

Endogeneous Matching in University-Industry Collaboration: Theory and Empirical Evidence from the UK*

Albert Banal-Estañol,[†] Inés Macho-Stadler[‡] and David Pérez-Castrillo[§]

May 2013

Abstract

This paper analyses research collaboration between academics and firms from a two-sided market perspective. We develop a matching model with heterogeneous academics and heterogeneous firms. We show that collaboration decisions are affected both by affinity-based and ability-based characteristics. We predict a positive assortative matching in terms of affinity for the type of research and in terms of scientific ability, but negative assortative in terms of ability on one side of the market and affinity in the other. Our model also shows that the most able and the most applied academic researchers and the most able and the most basic firms should prefer to collaborate rather than work independently. Our theoretical predictions receive strong support from our empirical analysis of the teams of academic researchers and firms that propose research projects to the Engineering and Physical Sciences Research Council in the UK.

JEL Classification numbers: O32, I23

Keywords: matching, industry-science links, research collaborations, basic versus applied research, complementarity

*We thank Christian Fons-Rosen, Bing Guo, Ernest Miguelez and Anna Toldrà for very useful comments, as well as Eduard Clariana, Carlos Marcos and Jonás Nieto for excellent research assistance. We also thank the very constructive comments received at the Katholieke Universiteit Leuven, Universitat de Barcelona, Ben-Gurion University of the Negev and at the workshops on "University-Industry Collaboration" in Barcelona, "Incentives and the Design of Mechanisms in Open Science" in Bordeaux and "Informal IO" in Barcelona. We gratefully acknowledge the financial support from the research grants (ECO2010-15052 and ECO2012-31962), Generalitat de Catalunya (2009SGR-169), the Severo Ochoa Programme for Centres of Excellence in R&D (SEV-2011-0075), Ramon y Cajal, and ICREA Academia. The last two authors are fellows of MOVE.

[†]Universitat Pompeu Fabra and Barcelona GSE.

[‡]Universitat Autònoma de Barcelona and Barcelona GSE.

[§]Universitat Autònoma de Barcelona and Barcelona GSE.

1 Introduction

Science and innovation in modern economies often involves collaboration across institutional boundaries. Academic research groups, for example, work sometimes independently, but inter-institutional and international collaborations and coauthorships are very common (Melin and Persson, 1996; Wagner and Leydesdorff, 2005). Similarly, while some technologies are developed by one single firm, many others are developed by research joint ventures (Kamien et al, 1992). Fortunately, a substantial body of research in the management and economics literatures has identified the causes and the consequences of inter-institutional collaboration *within* institutional markets, i.e. “one-sided market” partnerships (see Katz and Martin, 1997, and Caloghirou et al., 2003, for reviews).

But the full transformation of modern societies into knowledge and science-based economies also requires collaboration *across* institutional markets, i.e. “two-sided market” partnerships. Collaborative links through joint research, consulting or training arrangements, for example, are key channels of knowledge transfer, according to both the academics (Agrawal and Henderson, 2002) and the firms (Cohen et al., 2002). As a result, university-industry collaborations are nowadays stronger and more widespread than ever before (D’Este and Patel, 2007; Perkmann et al., 2013). Unfortunately, in spite of their tremendous importance, we know very little on which groups of which institutions engage in collaboration and which partnerships are actually formed.

This paper investigates the outcomes of the two-sided market collaboration process and, in particular, the characteristics of the resulting partnerships. We ask what type of groups in each side of the market are more likely to collaborate with each other, and what characteristics affect the groups’ likelihood of collaborating, as opposed to work independently. We consider both “horizontal” and “vertical” characteristics, i.e. those related to affinity (e.g. preferences for type of scientific research) and those related to ability (e.g. capacity to produce high-quality scientific output). We show theoretically and empirically that collaboration decisions are affected both by affinity-based and ability-based characteristics, as well as by individual and institutional characteristics, but to a various degrees.

Survey evidence helps identifying the costs and benefits of engaging in research collaboration. Academics report to collaborate with firms to complement their academic research, because collaboration provides them with additional funds and insights (Lee, 2000; Mansfield, 1995). Collaboration, however, might bias their selection of research topics and methodology (Cohen et al., 1998; Florida and Cohen, 1999). Firms report to collaborate with academics to get access to new university research and discoveries (Lee, 2000). Some of them, however, have no or little commercial potential. Firms are also concerned with the differences in terms of organizational and institutional structure, and with the existence of the open science culture in academia (Dasgupta and David, 1994).

Before deciding whether to collaborate with a particular partner, academics and firms must then weigh benefits and costs. Unfortunately, most of the em-

empirical evidence on performance for each side of the market has focused on average effects, across all partnerships. On the firm side, collaboration has been shown to lead to better patents (Cockburn and Henderson, 1998; Cassiman and Veugelers, 2006), to more products and to increased sales (Zucker et al., 2002; Belderbos et al., 2004). On the academic side, collaboration has been linked to a higher number of academic research publications (Calderini et al., 2007; Stephan et al., 2007; Fabrizio and DiMinin, 2008; Azoulay et al., 2009).¹ Recent evidence, however, stresses the importance of the characteristics of the matching partners in assessing collaboration outcomes. Banal-Estanol et al. (2013), for example, show that collaborative projects produce more scientific output than non-collaborative ones if and only if they involve research-intensive firms.

Therefore, the rewards from collaboration are highly heterogeneous and shall depend on own, as well as on the potential partner's, characteristics. For instance, all academics, but especially those that are more research-oriented, might prefer firms that encourage their employees to publish scientific articles (Cockburn and Henderson, 1998). Similarly, all firms might prefer to collaborate with "star" academics, as these collaborations lead to higher firm performance (Zucker et al. 2002).² Research oriented firms and star academics, however, might not be willing nor able to collaborate with all participants in the other side of the market. Given the costs and benefits of collaborating with each potential research partner, how do academics and firms mutually choose each other, and which of them decide to work independently?

To understand the mechanisms at work, we develop a two-sided matching market model of academic researchers and firms developing research projects. Participants in each side of the market are heterogeneous in terms of project preferences (degree of "appliedness") and scientific ability (past publications, patents, or know-how). Together with the endogenous investment levels (pecuniary or non-pecuniary resources), these characteristics determine the participants' value of a project (type and number of, or probability of obtaining, research results). We allow each participant to develop a project on her own, or actively search for an appropriate partner on the other side of the market to develop a collaborative project. Our model is thus part of the recent emerging literature on two-sided market matching models with endogenous contracts (Legros and Newman, 2002; Dam and Pérez-Castrillo, 2006; Serfes, 2008; Alonso-Paulí and Pérez-Castrillo, 2012).³

¹Agrawal and Henderson (2002), however, find no effect of the number of patents on the number of publications. Banal-Estañol et al. (2010) find an inverted U-shaped relationship between industry collaboration and academic research output.

²Academic researchers' individual characteristics and attitudes, as well as local group norms seem to play a role in the collaboration decision (Louis et al., 1989). Firms' size, absorptive capacity and the adoption of open search strategies are also important factors in the firms' willingness to collaborate (Mowery, 1983; Veugelers and Cassiman, 2005; Mohnen and Hoareau, 2003; Fontana et al., 2006; Laursen and Salter, 2004; Bercovitz and Feldman, 2007). Geographical proximity between the researchers' university and the firms has also been shown to be important, particularly for researchers in universities with modestly rated faculties (Mansfield and Lee, 1996; Audretsch and Stephan, 1996).

³Our paper is also related to the optimal assignment literature that follows Becker (1973).

We first derive results on the type of projects chosen, and individual investments made, by stand-alone and collaborating participants. Collaborating partners end up working in projects away from their ideal type, with a bias that is proportional to the relative value attached to the project by each partner. Investment in the project is decreasing in the distance between the ideal type of each partner. We then make predictions on who collaborates and who collaborates with whom using the stand-alone and joint project agreements. If the costs due to collaboration are not too large, the most able researchers and the most able firms collaborate whereas the least able do not. We also show that if the types of the academics are overall more basic than those of the firms, the most applied researchers and the most basic firms collaborate, whereas the most basic researchers and the most applied firms develop projects on their own. This is because the value of collaboration is decreasing in terms of the distance between ideal types.

With respect to the partnerships formed, our theoretical model makes three predictions. First, the matching is positive assortative in terms of scientific ability, i.e. top academics collaborate with top firms and less able academics collaborate with less able firms. This is because partner abilities are complementary in collaborative agreements: the higher the ability of an academic, the more she benefits from the higher investment from a firm with higher ability, and viceversa. Second, the matching is also positive assortative in terms of affinities, i.e. academics with more applied bias collaborate with firms with more applied bias. The reasons however are different. The equilibrium matching is positive assortative in affinity to minimize the total costs due to the distances between the ideal types of partners. Appropriate (pecuniary or non-pecuniary) transfers ensure that the matching formed maximizes total worth and not necessarily the worth of any particular partnership. Finally, we show that the matching is negative assortative in terms of the ability-affinity pair, i.e. the higher the ability of the academic, the closer from the firm she is in terms of type.

We test our theoretical predictions on the teams of academic researchers and firms that propose research projects to the Engineering and Physical Sciences Research Council (EPSRC), the main government agency for research funding for the engineering departments of the UK universities. The EPSRC grants are allocated to teams of academic researchers alone but also to teams that include one or more firms as industry partners. We proxy for the scientific ability and type of each partner using their publications in the years prior to the start of the project. We take normal count and the impact-factor-weighted sum of publications as a proxy for scientific ability and the proportion of publications in basic or applied journals as proxy for type of research (Narin et al., 1976; Godin, 1996 and van Looy et al., 2006). Our unique dataset allows us to construct continuous variables of ability and type of partner to best proxy for ability and affinity-based characteristics.

