor, Gerhart, and Boudreau, 1997). An external collaborator can better identify "diamonds in the rough" who are underperforming at their current employer but whose potential could be unlocked in a different context with different complementary assets. This allows collaborators to provide information that helps select individuals who will be more productive at and contribute to a new organization.

Additionally, all else equal, a move to a previous collaborator is more productive than moving to an organization without a previous collaborator because the focal employee knows that there is at least one person there with whom they can easily collaborate. Consequently, when there are cross-organization collaborative relationships, both sides can navigate the hazards associated with limited and asymmetric information and select into more productive matches relative to employer-employee dyads without prior connections (Burks *et al.*, 2015; Dustmann *et al.*, 2016)

In addition to the improved selection mechanisms, individuals who share collaborative experience are likely to share common work practices, language, and routines. By joining collaborators with whom they have already worked, new employees can rely on previously established work routines instead of building new ones from scratch (Campbell, Saxton, and Banerjee, 2014; Groysberg, Lee, and Nanda, 2008). A shared set of practices and routines helps to facilitate post-move productivity relative to moving to an organization without similar connections.

Furthermore, collaborations have transaction costs and it is particularly costly to coordinate and interact across organizational boundaries. Despite reductions in transportation costs and advances in communication technology (Ponds, van Oort, and Frenken, 2007), geographical proximity is important and has a positive effect on the intensity and frequency of collaborations in knowledge-intensive industries (Katz, 1994). When a focal individual moves to a previous collaborator, they reduce the costs of interacting with that collaborator, thus enhancing their joint performance: a conversation at a water cooler is less costly than a flight and potentially more productive than a virtual meeting.

We therefore highlight both a selection and an adaptation effect. Individuals who move to organizations where they have a collaborator are likely to be more productive due to better general quality selection on both sides of the market and because the individual will become even more productive when localized with the complementary assets of the new organization. As a result, we hypothesize:

H_2: Mobility to a previous collaborator is positively related to a subsequent increase in performance, compared to mobility to an organization with no previous collaborators.

Mobility to collaborators and match to human complementary assets

In the logic of the previous sections, we focused largely on how cross-organizational collaborations facilitate the identification of general human capital and how moving to a collaborator increases individual productivity primarily by enhancing productivity with prior collaborators. However, after an employee moves to a new organization, they have access to a new pool of complementary human resources (Byun, Frake, and Agarwal, 2018). When assessing potential match quality, firms and individuals gain from considering complementarities with the entire work unit. In line with the logic above, when a potential employee has a collaborator within a firm, the internal collaborator can assess not just the potential employee's general quality and the established fit with the collaborator, but can also assess how well the potential employee will fit with other employees in the organization. By knowing the full set of colleagues in their organization and by having deep insights on the abilities and personality of the potential employee, the collaborator can infer how well the individual will match to the other employees. This channel of knowledge is not available to a firm that is hiring an individual without collaborative experience. Thus, when an employee joins a collaborator, they are more likely to join an organization where they will benefit from matching with their new colleagues as compared to an otherwise identical individual who joins a new firm that does not have any prior collaborators.

Additionally, when an employee joins a collaborator, that collaborator can serve as a broker between the new hire and the other employees (Granovetter, 1995). The collaborator can introduce the new employee to the people with whom they are likely to be productive. This reduces the costs of searching for the most useful complementary assets in the new organization, thus enhancing the propensity to collaborate outside the prior relationships - relative to joining an organization without a prior collaborator to serve as a broker.

Further, if the focal individual shares common practices and routines with their prior collaborator at the new organization, and other new colleagues share the same practices and routines, this means that adapting to the new colleagues will be less costly within organizations in which the focal individual has a prior collaborator. Similarly, after a direct collaborator has identified a potentially valuable set of new collaborators and brokered the relationships, co-location with this set of potential collaborators facilitates productivity with these new curated colleagues – again relative to joining an organization without a prior collaborator.

So, in terms of matching to the other human complementary assets at a new firm, there is again a selection and adaptation effect. A prior collaborator can facilitate selection of a candidate that will match well to others in the organization, and then being co-located with this curated set of colleagues facilitates adaptation and enhances productivity with the new colleagues – relative to new colleagues at organizations without a direct prior collaborator. Thus:

H_{3a}: Mobility to a previous collaborator is positively related to the number of new collaborators in the new organization, relative to mobility to an organization with no previous collaborators.

H_{3b}: When moving to a previous collaborator, the number of new collaborators in the new organization is positively related to performance, relative to mobility to an organization with no previous collaborators.

METHOD

Academics in UK universities

In order to test our hypotheses, we focus on the context of academic research. Academic research is increasingly a collaborative endeavor (Wuchty, Jones, and Uzzi, 2007) and the nature of the work allows teams to be distributed across multiple institutions resulting in an increasing number of institutions on each co-authorship team (Adams *et al.*, 2005). We leverage the co-authorship patterns of academic research to capture the cross-organization and within-organization collaborations of academic bioscience researchers in the United Kingdom.

Universities in the UK are characterized by a high degree of autonomy over budget, recruitment, and curricula. In this context, government funding for university science and research activities is composed of block grant funding that is augmented by direct project funding through research agencies. Block grant funding provides resources for basic research infrastructure and permanent staff salaries but is rather limited compared to project funding. Permanent staff salaries are primarily funded through money the government distributes to higher education institutions for teaching activities.

In this context, academic researchers face a very fluid labor market where mobility barriers are very low and changing employers is common (DfES, 2003). Mobility in this context is shaped by several important features of the labor market. First, the absence of an up-or-out tenure system: once in a junior faculty position (i.e. lecturer), individuals have a three-year probationary period, after which, if the assessment is positive, the contract becomes permanent but does not necessarily lead to a promotion. In contrast to many other academic contexts, it is possible for researchers to spend their whole career as lecturers (the equivalent of assistant professor) in the same institution. Second, when researchers win funding through competitive sources as principal investigators (e.g., grants awarded by the Research Councils), they are free to take the grant with them to a new institution if they move. Third, academic salaries tend to vary within a well-defined national range based on years of experience, with more variation at the top of the career ladder (Deloitte, 2012), which makes capturing a higher salary only a minor benefit of mobility across universities. Fourth, the market is highly internationalized, with UK universities attracting researchers from all over the world and competing among themselves to hire the best scholars (BIS, 2011).

Academic co-authorship provides a rich context to study the relationship between mobility, cross-organization collaborations, and individual performance. While the academic labor market has some distinct characteristics (which we explore in the discussion section), there are a variety of characteristics that provide the foundation for generalizability. While operating mostly with a not-for-profit logic, universities are knowledge-intensive organizations that need to manage their human capital strategically in a competitive marketplace -- similar to professional services companies, R&D intensive firms, and other firms in the knowledge space. In line with this, universities' strategy statements unanimously underscore the importance of hiring, retaining, and supporting talented researchers, such as this statement from Imperial College London: "*Great discoveries begin with great people: talented individuals steeped in the knowledge of their core discipline, confident enough to work on risky, unsolved problems, adept at understanding and working with others from different fields and immersed in an atmosphere of excellence. […] We will make supporting and enabling all these people central to what we do*" (Imperial College London Strategy 2015-2020, p. 4). In addition, universities compete with other universities and with industry employers at the national and international level in hiring the most skilled researchers. As stated in the University of Oxford Strategic plan 2013-2018: "*Research and teaching at the highest level require people of outstanding talent. Oxford has a vital role to play in the promotion of global mobility for academic staff. We will analyse the size and composition of applicant pools to inform a review of recruitment arrangements which ensures that we are reaching potential candidates across the globe, including those working outside the university sector*" (p. 11). Finally, government initiatives related to the allocation of funding to higher education institutions may increase the importance of strategic management of human capital in universities. For example, in the United Kingdom, research funding to universities (outside competitive grants) is allocated on the basis of results obtained in the Research Excellence Framework (REF, formerly known as the Research Assessment Exercise[1]). In such an evaluation system, the incentives to perform are very strong and therefore there are strong incentives to hire extraordinary candidates (Barker, 2007). As noted by Elton (2000), the REF has led to a "*creation of a transfer market, not*

[1] The RAE (now REF – Research Excellence Framework) was a government-mandated program to assess the quality of research of all universities and colleges in the UK; it was conducted every seventh year, and its results were used to determine the allocation of research funding to universities other than that received through competitive bidding for grants.

unlike that well known in football, in which institutions bought active researchers with the express purpose of creating research excellences where there had been few or none before". The dynamics in this context have parallels to other knowledge-intensive industries.