Following Agrawal et al. (2008) and Gompers et al. (2012), we test for who

He presents a theory of marriage and shows that positive assortative matching arises when abilities (or any other characteristics) are product complements.

partners with whom using both the formed partnerships and a set of plausible alternatives, or counterfactual pairs, constructed using exogenous characteristics. We show that the cross-partial derivative of the measures of ability of each partner, as well as the cross-derivative of the measures of affinity, are positive, providing thus support for the theoretical prediction of positive matching in terms of ability and affinity. The cross-partial derivative of ability and distance of types is instead negative, providing thus support for the theoretical prediction of negative assortative matching in terms of ability and affinity-based characteristics.

We quantify the effects by computing the marginal effects of the likelihood of forming a link of several dummy variables that capture the relative position of each partner on each side of the market. We show that pairs of academics and firms that are both at the top quartile of the distribution of abilities are 29.5% more likely to be matched, whereas those pairs in which none of them is at the top quartile are 10.5% more likely, compared to those pairs in which one of them is. Similarly, academics and firms are 33% (38.5%) more likely to be matched if they are both above the median (both below the median) in terms of type. Although positive, the effects for being above the median in terms of ability are less strong. Taken together, these results suggest that matching occurs at the top of the distribution in terms of ability but over the whole distribution in terms of affinity.

We also assess the relative importance of the horizontal-affinity versus the vertical-ability characteristics, as well as the relative importance of the individual versus the institution characteristics. The horizontal characteristics are relatively more important than the vertical ones, both in terms of magnitude and significance of the effects. Importantly, the characteristics at the individual level appear to be more relevant than at the institutional level. A top firm tends to collaborate with a top researcher, and form links with a top academic institution only insofar as it includes top researchers. This reinforces the view that the fundamental unit of collaboration is composed of individuals, not institutions (Katz and Martin, 1997).

Finally, we test for the characteristics of the academics that submitted non-collaborative instead of collaborative projects. Confirming our theoretical predictions, the most applied as well as the most able researchers are significantly more likely to propose collaborative projects. Academics that are above the median in terms of ability and those who are more applied than the median are 16.3% and 37.4% more likely to propose collaborative projects, respectively. In terms of aggregate measures, we show that academics in larger universities, in terms of number of projects, are also more likely to submit collaborative projects. But other institutional variables, such as the scientific level of the department, are less important.

This paper is part of a small but rapidly growing literature on two-sided matching in business-science links. Agarwal and Ohyama (2012) study, both theoretically and empirically, the labour market for scientists. The academic and private sector choose among scientists who differ in their ability and preferences, and scientists choose between academia and industry. Our application of course

differs from theirs, and includes multiple partners in each side of the market.

Mindruta (forthcoming), perhaps the closest paper to ours, identifies, empirically, ability-based characteristics as a source of complementarity in university-industry collaboration. In addition to ability, we show that affinity-based characteristics can be at least as important to matching partners. Methodologically, she assumes a joint production function and estimates the interaction parameters and joint production values, following Fox’s (2008) empirical strategy. Instead, we derive a joint production function from first principles, i.e. from preferences and optimization, in our theoretical part. In our empirical part, we do not attempt to estimate the value of the formed pairs, and can thus avoid making assumptions on joint production functions. We rely on matched and non-matched counterfactual pairs to analyze which characteristics make participants more likely to be matched.

2 Theoretical model

We consider a “market” with m heterogeneous academic researchers $\mathcal{A} = \{A_1, A_2, \dots, A_m\}$, and n heterogeneous firms $\mathcal{F} = \{F_1, F_2, \dots, F_n\}$. Academics and firms can develop research projects on their own, labelled as “non-collaborative” projects, or form academic-firm partnerships and carry out “collaborative” projects. Both academic researchers and firms can actively search for an appropriate partner and agree on the terms of the project. That is, the matching and the projects are endogenous. Due to time and other constraints, the agents have limited capacity to work on projects. For simplicity, we assume that each academic and firm develops only one project. That is, we model a “one-to-one matching market”.⁴

In the following subsection, we describe the projects that would be independently developed by an academic researcher A and by a firm F , and the collaborative project they would develop shall they decide to form a partnership. In the second subsection, we endogenise the formation of partnerships. Proofs are in Appendix.

2.1 Collaborative and non-collaborative projects

We argue that an academic or firm has preferences on the “type” of projects and is endowed with a certain ability to develop projects. The participants (academic, firm, or academic and firm if the project is collaborative) decide on the type of the project and on the investment levels. The investment levels and the ability of the agents involved determine the results of the project (for example, the number of publications that are obtained). Then, we can compute the expected value of the project for the participants given their preferences, and

⁴A (two-sided) matching market is one in which there are two distinct sets of agents. It is one-to-one if an agent from one side of the market can be matched only with an agent from the other side or remain unmatched. For an introduction to matching markets, see Roth and Sotomayor (1990).

the type and results of the project. In the next subsection, we will use the value of each possible (collaborative and noncollaborative) project to characterize the equilibrium in this market.

Project type and preferences of the participants Projects can be of a more basic or of a more applied type. We identify the level of “appliedness” by a parameter $x \in [0, 1]$, where $x = 0$ corresponds to the least applied project (the most basic one) and $x = 1$ corresponds to the most applied project.

We denote x_A and x_F the most preferred type of project of academic researcher A and firm F , and by v_A (resp. v_F) the value of a positive result for an academic (resp. a firm) from a research project of its most preferred type. A successful project has less value for academic A if x is different from x_A ; the larger the distance $|x - x_A|$, the larger the loss in value. Following Pereira (2007)⁵ and Banal-Estañol et al. (2013), we model the loss in value as a “transportation cost”, in the spirit of the Hotelling model. That is, the value for academic A of a positive result in a project of type x is $v_A(1 - t(x - x_A)^2)$, where $t \leq 1$ denotes the transportation cost parameter. Similarly, the value for firm F of a positive result in project x is $v_F(1 - t(x_F - x)^2)$.

Figure 1 represents the value of a positive result for A and F , as a function of the type of project x .

[Insert Figure 1 here]

Investment levels and outcome of projects When academics or firms run projects on their own, the number of positive results (or the probability of obtaining a positive result) depends on their own ability and investment. For simplicity, we assume that it is given by $\delta_A I_A$ and $\delta_F I_F$, where δ_A (resp. δ_F) represents the academic’s (resp. firm’s) ability, or efficiency, and I_A (or I_F) represents the academic’s (resp. firm’s) investment levels. The parameter δ_A measures the technical and scientific level of the academic A , her publications, the patents and know-how she owns, the quality of the labs she works in, etc., whereas the parameter δ_F measures the scientific level of the firm F , its absorptive capacity, the level of its human capital, etc. The investment level I_A (or I_F) can be effort, time or money invested in the project. Investment has an associated cost $\frac{c}{2} I_A^2$ (resp. $\frac{c}{2} I_F^2$).

Summarizing, when an academic with characteristics (x_A, δ_A) runs a non-collaborative project of type x in which she invests I_A , her profits are

$$\pi_A(x, I_A) = v_A \left(1 - t(x - x_A)^2 \right) \delta_A I_A - \frac{c}{2} I_A^2.$$

⁵Pereira (2007) theoretically analyzes the characteristics of partnership agreements when informational problems are present. She shows that two different structures of partnership governance - centralized and decentralized - may optimally use the type of the project to motivate the supply of non-contractible resources. In her approach the partners are predetermined. In contrast, our paper ignores incentive issues and concentrates on analyzing which collaborative agreements will be formed.

Similarly, a firm with characteristics (x_F, δ_F) that develops a project (x, I_F) on its own obtains profits

$$\pi_F(x, I_F) = v_F \left(1 - t(x_F - x)^2\right) \delta_F I_F - \frac{c}{2} I_F^2.$$

In collaborative projects, the value to each party depends on the agreed type of project and on the investments of both participants; for the academic, it is given by

$$\pi_A(x, I_A, I_F) = v_A \left(1 - t(x - x_A)^2\right) \lambda_A (\delta_F + \delta_A) (I_F + I_A) - \frac{C}{2} I_A^2, \quad (1)$$

whereas for the firm it is given by

$$\pi_F(x, I_A, I_F) = v_F \left(1 - t(x_F - x)^2\right) \lambda_F (\delta_F + \delta_A) (I_F + I_A) - \frac{C}{2} I_F^2. \quad (2)$$

Parameters λ_A and λ_F lie in the interval $[0, 1]$. Following previous results on the literature,⁶ we argue that collaboration has advantages as well as costs. On the positive side, the probability or the number of positive results now depends on the ability and investment of both partners, represented by $(\delta_F + \delta_A) (I_F + I_A)$. On the negative side, there are two elements. The fraction of the outcome that is beneficial for the academic researcher or firm, represented by the parameter λ_A or λ_F might be less than one. In addition, the cost of investing in a collaborative project can be higher than in a non-collaborative project, $C \geq c$, because of for example the increased coordination costs. The specification of the previous two effects allows us to consider different degrees of synergies that partners can obtain.

Optimal non-collaborative projects In an stand-alone project, academic A (resp. firm F) chooses the type of project x and the investment I_A (resp. I_F) that maximizes her (resp. its) profits. Proposition 1 describes the optimal project.⁷

Proposition 1 *The optimal project $P_A^n = (x_A^n, I_A^n)$ for an academic A with individual characteristics (x_A, δ_A) is*

$$x_A^n = x_A \quad \text{and} \quad I_A^n = \frac{1}{c} v_A \delta_A,$$

whereas the optimal project $P_F^n = (x_F^n, I_F^n)$ for a firm F with individual characteristics (x_F, δ_F) is

$$x_F^n = x_F \quad \text{and} \quad I_F^n = \frac{1}{c} v_F \delta_F.$$

⁶See, for instance, Dasgupta and David (1994), Champness (2000), and Veugelers and Cassiman (2005).

⁷The proof of Proposition 1 is immediate.