Sample construction

We focus on a sample of 349 active research academics working in life science departments in UK universities from 1995 to 2009. To construct a representative sample and avoid selection bias issues, we employed a cohort approach. First, we selected seven research universities in the UK with a life science department (University of Cambridge, University of Oxford, University of Edinburgh, University College London, Imperial College London, University of Glasgow, and University of Birmingham). In 2001, as part of the Research Assessment Exercise (RAE) each university was required to provide a list of all faculty members. The faculty members were divided into Units of Assessment, which correspond broadly to departments. From the public records of the RAE, we collected the names of all faculty members that each university submitted in the Unit of Assessment (UoA) that corresponds to Biology. We were able to extract the surname and initials of 1,026 biology researchers active in 2001. From this list of names, we proceeded to manually collect researchers' CVs from their university or personal webpages. If the CVs were not available, we contacted the academics directly via email (when it was possible to find an active email address) asking for the CV. It is important to note that we chose to use names from the RAE in 2001 to ensure we had a sufficiently long history to assess mobility and research outcomes for most researchers. While some researchers could not be found as they had changed profession, retired, or passed away, the final percentage of retrieved CVs (409 retrieved CVs, 40%) is in line with usual response rates in surveys directed to academics (Perkmann *et al.*, 2013). We focused our attention on a single discipline (biology) so that output measures could be easily comparable across individuals. Moreover, we selected life sciences because researchers in this discipline tend to publish in smaller teams than in other fields such as experimental physics or medicine (Wuchty *et al.*, 2007) and therefore the link between specific individuals and their scientific production is more clear.

Career information taken from CVs was coded to construct comprehensive profiles of the researchers, including their education and employment history, resulting in a panel dataset spanning from 1952 (date of the first job position observed in the dataset) to 2014. CV data have been widely used in the economics of science literature because they provide reliable information both on job changes and personal publication records (Cañibano and Bozeman, 2009; Geuna *et al.*, 2015) and recently have also been employed in the study of employees' mobility (Ge, Huang, and Png, 2016; Slavova, Fosfuri, and De Castro, 2015).

From the full dataset (409 researchers), we first excluded all researchers with a hybrid career, i.e., those who had been moving between academia and industry.[2] Because our measure of individual performance is based on the number of articles published, we sought to ensure that researchers faced similar incentives to publish across their career. While it is common for industrial researchers to publish in peer-reviewed journals, and many firms use publications as a signal of the quality of research their employees perform, industrial research mainly follows commercial logic (Cohen, Nelson, and Walsh, 2002) and thus publications patterns are not comparable across the two domains. Additionally, we excluded academic researchers whose careers span multiple countries. This was done to assure that the researchers in the data face similar macro-level dynamics across their career, especially on the labor market side. Finally, we only considered individuals while they were employed in a permanent academic position, namely from lecturer

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[2] Individuals remained in the sample if they were *simultaneously* employed in academia and industry.

upwards. In life sciences, researchers are expected to complete several postdocs before being appointed as faculty members. Postdocs have a fixed time frame and therefore we did not want to confound mobility reflecting the end of a postdoc contract with voluntary mobility from one faculty position to another. After trimming, this procedure left us with 349 individuals with available information from 1995 to 2009.[3] All universities in the dataset were manually matched with their unique Higher Education Statistics Agency code (HESA code). The codes were then matched with data on student headcount, university and department income, and research quality.

To collect publication data for each of the 349 researchers in the sample, we proceeded in two steps. First, we coded a program to crawl through the Scopus Elsevier database to directly download all peer-reviewed publications.[4] Previous research on academic productivity has largely used Scopus Elsevier as a reliable source to collect publication data (Archambault *et al.*, 2009). Second, to check the accuracy of our program, we manually checked the number of publications for each researcher as follows: i) we hand-searched the first name and last name in Scopus Elsevier; ii) in the case of search results with multiple entries (i.e., homonymy), we disentangled the different names using affiliation information; iii) once we identified the correct focal entry, we manually collected the number of publications. In the case of discordance between outputs of the two steps, we kept the number of publications derived from the manual procedure.[5]

[3] The initial date was set to 1995 for two reasons. First of all, we wanted to ensure the best possible coverage from SCOPUS for researchers' publications. Second, data on student headcount and university and department income in the UK are only available starting from 1995. We decided to end the analysis period in 2009 to avoid the possibility of incomplete information for the last years, as researchers may not update frequently their CV and to allow the accumulation of citations for the most recent papers.

[4] Scopus Elsevier is a bibliographic database containing abstracts and citations for academic journal articles. It covers nearly 22,000 titles from over 5,000 publishers, of which 20,000 are peer-reviewed journals in the scientific, technical, medical, and social sciences (including arts and humanities) (Scopus Info, 2013). Scopus Elsevier allows legal downloading of data for research purposes.

[5] This data collection forms the basis for an additional paper by the same author teams (Tartari, Di Lorenzo, and Campbell, 2020). While the individuals analyzed are the same, in this paper we complement the original dataset with rich information about the co-authors of the focal individuals.

As a result, we collected 14,457 peer-reviewed publications from 1995 to 2009, which implies that, on average, each researcher had approximately 3 publications per year in the period of observation. Figure 1 shows the characteristics of the distribution of our sampled individuals for levels of total scientific productivity. As expected, the distribution is right-skewed. The skewness of this distribution is a common feature of scientific production first observed by Alfred Lotka in a study of 19th century physics journals (Lotka, 1926). Lotka's law has been found to fit data from several periods of time and scientific disciplines (Stephan, 1996). This observation suggests that we are likely capturing a representative sample of researchers.

Insert Figure 1 about here

Variables

Dependent variables

In order to test Hypothesis 1, we construct a dependent variable, *Mobility*, which tracks the mobility events of all researchers in the sample. For each individual in our sample we tracked their career and affiliations in every period. When an individual changes affiliation, we code the individual-year observation corresponding to the year of the move as: 1 if the individual moves to an institution where no co-authors are employed; 2 if the individual moves to an institution where at least one co-author is employed, and 0 if the individual did not move. A co-author is defined as an individual that appears as a collaborator in any publication with the focal individual within the previous five years. So, our dependent variable *Mobility* takes three values (0, 1, 2), which reflect the three different choices that a sampled individual can take in each time period. Figure 2 depicts the distribution of the 349 researchers per number of moves. As demonstrated in Panel A, the rate of mobility of 45% (156 out of 349) within our sample is quite high compared to previous studies on employee mobility (Campbell *et al.*, 2012b; Palomeras and Melero, 2010). Further, Panel B shows that out of the 156 moving individuals, 42% of them (66) move to co-authors.

Insert Figure 2 Panel A and Panel B about here

In order to test Hypothesis 2 and Hypothesis 3b, we define the dependent variable, *Post-Mobility Productivity*, as the cumulative count of journal articles published by each individual up to each point of time adjusted by academic tenure, within a 5-year rolling window.[6] One of the main goals of scientists is to establish priority of discovery (Merton, 1957). A necessary step in establishing priority is undoubtedly publication (Stephan, 1996); therefore, it has become common practice to measure scientific productivity in terms of number of articles published by a researcher.