The type of the optimal non-collaborative project corresponds to the most preferred type for the agent. Intuitively, the optimal investment increases with the value associated to a positive result and the ability whereas it is decreasing in the cost of the investment. Substituting into the profit functions, we can compute the profits of stand-alone projects:

$$\pi_A^n(x_A, \delta_A) = \frac{1}{2c} v_A^2 \delta_A^2 \quad \text{and} \quad \pi_F^n(x_F, \delta_F) = \frac{1}{2c} v_F^2 \delta_F^2.$$

Optimal collaborative projects When they decide to develop a collaborative project, academic and firm need to agree on the type x of the project and the level of investments, I_A and I_F , each will devote. In addition to $P_{AF} = (x, I_A, I_F)$, they may agree on a monetary transfer.⁸ The possibility to transfer profits implies that both the academic researcher and the firm have incentives to agree on the type and the investments that maximize joint profits. In other words, the chosen project $P_{AF}^c = (x^c, I_A^c, I_F^c)$ corresponds to the vector (x, I_A, I_F) that maximizes joint profits $\Pi_{AF}(x, I_A, I_F) \equiv \pi_A(x, I_A, I_F) + \pi_F(x, I_A, I_F)$.

Next proposition provides the optimal agreement.

Proposition 2 *The optimal collaborative project $P_{AF}^c = (x^c, I_A^c, I_F^c)$ between an academic A with individual characteristics (x_A, δ_A) and a firm F with individual characteristics (x_F, δ_F) is*

$$x^c = \frac{\lambda_A v_A}{\lambda_A v_A + \lambda_F v_F} x_A + \frac{\lambda_F v_F}{\lambda_A v_A + \lambda_F v_F} x_F,$$

and

$$I_A^c = I_F^c = \frac{1}{C} V_{AF} (|x_F - x_A|) (\delta_A + \delta_F),$$

where

$$V_{AF} (|x_F - x_A|) \equiv \lambda_A v_A + \lambda_F v_F - \frac{\lambda_A v_A \lambda_F v_F}{(\lambda_A v_A + \lambda_F v_F)} t(x_F - x_A)^2.$$

The type of a collaborative project lies between the most preferred type of project for the academic and the most preferred project of the firm. The distances between the agreed type and the ideal types, $|x^* - x_A| = \frac{\lambda_F v_F}{\lambda_A v_A + \lambda_F v_F} |x_F - x_A|$ and $|x^* - x_F| = \frac{\lambda_A v_A}{\lambda_A v_A + \lambda_F v_F} |x_A - x_F|$, depend on the relative value that the participants give to the project results and their capacity to appropriate them. The higher the value that the academic can appropriate from the project, the closer the type of project to her most preferred one. The optimal investment levels are a function of the partners' ability and the cost of investment, as well as the "joint value" of a result $V_{AF} (|x_F - x_A|)$, which depends on the distance $|x_F - x_A|$.

⁸We consider that the transfer, or compensation, from one partner to the other is monetary for simplicity. We discuss later the possible differences in the results if transfers were not possible.

Substituting the results in Proposition 2, the total profits from an optimal collaborative project, $\Pi_{AF}^c(x_A, \delta_A, x_F, \delta_F)$ are

$$\Pi_{AF}^c = \frac{1}{C} (V_{AF}(|x_F - x_A|))^2 (\delta_A + \delta_F)^2. \quad (3)$$

Total profits Π_{AF}^c are decreasing in the distance between the most preferred project for the academic and the firm.

2.2 The Market Equilibrium

Academic researchers and firms are heterogeneous in terms of preferences for type of research and ability, i.e. it is possible that $x_{A_i} \neq x_{A_{i'}}$, $x_{F_j} \neq x_{F_{j'}}$, $\delta_{A_i} \neq \delta_{A_{i'}}$, or $\delta_{F_j} \neq \delta_{F_{j'}}$ for $A_i, A_{i'} \in \mathcal{A}$ and $F_j, F_{j'} \in \mathcal{F}$. For simplicity, we assume that academics share the same valuation and appropriability in collaborative projects, i.e. $v_{A_i} = v_A$ and $\lambda_{A_i} = \lambda_A$ for every $A_i \in \mathcal{A}$ and similarly for the firms, i.e., $v_{F_j} = v_F$ and $\lambda_{F_j} = \lambda_F$ for every $F_j \in \mathcal{F}$. Therefore, each academic A_i is characterized by a pair (x_{A_i}, δ_{A_i}) and each firm F_j by a pair (x_{F_j}, δ_{F_j}) .

Notice that the two characteristics are radically different from the point of view of the partnership. The differences in ability represent “vertical” differentiation: an academic with a higher δ_A is a better academic than an academic with a lower δ_A , and the joint profits of a collaborative project increase with δ_A . The differences in the preference for type of research represent “horizontal” differentiation: an academic with a high x_A is not better or worse than an academic with a low x_A . The joint profits of a collaborative project increase when the types of academic and firm are similar, not when either of them is high or low.

We proceed as follows. After providing the formal definitions and some basic properties, we investigate which characteristics of an academic make her more likely to be matched with a given firm, and vice-versa. That is, we ask: who is matched with whom? Second, we study which characteristics of the academics and the firms make them more likely to engage in collaborative, versus non-collaborative, projects.

Formal definitions Any academic in the population of academics $\mathcal{A} = \{A_1, A_2, \dots, A_m\}$ (respectively any firm in the population of firms $\mathcal{F} = \{F_1, F_2, \dots, F_n\}$) either collaborates with some firm (resp. academic) or she (it) does not collaborate. We represent the collaboration decision through a function that links an academic and firm if they collaborate and an academic (firm) with herself (itself) if she (it) conducts a non-collaborative project.

A *matching* is a function that describes which academics and firms form partnerships and with whom. Formally, a matching is a mapping μ from $\mathcal{A} \cup \mathcal{F}$ (the union of the sets of academics and firms) to $\mathcal{A} \cup \mathcal{F}$ such that (i) $\mu(A) \in \mathcal{F} \cup \{A\}$ for all $A \in \mathcal{A}$, (ii) $\mu(F) \in \mathcal{A} \cup \{F\}$ for all $F \in \mathcal{F}$, and (iii) $\mu(A) = F$ if and only if $\mu(F) = A$ for all $A \in \mathcal{A}, F \in \mathcal{F}$. If A and F develop a collaborative project then $\mu(A) = F$ and $\mu(F) = A$. If A (resp. F) develops a non-collaborative project then $\mu(A) = A$ (resp. $\mu(F) = F$).

A matching μ is *positive assortative with respect to some characteristic y* if the partner $\mu(A_i)$ of an academic A_i with a higher y than an academic $A_{i'}$ has a higher (or equal) y than the partner $\mu(A_{i'})$ of the academic $A_{i'}$. And a negative assortative matching is defined in a similar manner.

An *outcome* is a pair (μ, \mathcal{P}) that describes which partnerships are formed and which projects are developed. In an *equilibrium outcome*, no academic or firm can improve upon her or its current payoff. That is, no academic or firm in a collaborative project can be better off by developing a non-collaborative project and, no academic and firm can be better off by quitting their current partners, if any, dropping their present projects and form a new partnership.

Basic properties We borrow from previous literature two basic properties of our equilibrium outcomes.^{9,10} First, *in an equilibrium outcome (μ, \mathcal{P}) , all the projects are optimal*. That is, it is not possible for any academic, firm or existing academic-firm pair to design an alternative project in which they are better off. As a result, the terms of the projects in any equilibrium outcome are the ones described in Propositions 1 and 2. Once we identify the matching μ in a equilibrium outcome, the two propositions uniquely determine the characteristics of the set of projects \mathcal{P} .

Second, in an equilibrium outcome, *the matching μ is efficient*, in the sense that it maximizes total surplus, i.e. the total surplus cannot be increased by reassigning firms and academics to different partnerships. This property derives from competition in the market: as firms compete among themselves for the best academic partner, and academics compete among themselves for the best firm partner, the resulting matching maximizes total market surplus. If this was not the case, an agent, or a pair of agents, would obtain more benefits in an alternative matching.

Partnerships formed We now focus on the properties of “matched” academics and firms, i.e. those that develop collaborative projects. We check first whether top academic researchers end up forming collaborative agreements with top firms. Then, we check whether more applied academics form partnerships with more applied firms. That is, we investigate whether the matching is positive or negative assortative with respect to ability and type.

To isolate the effects of heterogeneity in ability, we consider a market where all academics have the same preferences with respect to the type of project, and similarly for all the firms.

Proposition 3 *Consider a market $(\mathcal{A}, \mathcal{F})$ where $x_{A_i} = x_A$ for all $A_i \in \mathcal{A}$ and $x_{F_j} = x_F$ for all $F_j \in \mathcal{F}$. Then, for any equilibrium outcome (μ, \mathcal{P}) the*

⁹The proofs of the properties in this section follow the same arguments as those used in previous papers (see, for instance, Dam and Pérez-Castrillo, 2006, Serfes, 2008, and Alonso-Paulí and Pérez-Castrillo, 2012).

¹⁰In our setup, equilibrium outcomes always exist and therefore the solution concept that we use is well defined. This follows directly from Kaneko (1982). He generalizes the assignment game proposed by Shapley and Shubik (1972) and demonstrates the non-emptiness of the core in this setup.

matching is positive assortative in terms of ability: if $\mu(A_i) = F_j$, $\mu(A_{i'}) = F_{j'}$ and $\delta_{A_i} \geq \delta_{A_{i'}}$, then $\delta_{F_j} \geq \delta_{F_{j'}}$.

Therefore, among the collaborative partners, top academics collaborate with top firms. Figure 2 helps understanding the matching of an equilibrium outcome in terms of ability. Following the second property above, the matching is positive assortative if the efficient matching is positive assortative. But the efficient matching is positive assortative if the characteristics of each partner are complementary to each other in the sum of profits.¹¹ In this case, partner abilities are complementary because higher ability academics benefit more from collaborating with higher ability firms: the higher the ability of an academic, the more she benefits from the higher investment decided by a firm with higher ability, and viceversa. In numbers, Figure 2 shows two possible matchings, μ and μ' , where μ' cannot be an equilibrium. Academic A_1 benefits more from collaborating with firm F_1 than academic A_2 (in the figure, $20 - 12 > 10 - 5$). The same is true for the firms ($20 - 10 > 10 - 7$). Hence, the efficient outcome requires the collaboration of the best academic with the best firm ($40 + 12 > 22 + 20$).