Finally, to test Hypothesis 3a, we define the dependent variable, *Current Colleague-New Co-Authors*, which is the number of unique new co-authors that are also colleagues of the focal individual in the current employer in every period. For each publication of each focal individual, we classified each co-author as either a previous colleague, a current colleague, or neither, depending on the focal individual's affiliation at the time of the publication. We also classified co-authors as an old co-author or a new co-author, depending on whether the focal individual had collaborated in the past with the specific co-author or whether the co-author appeared in the 5-year rolling window for the first time. In addition, we developed a set of rules to deal with authors who possess double affiliations.[7]

Independent variables

[6] A 5-year rolling window implies that for each year *t* we use data between year *t*-1 and year *t*-5 to compute the variable of interest.

[7] Each unique author in SCOPUS is associated for each publication to one or more organization identifiers, which represent their affiliations at the moment of publication of the paper. Researchers may therefore be affiliated with multiple universities at the same time. See on-line Appendix 1 for detail on our classification strategy.

In order to test Hypothesis 1, our main independent variable, *Cross-Organization Collaborations*, is time variant and captures the number of unique co-authors working at external organizations (relative to the university of affiliation of the focal individual) over the preceding five years. For each focal individual, we first identified all their unique co-authors and their affiliations. For this purpose, we used the publication data collected from SCOPUS, where a unique personal identifier characterizes every author. For every publication, all authors are also associated with an affiliation (as indicated on the publication itself). All organizations are assigned a unique identifier; however, because of different spellings of organizations' names and other administrative issues, a single institution could possess several SCOPUS identifiers. In order to avoid overestimating the occurrence of collaborations spanning organizational boundaries, we manually checked all affiliations present in our publication sample (8,387 affiliations) and aggregated the SCOPUS identifiers pertaining to the same institution (which resulted in 7,298 unique affiliations). In order to determine if a co-author was affiliated with the same institution as the focal individual, we compared their affiliation (as identified by the aggregated SCOPUS identifier) to the focal individual's affiliation in that year (as identified in their CV and matched to the SCOPUS list of organizations).[8]

In order to test Hypothesis 2, Hypothesis 3a, and Hypothesis 3b, we identify researchers moving to a university where at least one of their co-authors has been affiliated. Thus, we construct the dichotomous variable *Mobility to Co-Authors*, which takes the value of 1 if a researcher moves to a university where one of their previous co-authors is affiliated (in a 5-year rolling time window), and 0 otherwise. As before, to determine the pool of co-authors, we use the authors list

[8] Because some papers are the result of experiments conducted in large-scale research facilities, they are co-authored by hundreds of individuals. Of course, in such large projects, it is not realistic to assume that each individual personally knows and directly collaborates with every other participant. We therefore considered only papers with less than twenty co-authors (which represent 99% of all papers authored by researchers in our sample).

from each focal researcher's publication history and their related affiliations. Finally, to test Hypotheses 3b we use *Current Colleague-New Co-Authors* constructed as mentioned in the previous section.

Control variables

To capture possible alternatives to *Cross-Organization Collaborations* as a determinant of inter-organizational mobility, we introduce a set of control variables in our models. Availability of resources is particularly important to explain scientific productivity (Stephan, 1996). In this regard, we control for *Individual Grants*, which is the total amount of research grants available to each researcher in the sample in every year. To collect this information, we manually checked each researcher in our sample in the database of awarded grants of the Biotechnology and Biological Sciences Research Council (BBSRC) since 1997.[9] While this source does not provide a complete overview of all grants awarded to the researchers (e.g. we cannot control for grants from private entities), it represents the major funding body in this scientific area. We also control for *Department Total Funds*, which is the amount of research funds available on average to each department employee. This information is collected through the records of the RAE in 2001 and 2008, and provides a complete overview (by year) of all funding received by each department. For this variable, the department is the one where our focal researcher is employed in each year. These two sources of funding research activities are independent and non-mutually exclusive.

We also include controls that are likely to shape both the individual propensity to move and the general labor market conditions researchers face every year. In order to capture labor market conditions, we introduce the variable *Students Enrolled*, which is the number of students

[9] The BBSRC was created in 1994, and it is currently the largest UK public funder of non-medical bioscience: in 2017/2018, it disbursed £498M for bio-scientific research.

enrolled at time t at the university where the researcher works in t+1.[10] The government (through HEFCE) allocates universities funding for teaching-related activities based on the number of students enrolled. Among other uses (such as financing grants for students), this money is used to open permanent faculty positions. These openings affect the academic labor market, influencing, in turn, individual researcher mobility (Tartari, Di Lorenzo, and Campbell, 2020). In order to model individuals' general propensity to move, we include two variables. The first one (*Mobility pre-1995*) takes value 1 if the focal researcher changed institutions during her career but before the sample window (which starts in 1995). In general, individuals who have moved across organizations in the past are more likely to move again (Topel and Ward, 1992). The second variable we use, *Educational Mobility*, is the number of different countries where each individual was educated up to the first job placement. Since we have data on the country where each individual performed high-school, bachelor, and Ph.D. studies, we code *Educational Mobility* as 0 if the country is the same for the three degrees, up to 3 if the three educational levels are taken in different countries. Since previous literature highlights that individual performance is strongly correlated to mobility (Campbell *et al.*, 2012b; Gambardella, Giarratana, and Panico, 2010; Hoisl, 2007; Di Lorenzo and Almeida, 2017; Zenger, 1992) we control for *Individual Productivity* by including the cumulative number of scientific publications in each year per each individual in the 5-year window prior to the focal year. We use *Academic Position* to capture the organizational position of each individual over time, which equals 1 for Assistant Professor, 2 for Associate Professor and 3 for Full Professor. We also control for *Entrepreneurial Experience* by including a dummy equal to 1 in any year in which an individual reported to be a founder or a joiner of a new venture, and 0 otherwise.

[10] For example, if researcher A works at University X in 2001 and moves to University Y in 2002, the variable we would use is the number of students at University Y in 2001.

Finally, co-authors are characterized along two dimensions: their institution relative to the focal individual (i.e. they were colleagues at a previous institution, they are colleagues at the current institution, or they have never been colleagues); and whether the co-author is a new or old one. To test hypotheses H3a and H3b, we use *Current Colleague-New Co-Authors* which is the number of unique new co-authors that are also colleagues of the focal individual in the current employer in every period. In order to control for the five alternative categories, we construct a measure for each category that is the number of unique co-authors in the category divided by the total number of unique co-authors in each period. Last, we include *Year* dummies to control for year effects.

Estimation approach

We first estimate a multinomial logit model of the likelihood that an academic (a) stays at their current employer, (b) moves to an institution where there are no co-authors, or (c) moves to an institution where there is at least one co-author employed (H1). We then focus on the set of moving academics and divide the 156 movers into two groups: 66 individuals who move to a co-author's institution and 90 individuals who move to an institution with no co-authors. Thus, *Mobility to Co-Authors* is 1 for the former group and 0 for the latter group. We then generate a variable *After Mobility*, which equals 0 for the years previous to the individual's mobility event, and 1 for the years after the mobility event.[11] Since all the 156 individuals move, we are able to identify a pre- and post-mobility period for all the academics. With this approach, we can specify our models for *Post-Mobility Productivity* (H2 and H3b) and for *Current Colleague-New Co-Authors* (H3a) as

[11] Out of 66 individuals moving to co-authors, 6 moved to co-authors 2 times. For these individuals we consider only the first move.

difference-in-differences estimations using Ordinary Least Squares (OLS).[12] In line with previous work (Singh and Agrawal, 2011), we acknowledge the potential endogenous nature of our treatment mobility to collaborators due to non-random job allocation for each individual and selection in mobility patterns. Yet, we believe this specification allows us to clearly represent the effect of the relationship between *Mobility to Co-authors* and *Post-Mobility Productivity* or *Current Colleague-New Co-Authors*. To further take into consideration potential selection issues, we also employ Fixed Effects (FE) at the individual level and robust standard errors to model heteroskedasticity in our data.

RESULTS

The descriptive statistics and correlation coefficients are provided in Table 1, Panels A and B. As shown in Table 1, each academic in our sample produces approximately 3 publications per year (14.52 in a 5-year window) and collects around 66,159 GBP in individual grants for research activities per year. Approximately a third of our sample changes institutions before the beginning of the analysis period (i.e. 1995) and 80% earned at least one degree (including high school, bachelor, and Ph.D.) from an international institution.

Insert Table 1, Panel A and Panel B about here

Table 2 Panel A shows coefficient estimates of the multinomial logit model with *Mobility* as the dependent variable and Panel B shows the corresponding relative risk ratio estimates. The relative risk ratio of *Cross-Organization Collaborations* in Model 2 in Panel B of Table 2 (*Mobility* outcome 2 = moving to co-author) is positive and significant ($z=1.94$; $p<0.06$), in accordance with

[12] An alternative specification to test for *Current Colleague-New Co-Authors* (H3a) is Negative Binomial Regression (NBREG). Results do not change when employing NBREG instead of OLS.

Hypothesis 1. An increase of 10% in the count of cross-organization collaborations out of the total unique collaborations increases the likelihood of moving to a different institution where a co-author is affiliated by 2.8%, compared to the baseline outcome of *Mobility* (non-moving = 0). Figure 3 plots the marginal effects for different level of *Cross-Organization Collaborations*. Moreover, *Cross-Organization Collaborations* do not relate significantly to the likelihood of moving to an institution where no coauthor is affiliated (*Mobility* outcome = 1) compared to no mobility. Thus, based on the results shown in Model 2 of Table 2 Panel B, we find moderate support for Hypothesis 1.

Insert Table 2 Panel A, Panel B and Figure 3 about here

Hypothesis 2 proposes that academics moving towards universities with which they share cross-organization collaborations experience a higher gain in productivity than academics moving to an institution where there is no prior collaborative experience. We use the difference-in-differences models in Table 3 to test this hypothesis. The coefficient of *Mobility to Co-Authors x After Mobility* shows the marginal post-mobility productivity of an academic moving towards an institution where she had prior collaborators compared to an academic that does not move to collaborators. Looking at the coefficient of interest, an academic moving toward co-authors reports a significant post-mobility increase in the yearly cumulated age-adjusted productivity of 0.73 publications ($t=3.32$; $p<0.01$), which reflects a 35% increase compared to their pre-move productivity and a 68% increase compared to productivity in the pre-move period of individuals moving to no co-authors. Thus, conditional on mobility, moving toward collaborators increases individual productivity relative to moving to organizations with no previous co-authors (see Figure 4). This result suggests support of H2.

Insert Table 3 and Figure 4 about here

Hypothesis H3a suggests that an academic's mobility to a previous collaborator is positively related to the number of new collaborators in the new organization compared to mobility to an organization with no previous collaborators. The coefficient of *Mobility to Co-Authors* x *After Mobility* in Table 4 shows the marginal post-mobility count of new co-authorships generated in the new organization of an academic moving towards an institution where she had prior co-authors compared to an academic that does not move to co-authors. Looking at the coefficient of interest and considering the log-transformation of the dependent variable *Current Colleague-New Co-Authors*, an academic moving toward co-authors reports a statistically significant positive increase in *Current Colleague-New Co-Authors* of 2.06 ($t=2.42$; $p<0.05$), which reflects an increase of 1.1 times of the count of new co-authors that are also colleagues in the new organization. Figure 5 shows the results of the interaction between *Mobility to Co-Authors* and *After Mobility*. Thus, this result suggests support of H3a.

Insert Table 4 and Figure 5 about here

Finally, Hypothesis H3b suggests that for academics moving towards co-authors, the number of new collaborators in the new organization is positively related to performance, compared to moving to an organization with no previous collaborators. The coefficient of *Mobility to Co-Authors* x *Current Colleague-New Co-Authors* in Table 5 Model 2 is the primary test of our results. Model 1 in Table 5 reports estimates for the period pre-move (*After Mobility=0)*, while Model 2 reports estimates for the period post-move (*After Mobility=1)*. The coefficients show that the marginal post-mobility productivity of academics moving towards an institution where they had prior co-authors compared to academics that do not move to co-authors is not significantly different in the pre-move period, but is significantly different in the post-move period (coefficient=0.08; p<0.001). The difference between the two coefficients of *Mobility to Co-Authors* x *Current Colleague-New Co-Authors* in Model 1 and Model 2 is statistically significant (Chi2=18.52, Prob > chi2 = 0.000). Thus, the effect of *Current Colleague-New Co-Authors* on individual productivity in the post period is significantly higher for those individuals moving to co-authors compared to those moving not to co-authors; this result suggests support of H3b.

Robustness Checks and Additional Analysis

We explore the robustness of our results in several ways. First, we use the count of publications to operationalize the scientific productivity of the academics in our sample. Despite being widely used as measure of productivity, this operationalization primarily captures the quantity of the academic scientific output, and it does not consider the quality of the output. To address this potential concern, we checked whether or not our models are robust to our choice of productivity measure (*Post-Mobility Productivity*). We have thus generated the variable *Post-Mobility Citation Productivity*, which is a citations-adjusted measure of the cumulated count of journal articles published by each individual up to each point of time adjusted by academic tenure, within a 5-year rolling time window. As reported in Model 2 of Table 3 and Models 3 and 4 of Table 5, the coefficients of this supplementary analysis replicate the results in Table 3 (Model 1) and Table 5 (Models 1 and 2), providing further support to H2 and H3b.

Second, to test the robustness of our findings for H1, we examine *Mobility to Collaborators* as an alternative operationalization to our three-category dependent variable *Mobility*. *Mobility to Collaborators* takes the value 1 if the individual-year corresponds to a move to an institution where at least one collaborator is employed, and 0 otherwise. Given the dichotomous nature of this alternative dependent variable, we estimate a probit random effects specification which allows us to take into account individual unobserved variation caused by academic-specific characteristics omitted in the model (Jenkins, 2005). The empirical strategy we adopt has been implemented in previous studies on employee mobility (Campbell *et al.*, 2012b; Di Lorenzo and Almeida, 2017; Palomeras and Melero, 2010). In on-line Appendix 2, we report the results in terms of average marginal effects. As shown in Model 2 of Appendix 2, the marginal effect for *Cross-Organization Collaborations* is again positive and significant (dy/dx = 0.004, $p<0.05$). Specifically, a 10% increase in external collaborations increases the likelihood of moving to a different institution where a collaborator is employed by 0.04 percentage points. Compared to the baseline probability of 1.6%, this reflects an 2.5% increase in the likelihood of moving to collaborators. Thus, the results shown in Model 2 of Appendix 2 continue to support Hypothesis 1.

Third, an alternative operationalization for *Cross-Organization Collaborations* (the straight count of co-authors working at external organizations) is the share of unique co-authors working at external organizations (relative to the university of affiliation of the focal individual) out of the total number of unique co-authors over the preceding five years. This share-based measure more accurately reflects the intensity to collaborate with external co-authors relative to internal co-authors as compared to a count-based measure. Specifying the variable as a share makes it necessary to control for the total number of unique co-authors. When doing so, the results of our models are unchanged.