[Insert Figure 2 here]

To isolate the effects of heterogeneity in preference for (relatively) more basic versus more applied research, we now consider a market where all academics have the same ability, and similarly for all the firms.

Proposition 4 Consider the market $(\mathcal{A}, \mathcal{F})$ where $\delta_{A_i} = \delta_A$ for all $A_i \in \mathcal{A}$ and $\delta_{F_j} = \delta_F$ for all $F_j \in \mathcal{F}$. Then, for any equilibrium outcome (μ, \mathcal{P}) , the matching is positive assortative in terms of type: if $\mu(A_i) = F_j$, $\mu(A_{i'}) = F_{j'}$ and $x_{A_i} \geq x_{A_{i'}}$, then $x_{F_j} \geq x_{F_{j'}}$.

Proposition 4 implies that, among the collaborative partners, academics with more applied interest collaborate with firms with more applied bias. Figure 3 represents two possible matchings μ and μ' in terms of preferences for (relatively) more basic versus more applied research. The preferences for applied research of each partner are again complementary to each other in the sum of profits. Matching μ' cannot be an equilibrium: although (in this example) the total distance between types in the two matchings is the same, there is more dispersion in the distances in matching μ' . Therefore, since the profits are convex in the distance, the profits in matching μ are larger. Notice that even if the individual profits for A_3 and F_2 are higher in μ' ($10 - 8 > 0$ for both A_3 and

¹¹In formal terms, the efficient matching is positive assortative with respect to the characteristic y if $\Pi_{RF}(y_{R_i}, y_{F_j}) + \Pi_{RF}(y_{R_{i'}}, y_{F_{j'}}) \geq \Pi_{RF}(y_{R_i}, y_{F_{j'}}) + \Pi_{RF}(y_{R_{i'}}, y_{F_j})$ whenever $y_{R_i} \geq y_{R_{i'}}$ and $y_{F_j} \geq y_{F_{j'}}$. A sufficient condition for the inequality is that $\frac{\partial^2 \Pi_{RF}}{\partial y_R \partial y_F} \geq 0$. See also Legros and Newman (2002) for more general sufficient conditions for positively or negatively assortative matchings.

F_2), matching μ' cannot be an equilibrium matching as their individual loss in μ can be compensated by A_2 and F_3 with the additional gains they obtain (8–3 each of them).

[Insert Figure 3 here]

Our model also generates predictions on the interaction between the two characteristics. Proposition 5 shows that the higher the ability of the academic, the more damaging is the distance to the most preferred type. Therefore, in an equilibrium outcome, there is an inverse relationship between ability and distance between the partners' types. We can say, with a small abuse of the definition of assortative, that the matching is negative assortative in terms of the ability-distance pair.¹² The proposition states this property in terms of ability and type of the academics, but we would have an equivalent one in terms of the firms.

Proposition 5 *Consider the market $(\mathcal{A}, \mathcal{F})$ where $\delta_{F_j} = \delta_F$ for all $F_j \in \mathcal{F}$ and $x_{A_i} = x_A$ for all $A_i \in \mathcal{A}$. Then, for any equilibrium outcome (μ, \mathcal{P}) , the matching is negative assortative in terms of the academic's ability-distance pair: if $\mu(A_i) = F_j$, $\mu(A_{i'}) = F_{j'}$ and $\delta_{A_i} \geq \delta_{A_{i'}}$, then $|x_{F_j} - x_A| \leq |x_{F_{j'}} - x_A|$.*

Discussion on the effect of transfers In our setup, we assume that transfers between firms and academic researchers are possible. We recognize the possibility that partners can make their collaborative project more appealing to their partner than other, competing offers for collaboration. But, what would be the equilibrium matching if those transfers were not possible?¹³

In terms of the vertical dimension, the ability, the matching would still be positive assortative. All academics agree that the best partner is the firm with the highest ability, and all the firms agree that the best partner is the academic with the highest ability. Given that the best academic wants to collaborate with the best firm and the best firm wants to match with the best academic, they are necessarily matched in the equilibrium matching (otherwise, they would deviate by joining in a collaborative project). By the same argument, once the best academic and firm are not available, the second best academic is certainly matched to the second best firm in an equilibrium matching and, by induction, the k th best academic is matched with the k th best firm. Therefore, without transfers, the matching is also positive assortative in ability.

However, the matching is not necessarily positive or negative assortative in types (in general, in any horizontal characteristic) if transfers are not possible.

¹²As it customary, we have formally defined a positively or negatively assortative matching in terms of one characteristic, or type, that affects both sides of the market. In the next proposition, we also use the term “negatively assortative” to refer to a property that affects one characteristic of one side of the market and a different characteristic for the other side.

¹³One-to-one matching models where monetary transfers are not possible are usually referred to as “marriage markets”. They were introduced by Gale and Shapley (1962).

In this case, the relevant information is the distance between the academic's and the firm's most preferred project. If the distribution of types of the academics is the same as the one of the firms (i.e. $x_{A_1} = x_{F_1}$, $x_{A_2} = x_{F_2}$, and so on), then each agent finds a partner in the other side of the market with the same type and the equilibrium matching is $\mu(x_{A_k}) = x_{F_k}$ for all k . In this example, the matching is positive assortative.

But, if the distribution of types is asymmetric, then the previous result may not hold. For instance, consider a market with two academics and two firms, where $x_{A_1} < x_{A_2} = x_{F_1} < x_{F_2}$. In this case, firm F_1 is the best partner for academic A_2 , who is the best partner for firm F_1 and, at equilibrium, $\mu(x_{A_2}) = x_{F_1}$. The other two agents collaborate among themselves and therefore $\mu(x_{A_1}) = x_{F_2}$. In this example, the matching is negative assortative. Therefore, although there is an effect that pushes towards a positive assortative matching (an academic with a high x_A prefers a firm with a high x_F), the matching is not always positive assortative in type if transfers among partners are not possible.

Collaborating versus non-collaborating We now identify which characteristics of the academics and the firms make them more likely to develop collaborative projects, as opposed to non-collaborative projects. Denote $\Delta(x_A, \delta_A, x_F, \delta_F)$ the “net benefits from collaboration”, i.e., the difference between the joint profits in a collaborative project and the sum of the individual profits in non-collaborative projects:

$$\Delta(x_A, \delta_A, x_F, \delta_F) \equiv \Pi_{AF}^c(x_A, \delta_A, x_F, \delta_F) - \pi_A^n(x_A, \delta_A) - \pi_F^n(x_F, \delta_F).$$

Collaboration is jointly beneficial if $\Delta(x_A, \delta_A, x_F, \delta_F) > 0$ and only partnerships that are jointly beneficial can form in equilibrium.

We first analyze the effects of ability. The ability has a positive impact on the benefits from collaboration but it also increases the profits in non-collaborative projects. Proposition 6 states that the crucial determinant in this trade-off is the ratio between δ_F and δ_A . The larger this ratio, the more likely it is that the net benefits increase with δ_A and decrease with δ_F .

Proposition 6 *The net benefits from collaboration (i) increase in δ_A if and only if*

$$\frac{\delta_F}{\delta_A} > \frac{C}{2c} \frac{v_A^2}{(V_{AF}(|x_F - x_A|))^2} - 1, \quad (4)$$

and (ii) increase in δ_F if and only if

$$\frac{\delta_A}{\delta_F} > \frac{C}{2c} \frac{v_F^2}{(V_{AF}(|x_F - x_A|))^2} - 1. \quad (5)$$

The net benefits from collaboration increase in δ_A for any δ_A if the right-hand side of (4) is negative. This happens if the relative cost of investing in a collaborative versus a non-collaborative project, C/c , is not large, or if the value of successes in collaboration, measured by $V_{AF}(|x_F - x_A|)$, is large. A similar

condition allows to ensure that net benefits from collaboration increase in δ_F for any δ_F . They are stated as Conditions 1a and 1b.

Condition 1a *The market $(\mathcal{A}, \mathcal{F})$ satisfies $x_{A_i} = x_A$ and $x_{F_j} = x_F$ for all $A_i \in \mathcal{A}, F_j \in \mathcal{F}$ and $\frac{2}{C} (V_{AF}(|x_F - x_A|))^2 \geq \frac{1}{c} v_A^2$.*

Condition 1b *The market $(\mathcal{A}, \mathcal{F})$ satisfies $x_{A_i} = x_A$ and $x_{F_j} = x_F$ for all $A_i \in \mathcal{A}, F_j \in \mathcal{F}$ and $\frac{2}{C} (V_{AF}(|x_F - x_A|))^2 \geq \frac{1}{c} v_F^2$.*

Proposition 7 *If condition 1a holds, high-ability academics collaborate with firms whereas low-ability academics develop non-collaborative projects, and similarly, if condition 1b holds, high-ability firms collaborate with academics whereas low-ability firms develop non-collaborative projects. That is, for any equilibrium outcome (μ, \mathcal{P}) (i) if Condition 1a holds and $\mu(A_i) = A_i$, then $\mu(A_{i'}) = A_{i'}$ if $\delta_{A_{i'}} < \delta_{A_i}$ and (ii) if Condition 1b holds and $\mu(F_j) = F_j$, then $\mu(F_{j'}) = F_{j'}$ if $\delta_{F_{j'}} < \delta_{F_j}$.*

We now consider how net benefits from collaboration depend on the agents' types. The effect is not monotone. For instance, net benefits from collaboration increase in the academic's type as long as it is lower than the firm's type, and decrease otherwise. As shown by Proposition 8, the net benefits from collaboration decrease in the distance between the partners' types.

Proposition 8 *The net benefits from collaboration (i) increase in x_A if and only if $x_A < x_F$, and (ii) increase in x_F if and only if $x_F < x_A$.*

This result is obtained because the joint profits decrease with the distance between partners' types whereas the individual profits do not depend on the agents' types. Still, Proposition 8 alone does not allow us to characterize which types of academics or firms are more likely to collaborate. It only states that collaboration is more likely for "similar" partners. Therefore, an agent is less likely to collaborate if her type is very different from the types of the agents in the other side.

Obtaining a precise prediction requires assumptions on the distribution of types of academics and firms. We now illustrate the consequences of two intuitive assumptions. Conditions 2a and 2b define two classes of distributions of types where the academics' preferences are, in general, more basic than those of the firms.

Condition 2a *The market $(\mathcal{A}, \mathcal{F})$ satisfies $\delta_{A_i} = \delta_A, \delta_{F_j} = \delta_F$ and $x_{A_i} \leq x_{F_j}$ for all $A_i \in \mathcal{A}, F_j \in \mathcal{F}$.*

Condition 2b *The market $(\mathcal{A}, \mathcal{F})$ satisfies $\delta_{A_i} = \delta_A, \delta_{F_j} = \delta_F$ for all $A_i \in \mathcal{A}, F_j \in \mathcal{F}$ and $x_{A_1} \leq \dots \leq x_{A_k} = x_{F_1} \leq x_{A_{k+1}} = x_{F_2} \leq \dots \leq x_{A_m} = x_{F_{m-k+1}} \leq x_{F_{m-k+2}} \leq \dots \leq x_{F_n}$.*

Proposition 9 *Suppose that either condition 2a or 2b holds. Then for any equilibrium outcome (μ, \mathcal{P}) the most basic academics and the most applied firms develop non-collaborative projects: (i) if $\mu(A_i) = A_i$, then $\mu(A_{i'}) = A_{i'}$ if $x_{A_{i'}} < x_{A_i}$ and (ii) if $\mu(F_j) = F_j$, then $\mu(F_{j'}) = F_{j'}$ if $x_{F_{j'}} > x_{F_j}$.*

3 Data and descriptive statistics

3.1 Sample

We test our theoretical predictions on the teams that propose research projects to the Engineering and Physical Sciences Research Council (EPSRC). The EPSRC is the main government agency for research funding for the engineering departments of the UK universities. More than half of the overall research funding of the engineering departments comes from the EPSRC.

The EPSRC grants are allocated to teams of academic researchers alone and also to teams of academics that include one or more firms as industry partners (teams of firms alone cannot apply to EPSRC grants). As defined by the EPSRC, “collaborative research grants” are those that involve other partners. Partners generally contribute either cash or ‘in-kind’ services to the full economic cost of the research.¹⁴

Our initial sample includes all the EPSRC project proposals with starting year 2005, 2006 or 2007. For each project, we know the holding organization, the principal investigator (PI), the coinvestigators (if any), and the industry partners (if any). We take the projects with at least one academic researcher (not necessarily the PI) in the longitudinal data set in Banal-Estañol et al. (2010), which contains calendar information and publication data on all the academics employed at the engineering departments of 40 major UK universities until 2007. Our final sample consists of 5,855 projects (1,912 in 2005, 1,835 in 2006, and 2,108 in 2007). In total, we have 2,411 unique academic researchers, and 1,735 firms, which are involved in 2,057 out of the 5,855 projects. That is, 35% of the projects in our database are “collaborative” projects. The average number of researchers in each project is 2.86, and the average number of firms in the collaborative projects is 2.43.

3.2 Proxies

We proxy for the scientific ability and type of each partner using past publications. As a measure of scientific ability, we use both the normal count and the “impact-factor-weighted” sum of publications in the Science Citation Index (SCI) prior to the start of the project. The weights in the second measure are the SCI Journal Impact Factors (JIF), attributed to the publishing journal in

¹⁴Some partners in the EPSRC database are not actually private firms, but university research centers and schools, large research infrastructures (e.g. the LNCC National Laboratory of Scientific Computing), government and municipal councils, public agencies, public hospitals, charities, and trade associations (e.g. the International Union of Railways). We disregard these partners as we want to analyze collaborations with private organizations.

the year of publication. The measure takes into account not only the quantity but also the quality of the publications. Therefore, we take the weighted sum as our baseline variable but report as well the results for the normal count.

As a measure of preference for the type of research, we use the Patent Board classification (version 2005), updated by Kimberley Hamilton for the National Science Foundation, building on the classification developed by Narin et al. (1976). Based on the cross-citation matrices, it classifies journals into four categories: (1) applied technology, (2) engineering and technological science, (3) applied and targeted basic research, and (4) basic scientific research. The first two categories are considered as “technology” and the last two as “science” (see Godin, 1996 and van Looy et al., 2006). We follow this distinction and define the type of a set of articles as the number of publications in the first two categories divided by the number of publications in the four categories.

To obtain a more precise measure of the scientific ability and preference for the type of research at the time they apply for a project, we use the publications of the years prior to the initial year of the project (we also include publications of the year of the project because they relate to research developed and finished before the start of the project). In particular, we construct measures that include information on the 6 years prior to the start of the project. For example, if the initial year of a project is 2007, then the variables summarize publications during the period 2002 – 2007, respectively.¹⁵

Some of the academic researchers are not in our sample for the whole period, for example because they are junior, or come from abroad. We take this into account by computing the average count and impact-factor-weighted-sum per year, using the years available (out of the six years prior to the start of the project).

3.3 Variables

Academic researchers We use the academics’ publication data in Banal-Estañol et al. (2010), extracted from the Thompson Web of Knowledge (WoK) database. In total, our 2,411 academic researchers have published 44,399 articles in the years 2000 – 2007. For 5,067 of our projects, we have publication information of the PI.

As variables, we use the count and the impact-factor-weighted-sum of publications per year of the PI, as well as the total of the team of academic researchers in the project. Similarly, we use the type of the PI, as well as the average type for the team of academic researchers.

In addition, we use aggregate measures of organization performance. That is, for the holding organization of the grant (or the organization to which the PI and the other academic researchers belong), we obtain information on the strength of the research developed by the engineering departments from the “2008 Research Assessment Exercise Results”. This assessment incorporates total information

¹⁵We present our results using the variables that include information for 6 years, which seem to better characterize researchers and firms. However, we have also replicated all the analysis using information for 2 or 4 years and the results are very similar.

on the number of active academics and their publications for the period 2001 – 2007. We construct variables that measure the quality and quantity of ISI publications by the engineering departments at the university, as well as the research funds obtained by the university, decomposed by different types of funding (public, private, and other funding). Also, using data from the Higher Education Statistics Agency, we include variables on general characteristics of the university: total number of undergraduate and graduate students and total university’s income and expenses. Finally, we retrieved the postal code of the holding organization.

Firms We include in our dataset the WoK publications of the industrial partners. In total, we identify 201,296 publications for the period 2000 – 2007 for the 1,735 firms involved in the collaborative projects.

As in the case of the academic researchers, the variables we use are the total count and impact-factor-weighted-sum of publications per year of the team of firms participating in the project (there is no equivalent to the PI in the case of the firms). Similarly, we use the average type of the team of firms in the project.

In addition, we include variables related to the firms’ financial and employment information, using the FAME and ORBIS databases. In particular, we include the average (per firm in the team and per year) number of employees, turnover, tangible assets, profits before tax and profit margin. We also include the postal code of the headquarter of the firms.

3.4 Descriptive statistics

As shown in Table 1, the average academic team in our data base published 10.6 articles per year during the six-year period prior to the initial date of the project. Not surprisingly, this variable is very correlated (correlation is 0.889) to the average impact-weighted sum of these publications, which is 16.9. We also report the numbers for the PI of the projects, which are quite correlated with those of the team (the correlation between the count of academic and PI is 0.562 and it is 0.636 between their impact). Similarly, the average count and impact for the firms that participate in the 2,057 collaborative projects is 749 and 1,448 respectively. The variance of the publications of the firms is much larger than that of the publications of the academics. The proxies for the scientific level of the academics are positive correlated to the proxies for the scientific level of the firms in the same project. The correlation is 0.194 for the count and it is even stronger, 0.219, for the impact. This correlation suggests that the best academics collaborate with the best firms.

[Insert Table 1 here]

Concerning the type, we can only provide a proxy for the 5,519 academic teams, 4,674 PIs and 1,563 teams of firms with at least one publication in a

journal included in the Patent Board classification. The average type of the academic teams is 0.653, very similar to the average type of the PIs, which is 0.666. The very high correlation (0.938) explains the similarity between the two variables. The average type of the firms is more basic (0.579) than the type of the academics. This is probably because firms do not allow their employees to publish their most applied discoveries, which may be directly profitable for the firms. The correlation between their type (0.358) suggests that more applied academics seem to collaborate with more applied firms.

We also include cross-correlations between type and impact, which are quite negative: the correlation is -0.351 for academics, -0.396 for the PIs and is still very significant but lower for firms (-0.123). The cross-correlations indicate that more applied researchers, PIs and firms publish less and they do so in journals with lower impact factor. This last consideration is suggested by the fact that we obtain similar (unreported) results for the cross-correlations between type and count but the magnitudes are a bit smaller.

3.5 Counterfactual pairs

For the analysis of the factors that lead to the formation of some partnerships instead of other possible partnerships, we construct a set of plausible potential collaborations that were possible but were not formed (see Agrawal et al., 2008, and Gompers et al., 2012, for a similar procedure). This set (which constitutes a control group) will allow us to analyze the pairwise characteristics of the academics/firms partnerships that make it more likely that a particular collaborative agreement emerges instead of alternative collaborative partnerships.

We construct the set of plausible potential collaborations as follows. We take all the teams of academics and all the teams of firms and we consider that a pair formed by a team of academics and a team of firms is a plausible collaboration (that is, it belongs to the set of plausible potential collaborations) if the academics and the firms do not form an actual collaboration but they have a collaborative project in the same year and in the same sector.¹⁶ Once we have build this set, we choose four counterfactual pairs for each actual collaborative project in the following way. We randomly choose one plausible collaboration in which the team of researchers coincides with the one in the actual project; then one plausible collaboration in which the team of firms corresponds to the one in the actual project; then another one for the academics and for the firms. We alternate the choice to have a more balanced set of counterfactuals. Moreover, we avoid repetitions so that a counterfactual pair can only appear once.