Fourth, to better understand the relationship between individual post-mobility performance and the formation of new unique collaborations with new colleagues, we perform an OLS model of *Post-Mobility Productivity* on the interaction between *Current Colleagues-New Co-Authors* and *Mobility to Co-Authors*, with one model for the pre-move period and one model for the post-move period (see Table 5). An alternative approach to test H3b is to specify the OLS model of Table 5 with a triple interaction between *Current Colleagues-New Co-Authors*, *Mobility to Collaborators,* and *After Mobility*. On-line Appendix 3 reports the results of this alternative specification. The coefficient for the triple interaction term is positive and significant (coeff.=0.207, $p<0.001$), which again provides support for our Hypothesis 3b.

Finally, an additional potential concern is that complementarities with other (non-human) assets of the destination organization influence post-mobility performance, which might confound our primary focus on *Current Colleagues-New Co-Authors*. Thus, in analyses analogous to those in Model 2 in Table 5, we show that the largest post-move to co-author productivity gain is associated with collaborating with *Never Colleagues-New Co-Authors* (coeff.=0.035, $p<0.05$, see on-line Appendix 4). Hence, the effect of newly established collaborations with individuals that have never been a colleague on individual productivity in the post period is significantly higher for those individuals moving to co-authors compared to those moving to no co-authors. While we cannot measure the underlying mechanism, this result is consistent with cross-organization collaborations facilitating matches to other sources of complementary assets that we cannot observe well in our data – but that promote individual productivity even outside the boundaries of the organization.

DISCUSSION

We explore how cross-organization collaborations can facilitate matching employees and firms' complementary assets. Drawing on human capital and social capital theory, we hypothesize that cross-organization collaborations facilitate employee mobility towards prior collaborators. Moreover, we hypothesize that conditional on mobility, moving to an organization with which an individual has a prior collaboration is positively related to the individual's post-mobility performance (relative to an in individual who moved to an organization where there were no prior collaborators).

Further, we examine to what extent this matching effect is associated with co-location with the previous collaborators versus accessing new complementary colleagues. Accordingly, we hypothesize that after the move, individuals who joined organizations where their prior collaborators are employed will work more with their new colleagues with whom they have not worked before, relative to individuals moving to an organization where no former collaborator is present. Additionally, we posit that these novel collaborative relationships with the new colleagues are an important driver of the individual's post-mobility performance increase.

We test these hypotheses using novel data on bioscience academics in life science departments of universities in the United Kingdom. Using these data, we construct measures of within- and cross-organization collaborations, individual mobility, and scientific productivity. Our empirical results are consistent with our hypothesized relationships.

The theory and empirics highlight the role of cross-organization collaboration in employer-employee matches. We propose that the direct interaction in the context of a work project mitigates the informational asymmetries and transaction costs that are present when complementary assets are important to the production process. Thus, cross-organization collaborations lead to increased mobility to prior collaborators and the prior collaborators may help select individuals who will thrive when embedded with the complementary assets of the new organization. Accordingly, employees who move to a prior collaborator are more productive not only because of co-location with their prior co-authors, but because of new relationships with their new colleagues. Further, in our additional analyses we show that employees who move to a prior collaborator are also more productive with new co-authors outside of the new organization. Together, the results suggest that cross-organization collaboration facilitates matching to not only to the focal human assets installed in an organization, but also to other complementary assets that can facilitate productivity in external relationships.

Limitations and future research

The limitations of our study suggest several avenues for future research. First, the results we present are subject to limited causal interpretation due to potential omitted variable bias and, like all studies of employee mobility, a lack of random allocation of mobility events across our sampled individuals. These features of our empirical analysis constrain the extent of causal claims we can draw from our results. In line with previous studies (Hoisl, 2007; Singh and Agrawal, 2011), we attempt to reduce these concerns in various ways, including employing fixed-effects in our models specification and collecting additional individual information from CV data. Future research in this space should work towards continuing to rule out more alternative explanations and build even stronger causal claims.

Second, although we develop a schema to categorize types of within and cross-organization collaborations (i.e. old/new collaborator at previous/current/neither employer), there are opportunities to further parse out types of cross-organization collaborations. For example, categorizing whether the new collaborations an individual creates in the post-mobility period are formed within or across topic areas, or with junior or senior colleagues, or with star colleagues, or more generalist vs specialist collaborators could support theoretical contributions to the innovation literature, the star scientist literature, and to the strategic human capital literature.

Third, organizations might be heterogeneous in their ability to integrate their complementary assets with newly acquired human resources (Morrison, 2002). Some organizations are increasingly investing resources to facilitate the onboarding of new hires into the organization in order to minimize the productivity shock expected given the disruptive nature of changing employers. If firms that are better at onboarding new employees are also more likely to hire employees who have had previous collaborations with the organization, then our results could reflect this relationship. Additionally, some organizations may intentionally hire new employees who do not match with existing complementary assets in order to expand the scope of their activities. This creates challenges for incoming employee integration which would lead to short-term adverse impacts on both the individuals' local collaborations and performance. Future research with richer organizational-level insights could distinguish between the role of selection and treatment when hiring prior collaborators.

Finally, the scope of this manuscript is confined to just the hiring interface of the employee match process. This ignores the dynamic aspects of employee-employer matching that occur within an organization (Weller *et al.*, 2019). As Weller et al. (2019) indicate, the matching process evolves across the duration of the employer-employee relationship. An extension to the arguments in this manuscript would be to examine how the importance of complementary assets shape the dynamics of the match process that occurs after initial selection. In our context, it would be valuable to examine the long-term publication trajectories post-mobility, and to examine how collaboration patterns impact who goes into administrative roles and how collaboration patterns shape involuntary turnover.

Generalizability

Empirically we focus on the context of mobility of academic researchers in the life sciences. The institutions that affect the labor market for academics are idiosyncratic, thus raising concerns on the generalizability of our results. Given the context analyzed, we believe that our study likely represents a conservative test of the effect we would likely observe if looking at employees in more representative industries. The intuition is that because individual productivity and organizational complementary assets are very easily observable in this context, the marginal benefit of inside information provided by a collaboration would be smaller than the benefit of inside information in a more opaque context. Thus, we argue that if we see an effect in such a transparent industry, the effect could be potentially stronger in a more typical industry context.

Additionally, in this context, university researchers are not prevented from collaborating across universities and they have the possibilities to belong simultaneously to multiple organizational communities (the so-called “invisible colleges”) while developing their research activities (Crane, 1972). This has two implications. First, scientists can easily pursue their research goals through collaborations independent of their organizational affiliation. However, research has shown there are benefits to co-location of scientific collaborators (Katz, 1994). Thus, it is impossible to perfectly substitute mobility with cross-organizational collaboration. Second, in the context of academia, it is more common for relationships to persist after mobility than in other industry contexts. In many cases of inter-organizational mobility, different organizational communities are mutually exclusive for the individual; in other words, when employees change employers, they generally leave behind previous colleagues with very limited chances to keep formal collaborations with them. This is clearly not the case of academic scientists: after moving, an academic will not lose the opportunity to collaborate with previous colleagues, potentially diminishing the negative shock on productivity due to post-mobility disruption in social capital (Campbell *et al.*, 2014; Groysberg *et al.*, 2008).

Another limitation associated with focusing on academics is that academic jobs provide an idiosyncratic level of autonomy where academic scientists have great discretion regarding with whom they choose to work (Stern, 2004). This level of agency may not be relevant in other industries and occupations where employees face greater constraints on their ability to design their own jobs. However, there is a growing trend towards employee agency as traditional employment relationships evolve towards more contract-based arrangements (Cappelli, 1999; Osterman *et al.*, 2002), which make our findings potentially interesting for a wider set of contexts.