For some collaborative pairs, it is not possible to create four counterfactual pairs due to the lack of plausible partners. However, for most of the cases we are able to complete the construction and we end up with 8,195 counterfactual

¹⁶We classify firms' activity according to the 10 US SIC division structure. For those firms for which we only have a UK SIC code, we make a simple translation from the two-digit UK SIC codes to US divisions. If the activity of the firms in the project concerns several divisions, we randomly assign one of them. Finally, we assign the "artificial division" 11 to those projects for which we can not associate any division to the firms.

projects. We will add these pairs to the 2,057 actual pairs in the matching regressions.

For the (actual and counterfactual) collaborative projects, we build the variable “geographical distance” among the partners. Using an application of the department of education in the UK based on the post codes,¹⁷ we compute the distance in miles between the location of the holding university and the firms based in the UK participating in the project. As distance with foreign firms based outside the UK, we use the amount of 1,000 miles. When there are several firms in a (actual or counterfactual) collaborative project, we use as measure of geographical distance the minimum distance between the university and the firms.¹⁸

4 Empirical results

Our theoretical analysis provides predictions on the characteristics of the academics and the firms that make them more likely to collaborate with each other as well as on the characteristics that lead them to develop non-collaborative instead of collaborative projects. In this section, we test these predictions.

In our empirical analysis, the partners are teams of academics and teams of firms. We treat a “team of academics” as an academic and a “team of firms” as a firm. Therefore, when we talk, for instance, about the ability of an academic, we mean the ability of the “team of academics”. Similarly, when we say that there is a positive matching between academics and firms, we mean that there is a positive matching between “teams of academics” and “teams of firms”.

4.1 Partnerships formed

According to Propositions 3 and 4, the matching between academics and firms should be positive assortative in terms of ability and type. That is, more applied academics collaborate with more applied firms, and higher ability academics collaborate with higher ability firms. Proposition 5, instead, suggests that the matching is negative assortative in terms of ability and distance between the partners’ types. That is, higher ability academics (firms) should collaborate with less distant firms (academics) in terms of type.

We test these hypotheses using the actual formed partnerships, as well as the counterfactual partnerships we have constructed. We run probit regressions on the likelihood to form a partnership, using a dependent variable which has a value of 1 if the partnership is an actual pair and a value of 0 if it is a counterfactual pair.

Following the predictions of our model, we test for the effect of joint characteristics on the probability of forming a partnership. By construction of the

¹⁷<http://www.education.gov.uk/cgi-bin/inyourarea/distance.pl?postcode1=NW6+1qx&postcode2=EC1V+0HB>

¹⁸This can reflect the fact that the closest firm is the one that establishes the link with the university. We have also run all the regressions using the average distance in the collaborative projects, considering only the firms in the UK, and we obtain similar results.

counterfactual pairs, the individual characteristics have no impact on the likelihood of forming a partnership, as each academic and firm in an actual pair are also included in four counterfactual pairs.

Table 2 shows the probit regressions over several continuous joint variables that measure first, the ability of the academics and the firms; second, the type of the academics and the firms; and third, the ability of one partner and the distance in terms of type between the two partners.

[Insert Table 2 here]

Columns 1 to 5 in Table 2 show the results on the assortativeness in terms of ability and type. We show first the effect of the product academic-firm for the type and for the two measures of scientific ability, the impact-weighted sum and normal count of publications. Each coefficient represents the cross derivative of the probability of being matched over the characteristic (ability or type) of the academic and the characteristic of the firm. The matching will be, on average, positive or negative assortative if the associated coefficient is positive or negative, respectively. Columns 1 and 2 show that the cross-derivatives for both the ability and the type are positive and significant, providing thus strong support for the prediction of positive matching in terms of ability and type. Therefore, higher ability and more applied academics paired with higher ability and more applied firms (and lower ability and less applied academics paired with lower ability and less applied firms) are more likely to be an actual formed partnership, as opposed to a counterfactual non-formed partnership. As shown in column 3, we obtain similar results if we use the measures for the principal investigator instead of the ones for the entire team of academics in the project.

A more indirect test of assortativeness in types consists in analyzing the effect of the distance between types. According to our theoretical model, the matching is positive assortative because it minimizes the sum of the (square of) distances between partners. This suggests that the distance of the type of an academic and a firm should lower the probability of being matched. Column 4 confirms this intuition: there is a strong negative effect of the distance in types on the probability of matching.

We also consider an adjusted measure of the distance between types. As mentioned earlier, the distribution of firms' types in our database is more basic than the distribution of the academics' types. This might be due to the difficulty for the firms' researchers to publish their most applied discoveries. This suggests that the "true" type of a firm is more applied than the one observed in our data. We therefore define a new distance variable obtained after increasing the type of all firms by a fraction of 0.1.¹⁹ As column 5 shows, this variable has an even stronger effect than the original distance measure.

Column 6 shows the probit regression also taking into account the joint variables on the ability of one partner and the distance in terms of type between the

¹⁹Increases of fractions around 0.1 give the best estimates.

two partners. The coefficients of the two variables are negative and significant, providing thus support for the prediction of negative assortative matching in Proposition 5. That is, a better academic (or firm) is less likely to be matched with a very different firm (academic) in terms of type probably because, as suggested by our model, better academics (firms) suffer relatively more than worse ones from collaborating with distant firms (academics). As in Column 4, the coefficient of the joint variable for impact is positive and significant and that of the type distance is negative and significant. Similar (unreported) results are obtained with the adjusted measure of distance.

In the last column of Table 2, we have included the joint variables “Academics’ impact *Firms’ type” and “Firms’ impact *Academics’ type”. The coefficient for both variables is negative and significant. This result suggests that a better academic (or firm) is less likely to be matched with a more applied firm (academic).

Given that previous literature has highlighted the role of geographical proximity in the collaboration decisions, we also include in all the regressions the variable that measures the geographical distance between academics and firms. However, this variable turns out to be non-significant in all the regressions.

Table 3’s columns 1 to 4 present the marginal effects of the probit regressions over several dummy and discrete variables accounting for the relative position of each agent on each side of the market. For example, the dummy variable “Both above median in impact (type)” takes value of 1 if both the academic and the firm are above their respective median in terms of ability (type). According to the results in column 1, the academics and the firms are 1,4% and 1.5% more likely to be matched if they are both above the median and both below the median, respectively. Given that the unconditional probability of being matched is 20%, this represents 7% and 7.5% of the unconditional probability. Albeit positive, the effect for the median in terms of ability is not significant, while it is very significant and strong for types. The academics and the firms are 6.6% and 7.7% more likely to be matched if they are both above the median and both below the median in terms of type, respectively (33% and 38.5% in terms of unconditional probability). In column 2 of the table, we show that the impact matters when both the academic and the firm are in the first quartile (or none of them is in the first quartile) in terms of ability. When both are (respectively, none is) in the top 25% in terms of impact, the conditional probability that they match is 5.9% higher (2.1% higher), which in terms of the unconditional probability means 29.5% higher (10.5% higher). This suggests that, for the likelihood of a matching, both being or not at the top in terms of ability is more important than both being above or below the median.

[Insert Table 3 here]

To further understand the effect of the relative position of academics and firms, we first divide the set of academics and the set of firms in quartiles with

respect to each characteristic (impact and type), assign to all of them their quartile (from 1 to 4), and compute the pair's quartile difference, defined as the absolute value of the difference between the quartile of the academic and the quartile of the firm. Column 3 shows that for each unit change of quartile in impact, the probability of being matched decreases by 1.5% (or an unconditional probability of 7.5%). Similarly, a unit change of quartile in type decreases the probability of being matched by 4% (or an unconditional probability of 20%).

Column 4 reports a similar exercise but with a complete ranking of academics and firms in terms of ability and type. For example, we order all the academics in terms of impact by assigning to each academic his rank in impact. Our ordering considers the equal numbers as average ranking, that is, if the impacts were 1, 7, 7, 20, then the associated ranks would be 1, 2.5, 2.5, 4. We construct two variables that measure the differences in ranking between academics and firms for impact and type. To be able to observe the magnitude, we divide the ranking by one thousand, so that the effect is in thousands. As expected, a higher distance in the ranking in impact and type leads to a lower likelihood of matching. In terms of magnitudes, an additional unit in the distance of rankings of impact, lowers the conditional probability of being matched by 0.0023% (in thousands, one unit of distance, lowers the unconditional probability by 11.5%), whereas the effect in types is 0.01% in units of distance (or a decrease in the unconditional probability of 50%).

The first four columns in Table 3 confirm that the matching is positive assortative in both characteristics. They also suggest that the positive nature of the matching is stronger for the type, which is a horizontal characteristic, than for the impact, which is a vertical attribute. The coefficients for the joint variables in types are three to four times higher than the coefficients for the corresponding variables for impact. The numbers are meaningful because the variables in Table 3 reflect relative positions of the agents, which allow for the comparison of the two characteristics.

In the spirit of the matching model, the next three columns in Table 3 consider the full rank of academics and firms in the two characteristics, ability and type. Column 5 shows that the joint variable of ranking in impact, as well as the one in type, increases the probability of being matched. Column 6 tests Propositions 5, 6, and 7 simultaneously. As compared to the previous column, this regression also takes into account the joint variables on the ability of one partner and the distance in terms of type between the two partners and the coefficients of these two variables are negative and significant. The coefficient of the joint variable of rank in types is now not significant (even if it has the right sign) possibly because the effect is taken by distance in rank of types included in the new variables.

Finally, similarly as column 7 in Table 2, in column 7 in Table 3 we include a regression combining the rank in type of one side of the market and the rank in impact of the other side. The coefficient for both variables is negative and significant, which provides support for the idea that a better academic (or firm) is less likely to be matched with a more applied firm (academic).

Researcher or university effects For completeness, we also study whether there is positive or negative assortative matching using some aggregate characteristics of the universities and other aggregate characteristics of the firms besides ability and type. For instance, we want to understand whether the more able firms select the researchers because of their individual qualities or also because of the qualities of the university they work for. The first six columns of Table 4 shows several joint regressions of firms’ ability with different university variables.²⁰ The only coefficients that are significant are those that correspond to the joint variables in columns 2 and 4, where university research and private funds are considered. This could suggest a positive assortative matching between firms’ ability and universities’ research financing. However, as it can be seen in columns 3 and 5, the coefficients lose their significance if we also include in the regressions the joint variable of academics’ and firms’ ability.