Ultimately, understanding how collaborations can enhance attracting potential employees that fit with the organization's complementary assets has managerial implications that are relevant outside the world of autonomous scientists in academia. In contexts where individuals do not have full autonomy over their collaboration patterns and instead managers drive collaborative relationships, then managers should consider how to design and utilize collaborations to gain access to the additional knowledge flow that collaborations can provide.

Conclusion

The study makes multiple contributions. We contribute to the matching literature by showing how collaborations that cross organizational boundaries give additional information to both employers and employees that facilitate matches into broader organizational units. We theorize and demonstrate that collaborations lead to more productive matches and that the enhanced individual productivity reflects increased new collaborations with new colleagues – relative to new hires that do not have any prior collaborators at the hiring organization.

Cross-organization collaborations are particularly effective in facilitating effective matches because they combine both internal and external relational capital (Coff, 1997). Internal relational capital (i.e. relationship capital shared with co-workers) exists within the boundaries of the organization, and contribution and output are shared jointly among colleagues (e.g. Groysberg *et al.*, 2008; Huckman and Pisano, 2006; Selby and Mayer, 2013; Sturman, Walsh, and Cheramie, 2008). In contrast, external relational capital (i.e. relationship capital shared with external stakeholders such as customers or suppliers) exists across the boundaries of the organization, and contribution and output are contracted across the focal parties (e.g. Broschak, 2004; Carnahan and Somaya, 2013; Raffiee, 2017).

However, cross-organization collaborations are work activities where contribution and output are shared (as in internal relational capital, but in contrast to traditional conceptualizations of external relational capital), and the relationships exist across some boundary (as in external relational capital, but in contrast to internal relational capital). As such, the hybrid relational capital generated through such collaborations helps employers navigate the hiring challenges associated with both internal social complexity and external social complexity (Coff, 1997) and thus leads to more effective matching by providing better information on individual quality and by better forecasting how the individual will fit with the assets of the new organization. In so doing, they provide many of the same benefits as external hiring pipelines which provide an alternate route to address the limited information and mobility costs that create frictions in the labor market (Brymer *et al.*, 2018, 2014)

Our matching framework also has implications for the study of scientists, as it illuminates a possible mechanism that underlies the relationship between mobility and individual scientific performance (Tartari *et al.*, 2020). While shortening the distance to collaborators reduces the transactions costs involved in those collaborations and therefore increases productivity, we highlight the role of employee match with relevant complementary assets (in the form of new colleagues) in contributing to the increase in productivity that follows a move to a new university.

Finally, our results have important managerial implications. First, managers can benefit from the information they can gather about potential employees that have been engaging in a collaboration. As we discuss in our theory development, these collaborations do not simply reduce the information asymmetry about the quality of the human capital of a potential new hire, but they provide a testing ground for gauging information on the match of a specific external job candidate with the complementary assets of the organization. Employees can also benefit from the extra information regarding the value of complementary assets at alternative employers, enhancing their likelihood to leave their current organization.

Together, this highlights a double-edged sword in investing in cross-organization collaboration, but one side of the sword is likely sharper than other. When complementary assets matter to the production process, collaborations would facilitate poaching employees who match the focal organization well (Gardner, 2002). On the other side of the sword, collaborations facilitate outbound mobility, but the exiting employees would be moving to organizations where they fit better – in other words, the leaving employees would be employees who potentially fit less well at the focal firm. Our intuition is that in terms of collective turnover it would thus be a net positive for firms to invest in cross-organization collaborations (particularly if the firm has idiosyncratic complementary assets): such firms attract employees that fit better than the ones they might lose (Call *et al.*, 2015). Richer analysis at the organizational/unit level on the impact of investing in cross-organization collaborations would be a rich avenue for future research.

Firms also can design other forms of collaborative activities with potential employees which still provide them with the information they need about their match, but may reduce some of the costs related to this learning process. For example, large tech companies such as Facebook or Twitter are actively engaging in sharing part of their code as open source in order to show prospective employees what they will be working on and what the company has to offer before they are even hired. This moves beyond the usual requirement for programmers to show some of their code during a job interview (which is a way to reduce the information asymmetry about the quality of the programmer), as it opens up a window to the company through which a match between a potential employee and the complementary assets of the organization can be assessed prior to employment. Another example is corporate sponsorships of academic scientists. For research-intensive organizations such as pharmaceutical companies, finding the right human capital is crucial to innovation, and ultimately to perform well in the market. While the general quality of the human capital of potential hires can be approximated by their list of publications, the reputation of the laboratory where they got their training, and other signals - the actual fit with the organization remains difficult to forecast. Pharmaceutical companies therefore often sponsor PhDs and Postdocs at universities in order to spot the best talent and to make promising candidates aware of the possibilities of developing their research in a specific company while also allowing managers to assess how well the candidate will fit with the new organization.

To conclude, while many sources of relational capital are valuable in the job matching process, they often have limitations when complementary assets are part of the production function. Relational capital, for example social ties, can facilitate information flow regarding an employee's general human capital, but provide limited information when complementary assets are important because it is hard to forecast the match between an employee and the complementary assets *a priori*. Cross-organization collaborations are distinct because they provide deeper insights on employee performance when an individual is exposed to an alternative firm's complementary assets.

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Table 1A. Descriptive Statistics (Individual Level)

Variable	count	mean	sd	min	max
Mobility	349	0.64	0.78	0	2
Mobility to Co-Authors	156	0.42	0.49	0	1
Post-Mobility Productivity	349	1.36	1.26	0	9.75
Post-Mobility Citation Productivity	349	600	1,272	0	14,729
Cross-Organization Collaborations	349	0.57	0.25	0	1
Individual Productivity	349	14.52	13.90	0	85
Mobility pre-1995	349	0.38	0.49	0	1
Educational Mobility	349	0.81	0.68	0	3
Individual Grants	349	66,519	163,412	0.30	2,189,673
Academic Position	349	2.08	0.80	1	3
Entrepreneurial Experience	349	0.07	0.25	0	1
Student Enrolled	349	20,904	4,294	9,719	36,266
Department Total Funds (in 000)	349	17,518	6,657	1,815	33,861
Year	349	2001	1.71	1995	2009
Current Colleagues-Old Co-Authors (count)	156	0.27	0.54	0	4.21
Current Colleagues-New Co-Authors (count)	156	2.72	2.69	0	15.33
Previous Colleagues-Old Co-Authors (count)	156	0.31	0.48	0	2.67
Previous Colleagues-New Co-Authors (count)	156	0.57	1.04	0	8.67
Never Colleagues-Old Co-Authors (count)	156	0.74	0.93	0	4.86
Never Colleagues-New Co-Authors (count)	156	5.93	6.16	0	31.30

Table 1B. Correlation Matrix (Individual Level)

	Variable	**N**	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	Mobility	349	1.00										
(2)	Mobility to Co-Authors	156	0.78	1.00									
(3)	Post-Mobility Productivity	349	0.34	0.38	1.00								
(4)	Post-Mobility Citation Productivity	349	0.36	0.37	0.66	1.00							
(5)	Cross-Organization Collaborations	349	0.19	0.20	0.39	0.23	1.00						
(6)	Individual Productivity	349	0.43	0.43	0.62	0.69	0.33	1.00					
(7)	Mobility pre-1995	349	-0.02	-0.09	0.10	-0.19	-0.03	-0.33	1.00				
(8)	Educational Mobility	349	-0.01	-0.02	0.03	-0.11	0.00	-0.15	0.26	1.00			
(9)	Individual Grants	349	0.18	0.16	0.04	0.12	-0.03	0.10	-0.01	0.15	1.00		
(10)	Academic Position	349	0.31	0.29	0.10	0.26	0.06	0.53	-0.29	-0.11	0.26	1.00	
(11)	Entrepreneurial Experience	349	0.09	0.05	-0.05	-0.04	-0.05	0.12	-0.03	-0.02	0.17	0.18	1.00
(12)	Student Enrolled	349	-0.12	-0.18	-0.01	-0.02	-0.10	-0.09	0.08	-0.01	-0.16	-0.08	-0.17
(13)	Department Total Funds (in 000)	349	-0.02	-0.04	-0.01	0.03	-0.27	-0.12	0.12	0.11	0.07	-0.04	0.09
(14)	Year	349	0.15	0.19	0.04	-0.02	0.00	0.08	0.01	-0.01	0.19	0.11	0.02
(15)	Current Colleagues-Old Co-Authors	156	0.33	0.40	0.20	0.29	0.12	0.52	-0.18	-0.05	0.19	0.36	0.20
(16)	Current Colleagues-New Co-Authors	156	0.32	0.29	0.25	0.31	-0.04	0.45	-0.28	-0.03	0.05	0.36	0.16
(17)	Previous Colleagues-Old Co-Authors	156	0.20	0.26	0.12	0.20	-0.01	0.23	-0.16	-0.12	-0.05	0.00	0.17
(18)	Previous Colleagues-New Co-Authors	156	0.15	0.17	0.02	0.19	0.00	0.19	-0.21	-0.12	-0.06	0.15	-0.04
(19)	Never Colleagues-Old Co-Authors	156	0.25	0.27	0.26	0.26	0.48	0.53	-0.20	0.02	-0.09	0.23	0.15
(20)	Never Colleagues-New Co-Authors	156	0.25	0.25	0.26	0.40	0.34	0.53	-0.33	0.06	-0.05	0.29	-0.05

Table 1B. Correlation Matrix (Individual Level) continued

Variable		N	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(12)	Student Enrolled	349	1.00								
(13)	Department Total Funds (in 000)	349	0.18	1.00							
(14)	Year	349	0.01	0.15	1.00						
(15)	Current Colleagues-Old Co-Authors	156	-0.25	-0.02	0.13	1.00					
(16)	Current Colleagues-New Co-Authors	156	-0.14	0.12	0.22	0.40	1.00				
(17)	Previous Colleagues-Old Co-Authors	156	-0.17	-0.01	-0.08	0.10	0.10	1.00			
(18)	Previous Colleagues-New Co-Authors	156	-0.08	-0.07	-0.20	-0.04	0.06	0.54	1.00		
(19)	Never Colleagues-Old Co-Authors	156	-0.09	-0.09	-0.01	0.31	0.22	0.11	0.00	1.00	
(20)	Never Colleagues-New Co-Authors	156	-0.14	-0.03	0.16	0.31	0.54	0.02	-0.01	0.49	1.00

Correlation coefficients greater than 0.16 are significant at p<0.05

Table 2: Multinomial Logit Model for Mobility

	Panel A: Coefficient of Mobility		Panel B: Relative-Risk Ratio	
(Baseline outcome = No mobility)	(Model 1) Mobility to non-co-authors	(Model 2) Mobility to co-author	(Model 1) Mobility to non-co-authors	(Model 2) Mobility to co-author
Cross-Organization Collaborations	-0.022	0.243^{+}	0.979	1.275^{+}
	(0.061)	(0.125)	(0.059)	(0.159)
Individual Productivity	-0.083	0.067	0.920	1.069
	(0.075)	(0.125)	(0.069)	(0.197)
Mobility pre-1995	0.159	0.357	1.173	1.430
	(0.179)	(0.251)	(0.210)	(0.360)
Educational Mobility	-0.037	-0.035	0.964	0.966
	(0.127)	(0.200)	(0.122)	(0.194)
Individual Grants	-0.042*	0.015	0.959*	1.015
	(0.019)	(0.020)	(0.018)	(0.021)
Academic Position	-0.943***	-0.608***	0.389***	0. 545***
	(0.135)	(0.164)	(0.053)	(0.089)
Entrepreneurial Experience	-0.288	-0.302	0.750	0.739
	(0.590)	(0.557)	(0.443)	(0.411)
Students Enrolled	-0.790***	-0.580*	0.454***	0.560*
	(0.159)	(0.242)	(0.072)	(0.136)
Department Total Funds	-0.046	0.104	0.955	1.110
	(0.174)	(0.274)	(0.166)	(0.033)
Year Dummies	YES			
Constant	Included			
Number of Groups (IDs)	349			
Observations	4,129			
Pseudo R^2	0.101			
Wald chi2	151.44			
Prob> chi2	0.000			

Clustered standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 3: Difference-in-Differences (DiD) Ordinary Least Squared for Post-Mobility Productivity

	(Model 1) Post-Mobility Productivity	(Model 2) Post-Mobility Citation Productivity
Mobility to Co-Authors	0.193	-302.127+
	(0.258)	(180.795)
After Mobility	-0.510***	-379.581***
	(0.095)	(87.337)
Mobility to Co-Authors x After Mobility	0.734**	930.493***
	(0.221)	(224.829)
Cross-Organization Collaborations	-0.034	-2.608
	(0.030)	(17.499)
Individual Productivity	0.120**	38.364*
	(0.036)	(19.244)
Individual Grants	-0.002	-2.376
	(0.006)	(6.430)
Academic Position	0.130	99.907
	(0.096)	(91.904)
Entrepreneurial Experience	-0.260	-207.621
	(0.341)	(197.401)
Students Enrolled	0.103+	103.566*
	(0.060)	(41.712)
Department Total Funds	-0.034	-4.131
	(0.088)	(57.929)
IDs FE	YES	YES
Year dummies	YES	YES
Constant	Included	Included
Number of Groups (IDs)	156	156
Observations	1,583	1,583
Adjusted R-Squared	0.423	0.254
F statistic	14.18	4.593
Prob > F	0.000	0.000

Robust standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 4: Difference-in-Differences (DiD)
Ordinary Least Squared for Current Colleagues-New Co-Authors

	(Model 1) Current Colleagues-New Co-Authors
Mobility to Co-Authors	-0.060
	(0.807)
After Mobility	2.663***
	(0.513)
Mobility to Co-Authors x After Mobility	2.056*
	(0.851)
Cross-Organization Collaborations	-0.099
	(0.063)
Current Colleagues-Old Co-Authors	-4.085***
	(0.998)
Previous Colleagues-Old Co-Authors	-5.229***
	(0.681)
Previous Colleagues-New Co-Authors	-4.079***
	(0.417)
Never Colleagues-Old Co-Authors	-5.293***
	(0.427)
Never Colleagues-New Co-Authors	-2.810***
	(0.294)
Individual Productivity	0.571***
	(0.169)
Individual Grants	0.010
	(0.019)
Academic Position	0.013
	(0.216)
Entrepreneurial Experience	0.794
	(0.991)
Students Enrolled	-0.141
	(0.227)
Department Total Funds	-0.083
	(0.168)
IDs FE	YES
Year dummies	YES
Constant	Included
Number of Groups (IDs)	156
Observations	1,428
Adjusted R-Squared	0.49
F statistic	54.95
Prob > F	0.000

Robust standard errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table 5: Difference-in-Differences (DiD) Ordinary Least Squared for Post-Mobility Productivity