[Insert Table 4 here]

Columns 7 and 8 show two of the possible regressions that use joint variables on academics’ ability and firms characteristics (besides ability and type) which all of them turn to be non-significant.²¹ Finally, we have run regressions on all the possible joint characteristics of firms and universities (besides ability and type); they are all non-significant. Columns 9 and 10 report two such regressions.

4.2 Collaborating versus non-collaborating

Our theoretical analysis also generates predictions on the characteristics of the academics that make them more likely to be involved in a collaborative project rather than in a non-collaborative project. Under reasonable conditions, Propositions 7 and 9 show that, in equilibrium, the most able and the most applied academics should develop collaborative projects whereas the least able and the most basic should develop non-collaborative projects.

We test these hypotheses using the data on the academics that proposed collaborative projects as well as those that submitted non-collaborative projects (we do not use the counterfactual observations here). Unfortunately, we cannot test which firms would be more likely to conduct non-collaborative projects because in those cases they cannot get funding from the EPSRC and, therefore, they are not in our dataset. We run probit regressions on the academic’s likelihood to collaborate, using a dependent variable which has a value of 1 if the

²⁰University funds and income are in million pounds. We have also run regressions using other university characteristics such as number of “active engineers”, in the sense that they appear in the “2008 Research Assessment Exercise Results”, number of postdoc students, number of undergrad students, and university expenses. All of them are not significant. The results of the regressions are similar if we use the firms’ count instead of firms’ impact as measure of firms’ ability.

²¹In addition to firms’ employees (in thousands) and firms’ profits (in millions), we have also run regressions using firms’ turnover and firms’ assets.

academics chose to submit a collaborative project and a value of 0 if they chose to submit a non-collaborative one.

Table 5 shows the probit regressions over several measures of academic type and ability. In the regressions, we control for year, and university fixed effects. Columns 1 and 2 show that the most applied as well as the most able researchers are significantly more likely to collaborate, both if we measure ability in terms of impact-weighted sum of publications or in terms of normal count. Columns 3 and 4 show that the results are similar if we use variables that refer to the principal investigator instead of the team of researchers, although the PI's impact appears not to be significant. Column 5 shows that the researchers that are above the median in terms of ability and those who are more applied than the median are 3.2% and 13.8% more likely to collaborate, respectively (given that the unconditional probability of collaborating is 35%, the increases in probability are 9.1% and 39.5% in terms of the unconditional probability). In column 6 we consider the rank for all academics in collaborative and noncollaborative projects in terms of impact and type (and divide each rank by one thousand). The regression shows that an increase in the ranking in any of the two characteristics has a positive and significant effect on the probability of collaboration. In terms of aggregate measures, column 7 shows that researchers in larger universities, in terms of number of projects, are also more likely to collaborate. However, the other university variables are not significant. We report in Table 5 the coefficients for the variables that reflect the scientific level of the engineer departments at the university: number of papers with three starts and number of "active engineers". We also control for the number of postdoc students at the university as well as total income.²²

[Insert Table 5 here]

The empirical results provide strong support to the theoretical predictions of propositions 7 and 9: the likelihood of collaboration increases with the type and ability of the academic researchers. They also suggest that, as it was the case in the matching regressions, the type of the academics has a stronger effect than their ability.

5 Conclusion

This paper develops first a two-sided market matching model of heterogeneous academic researchers and firms. Our model predicts that the most able and the most applied researchers and the most able and the most basic firms prefer to develop two-sided market collaborative projects, rather than stand-alone projects. Among those that develop collaborative projects, we predict a positive assortative matching, both in terms of ability and affinity, i.e. more prolific academic

²²Similar results are obtained when we use total number undergraduate students and total expenses.

researchers collaborating with more research-productive firms, and academics with more applied bias collaborating with firms with more applied bias. But, we also predict a negative assortative matching across the two characteristics, i.e. the academics with higher ability being those collaborating with firms with which they have more affinity.

We then verify our theoretical predictions on the teams of academic researchers and firms that propose research projects to the EPSRC. We also show that the affinity-based characteristics are relatively more important than the ability ones. The characteristics at the individual-researcher level appear to be more relevant than at the aggregate institutional level.

This paper provides one of the rare efforts in the academic literature to understand collaboration across institutional boundaries, i.e. the two-sided market partnerships. Fortunately, we know a significant deal more about collaboration across institutions within institutional markets, i.e. one-sided market partnerships. Many papers have studied the causes and the consequences of collaboration among academic researchers (Katz and Martin, 1997; Wagner and Leydesdorff, 2005), firms (Caloghirou et al., 2003), venture capitalists (Gompers et al, 2012), etc. A natural next step should be to study the interaction between the two, and identify for example if collaboration between academic researchers substitutes or complements collaboration between academic researchers and firms.

References

- [1] Agarwal, R. and Ohyama, A. (forthcoming): “Industry or Academia, Basic or Applied? Career Choices and Earnings Trajectories of Scientists”. *Management Science*.
- [2] Agrawal, A. and Henderson, R. (2002): “Putting Patents in Context: Exploring Knowledge Transfer from MIT”, *Management Science* 48, 44-60.
- [3] Agrawal, A., Kapur, D. and McHale, J. (2008): “How do Spatial and Social Proximity Influence Knowledge Flows? Evidence from Patent Data”, *Journal of Urban Economics* 64, 258-269.
- [4] Alonso-Paulí, E. and Pérez-Castrillo, D. (2012): “Codes of Best Practice in Competitive Markets for Managers”, *Economic Theory* 49 (1), 113-141.
- [5] Audretsch, D.B. and Stephan, P. (1996): “Company-Scientist Locational Links: The case of Biotechnology”, *The American Economic Review* 86 (3), 641-652.
- [6] Azoulay, P., Ding, W. and Stuart, T. (2009): “The Impact of Academic Patenting on The Rate, Quality and Direction of (Public) Research Output”, *The Journal of Industrial Economics* 57 (4), 637-676.

- [7] Banal-Estañol, A., Jofre-Bonet, M. and Meissner, C. (2010): “The Impact of Industry Collaboration on Research: Evidence from Engineering Academics in the UK”, W. P. City University London.
- [8] Banal-Estañol, A., Macho-Stadler, I. and Pérez-Castrillo, D. (2013): “Research Output from University-Industry Collaborative Projects”, *Economic Development Quarterly* 27 (1), 71-81.
- [9] Becker, G.S. (1973): “A Theory of Marriage: Part I”, *The Journal of Political Economy* 81, 813-846.
- [10] Belderbos, R., Carree, M. and Lokshin, B. (2004): “Cooperative R&D and Firm Performance”, *Research Policy* 33 (10), 1477-1492.
- [11] Bercovitz, J. and Feldman, M. (2007): “Fishing Upstream: Firm Strategic Research Alliances with Universities”, *Research Policy* 36 (7), 930-948.
- [12] Calderini, M., Franzoni, C. and Vezzulli, A. (2007): “If Star Scientists do not Patent: An Event History Analysis of Scientific Eminence and the Decision to Patent in the Academic World”, *Research Policy* 36, 303-319.
- [13] Caloghirou, Y., Ioannides, S. and Vonortas, N.S. (2003): “Research Joint Ventures”, *Journal of Economic Surveys* 17, 541-570.
- [14] Cassiman, B. and Veugelers, R. (2006): “In Search of Complementarity in Innovation Strategy: Internal R&D and External Knowledge Acquisition”, *Management Science* 52 (1), 68 - 82.
- [15] Champness M. (2000): “Helping Industry and Universities Collaborate”, *Research Technology Management* 43 (4), 8-10.
- [16] Cohen, W.M., Florida, R., Randazzese, L. and Walsh, J. (1998): "Industry and the Academy: Uneasy Partners in the Cause of Technological Advance". In: Noll, R.G. (Ed.), *Challenges to Research Universities*. Brookings Institution Press, Washington, DC.
- [17] Cohen, W.M., Nelson R.R. and Walsh J.P. (2002): “Links and Impacts: The Influence of Public Research on Industrial R&D”, *Management Science* 48, 1-23.
- [18] Cockburn, I. and Henderson, R. (1998): “Absorptive Capacity, Coauthoring Behavior, and the Organization of Research in Drug Discovery”, *Journal of Industrial Economics* 46 (2), 157-182
- [19] Cummings, J. and Kiesler, S. (2007): “Coordination Costs and Project Outcomes in Multi-university Collaborations”, *Research Policy* 36 (10), 1620-1634.
- [20] Dam, K. and Pérez-Castrillo, D. (2006): “The Principal Agent Market”, *Frontiers in Economic Theory, Berkeley Electronics* 1 (Republished in *BePress Advances in Theoretical Economics*).