	(Model 1) Post-Mobility Productivity *Pre-Move*	(Model 2) Post-Mobility Productivity *Post-Move*	(Model 3) Post-Mobility Citation Productivity *Pre-Move*	(Model 4) Post-Mobility Citation Productivity *Pre-Move*
Current Colleagues-New Co-Authors	0.036	-0.011	1.324	-9.932
	(0.036)	(0.013)	(44.779)	(11.618)
Mobility to Co-Authors	1.356	-0.147	1,599.000	-1,125.497***
	(0.887)	(0.256)	(1,103.794)	(228.731)
Current Colleagues-New Co-Authors x Mobility to Co-Authors	0.006	0.077***	40.096	62.465***
	(0.063)	(0.016)	(78.375)	(13.928)
Cross-Organization Collaborations	-0.119***	0.004	-51.921	4.418
	(0.033)	(0.031)	(41.573)	(27.934)
Current Colleagues-Old Co-Authors	-1.092	-0.179	609.860	-117.806
	(1.086)	(0.219)	(1,351.767)	(195.321)
Previous Colleagues-Old Co-Authors	-0.020	0.601**	244.721	96.736
	(1.533)	(0.209)	(1,907.767)	(186.900)
Previous Colleagues-New Co-Authors	0.535	0.290+	384.878	81.419
	(0.476)	(0.152)	(592.088)	(135.954)
Never Colleagues-Old Co-Authors	0.507	0.113	962.250+	-190.189
	(0.435)	(0.153)	(540.936)	(136.140)
Never Colleagues-New Co-Authors	0.439+	0.161+	444.876	128.405
	(0.257)	(0.093)	(320.206)	(82.817)
IDs FE	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Constant	Included	Included	Included	Included
Control variables	Included	Included	Included	Included
Numbers of Groups (IDs)	156	156	156	156
Observations	530	1,053	530	1,083
Adjusted R-Squared	0.121	0.338	0.170	0.238
F statistic	15.96	53.32	7.80	53.72
Prob > F	0.000	0.000	0.000	0.000

Robust errors in parentheses.
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

FIGURES

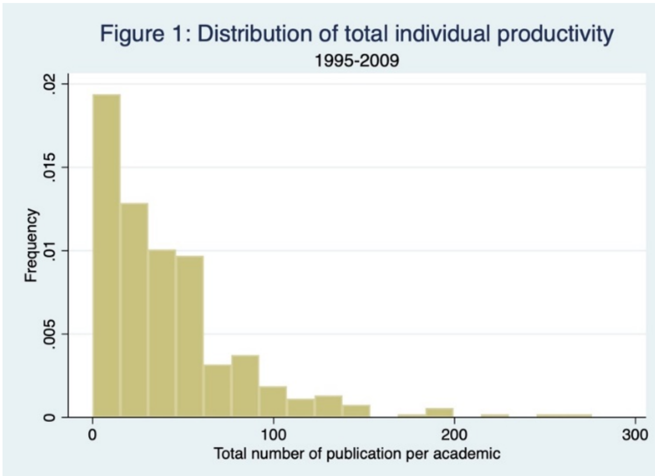


Figure 1: Distribution of total individual productivity
1995-2009

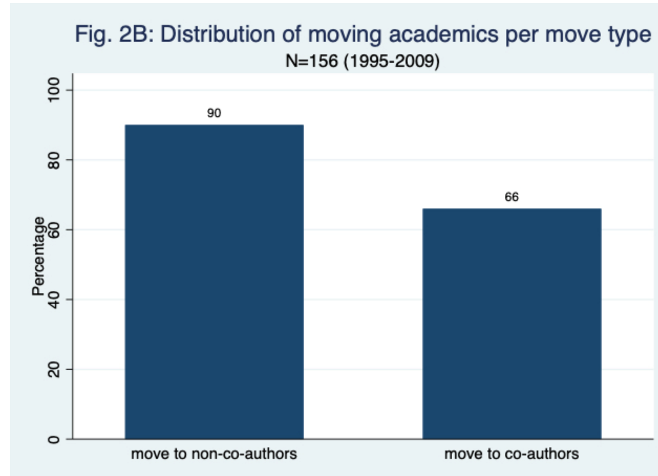


Fig. 2B: Distribution of moving academics per move type
N=156 (1995-2009)

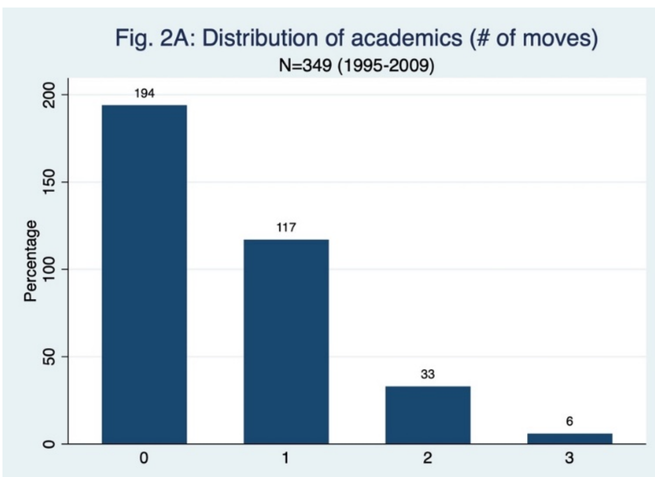


Fig. 2A: Distribution of academics (# of moves)
N=349 (1995-2009)

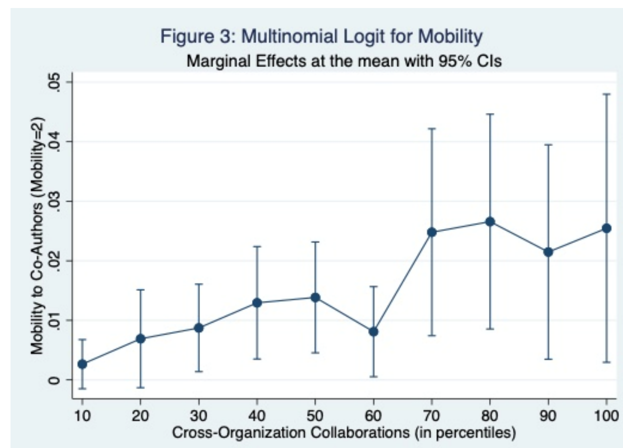


Figure 3: Multinomial Logit for Mobility
Marginal Effects at the mean with 95% CIs

Figure 4: DiD OLS for Post-Mobility Productivity

Predictive Margins with 95% CIs

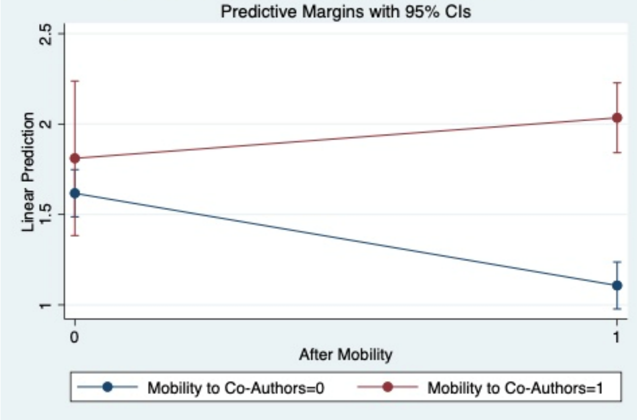
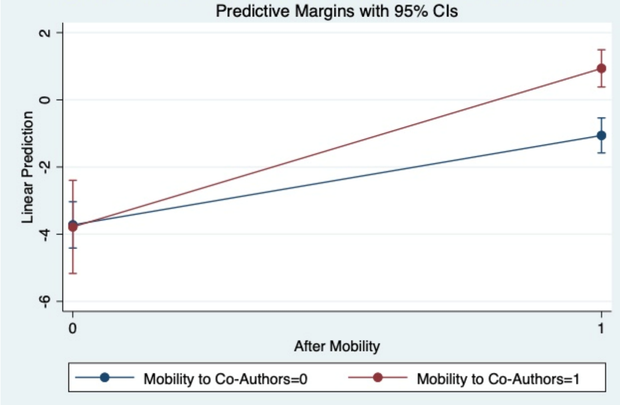


Figure 5: DiD OLS for Current Colleagues-New Co-Authors

Predictive Margins with 95% CIs



Biographical Sketches

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