- [21] Dasgupta, P. and David, P. (1994): “Towards a New Economics of Science”, *Research Policy* 23 (5): 487-522.
- [22] D’Este P. and Patel, P. (2007): “University-Industry Linkages in the UK: What Are the Factors Underlying the Variety of Interactions with Industry?”, *Research Policy* 36, 1295-1313.
- [23] Fabrizio, K. and DiMinin, A. (2008): “Commercializing the Laboratory: Faculty Patenting and the Open Science Environment”, *Research Policy* 37, 914-931.
- [24] Florida, R. and Cohen, W.M. (1999): “Engine or Infrastructure? The University Role in Economic Development”, in Branscomb, L.M., Kodama, F., Florida, R. (eds.), *Industrializing Knowledge: University-Industry Linkages in Japan and the United States*, MIT Press, London, 589-610.
- [25] Fontana, R., Geuna, A. and Matt, M. (2006): “Factors Affecting University-Industry R&D Projects: The Importance of Searching, Screening and Signalling”, *Research Policy* 35, 309-323.
- [26] Fox, J. (2008), “Estimating Matching Games with Transfers,” NBER W. P. No. W14382.
- [27] Gale, D. and Shapley, L.S. (1962): “College Admissions and the Stability of Marriage”, *American Mathematical Monthly* 69, 9-15.
- [28] Godin, B. (1996): “The State of Science and Technology Indicators in the OECD Countries”, Research Paper, Statistics Canada.
- [29] Gompers, P., Mukharlyamov, V. and Xuan, Y. (2012): “The Cost of Friendship”, NBER W. P.
- [30] Gulbrandsen, M. and Smeby, J.C. (2005): “Industry Funding and University Professors’ Research Performance”, *Research Policy* 34, 932-950.
- [31] Kamien, M., Muller, E. and Zang, I. (1992): “Research Joint Ventures and R&D Cartels”, *The American Economic Review* 82 (5), 1293-1306.
- [32] Kaneko, M. (1982): “The Central Assignment Game and the Assignment Markets”, *Journal of Mathematical Economics* 10, 205-32.
- [33] Katz, J.S. and Martin, B.R. (1997): “What is Research Collaboration?”, *Research Policy* 26, 1-18.
- [34] Laursen, K. and Salter, A. (2004): “Searching Low and High: What Type of Firms Use Universities as Sources of Innovation?”, *Research Policy* 33 (8), 1201-1215.
- [35] Lee, Y.S. (2000): “The Sustainability of University-Industry Research Collaboration: An Empirical Assessment”, *The Journal of Technology Transfer* 25, 111-133.

- [36] Legros, P. and Newman, A. (2002): “Monotone Matching in Perfect and Imperfect Worlds”, *Review of Economic Studies* 69, 925-942.
- [37] Louis, K.S. , Blumenthal, D., Gluck, M.E. and Stoto, M.A. (1989): “Entrepreneurs in Academe: An Exploration of Behaviors among Life Scientists”, *Administrative Science Quarterly* 34 (1), 110-131.
- [38] Manjarres-Henriquez, L., Gutierrez-Gracia, A., Carrion-Garcia, A. and Vega-Jurado, J. (2009): “The Effects of University-Industry Relationships and Academic Research on Scientific Performance: Synergy or Substitution?”, *Research in Higher Education* 50 (8), 795-811.
- [39] Mansfield, E. and Lee J.-Y. (1996): “The Modern University: Contributor to Industrial Innovation and Recipient of Industrial R&D Support”, *Research Policy* 25, 1047-1058.
- [40] Melin, G. and Persson, O. (1996): “Studying Research Collaboration using Co-authorships”, *Scientometrics* 36 (3), 363-377.
- [41] Mindruta, D. (forthcoming): “Value Creation in University-Firm Research Collaborations: A Matching Approach”, *Strategic Management Journal*.
- [42] Mohnen, P. and Hoareau. C. (2003): “What Type of Enterprise Forges Close Links with Universities and Government Labs? Evidence from CIS 2”, *Managerial and Decision Economics* 24 (2-3), 133-145.
- [43] Mowery, D. C. (1983): “The Relationship between Intrafirm and Contractual Forms of Industrial Research in American Manufacturing, 1900-1940”, *Exploration in Economic History* 20, 351-374.
- [44] Narin, F., Pinski G. and Gee H. (1976): “Structure of the Biomedical Literature”, *Journal of the American Society for Information Science*, 25-45.
- [45] Pereira, I. (2007): “Business-Science Research Collaboration under Moral Hazard”, W. P. Universitat Autònoma de Barcelona.
- [46] Perkmann, M., Tartari, V., McKelvey, M., Autio, E., Broström, A., D’Este, P., Fini, R., Geuna, A., Grimaldi, R., Hughes, A., Kitson, M., Krabel, S., Llerena, P., Lissoni, F., Salter, A. and Sobrero, M. (2013): “Academic Engagement and Commercialization: A Review of the Literature on University-Industry Relations”, *Research Policy* 42 (2), 423-442.
- [47] Roth, A. and Sotomayor, M. (1990): “*Two-Sided Matching: A Study in Game-Theoretic Modeling and Analysis*”, Cambridge University Press, New York and Melbourne, Econometric Society Monographs.
- [48] Serfes, K. (2008): “Endogeneous Matching in a Market with Heterogeneous Principals and Agents”, *International Journal of Game Theory* 36 (3-4), 587-619.

- [49] Shapley, L.S. and Shubik, M. (1972): “The Assignment Game I: The Core”, *International Journal of Game Theory* 1, 111-130.
- [50] Stephan, P., Gurmu, S., Sumell, A.J. and Black, G. (2007): “Who’s Patenting in the University?”, *Economics of Innovation and New Technology* 61, 71-99.
- [51] van Looy, B., Callaert, J. and Debackere, K. (2006): “Publication and Patent Behaviour of Academic Researchers: Conflicting, Reinforcing or Merely Co-existing?”, *Research Policy* 35, 596-608.
- [52] Veugelers, R. and Cassiman, B. (2005): “Cooperation between Firms and Universities. Some Empirical Evidence from Belgian Manufacturing”, *International Journal of Industrial Organization* 23, 355-379.
- [53] Wagner, C.S. and Leydesdorff L. (2005): “Network Structure, Self-organization, and the Growth of International Collaboration in Science”, *Research Policy* 34 (10), 1608-1618.
- [54] Zucker, L., Darby M.R. and Armstrong J.S. (2002): “Commercializing Knowledge: University Science, Knowledge Capture, and Firm Performance in Biotechnology”, *Management Science* 48 (1), 138 - 153.

6 Appendix

Proof of Proposition 2. The optimal agreement P solves the following program:

$$\underset{x, I_F, I_A}{Max} [\pi_A(x, I_A, I_F; x_A, \delta_A) + \pi_F(x, I_A, I_F; x_F, \delta_F)]$$

where the expressions for $\pi_A(x, I_A, I_F; x_A, \delta_A)$ and $\pi_F(x, I_A, I_F; x_F, \delta_F)$ are in the main text. This function is concave in all its arguments. The FOC with respect to x is

$$-2\lambda_A v_A (\delta_A + \delta_F) (I_A + I_F) t(x - x_A) + 2\lambda_F v_F (\delta_A + \delta_F) (I_A + I_F) t(x_F - x) = 0.$$

From this condition we obtain

$$x^* = \frac{\lambda_A v_A x_A + \lambda_F v_F x_F}{\lambda_A v_A + \lambda_F v_F}.$$

The FOCs with respect to the investments are

$$\lambda_A v_A (\delta_A + \delta_F) (1 - t(x - x_A)^2) + \lambda_F v_F (\delta_A + \delta_F) (1 - t(x_F - x)^2) - CI_A = 0$$

$$\lambda_A v_A (\delta_A + \delta_F) (1 - t(x - x_A)^2) + \lambda_F v_F (\delta_A + \delta_F) (1 - t(x_F - x)^2) - CI_F = 0$$

from which the expressions for I_A^* and I_F^* in the proposition are easily derived. Note that $I_A^* = I_F^* > 0$: a sufficient condition for this to hold is $\lambda_A v_A + \lambda_F v_F - \frac{\lambda_A v_A \lambda_F v_F}{(\lambda_A v_A + \lambda_F v_F)} > 0$, or $\lambda_A^2 v_A^2 + \lambda_F^2 v_F^2 + \lambda_F \lambda_A v_F v_A > 0$, which is satisfied. ■

Proof of Proposition 3. We have computed the level of profits of the partners at the optimal project Π_{AF}^* after Proposition 2. From that expression, it easily follows that

$$\frac{\partial^2 \Pi_{AF}}{\partial \delta_A \partial \delta_F} = \frac{2}{C} (V_{AF} (|x_F - x_A|))^2 > 0,$$

which implies that the matching is positive assortative (see footnote 11). ■

Proof of Proposition 4. We prove that $\frac{\partial^2 \Pi_{AF}}{\partial x_A \partial x_F} > 0$.

$$\frac{\partial \Pi_{AF}}{\partial x_F} = -\frac{2(\delta_A + \delta_F)^2}{C} \frac{\lambda_A v_A \lambda_F v_F}{(\lambda_A v_A + \lambda_F v_F)} 2t(x_F - x_A) V_{AF} (|x_F - x_A|).$$

The cross derivative $\frac{\partial^2 \Pi_{AF}}{\partial x_F \partial x_A}$ is proportional to

$$\begin{aligned} V_{AF} (|x_F - x_A|) - 2 \frac{\lambda_A v_A \lambda_F v_F}{(\lambda_A v_A + \lambda_F v_F)} t(x_F - x_A)^2 \\ = \lambda_A v_A + \lambda_F v_F - \frac{3\lambda_A v_A \lambda_F v_F}{(\lambda_A v_A + \lambda_F v_F)} t(x_F - x_A)^2. \end{aligned}$$

Therefore, $\frac{\partial^2 \Pi_{AF}}{\partial x_F \partial x_A} > 0$ if $\lambda_A v_A + \lambda_F v_F - \frac{3\lambda_A v_A \lambda_F v_F}{(\lambda_A v_A + \lambda_F v_F)} > 0$, that is, $\lambda_A^2 v_A^2 + \lambda_F^2 v_F^2 - \lambda_A v_A \lambda_F v_F > 0$, which always holds. ■

Proof of Proposition 5. The proposition holds if $\frac{\partial^2 \Pi_{AF}}{\partial \delta_A \partial d} < 0$, where $d = |x_F - x_A|$, that is, if

$$-\frac{8}{C} (\delta_A + \delta_F) t d (V_{AF} (|x_F - x_A|))^2 < 0,$$

which is satisfied. ■

Proof of Proposition 6. (i) The derivative of $\Delta(x_A, \delta_A, x_F, \delta_F)$ with respect to δ_A is

$$\frac{\partial \Delta}{\partial \delta_A} (x_A, \delta_A, x_F, \delta_F) = \frac{2(\delta_A + \delta_F)}{C} (V_{AF} (|x_F - x_A|))^2 - \frac{1}{C} \delta_A v_A^2$$

and the proposition follows from this expression. (ii) The proof is similar. ■

Proof of Proposition 7. (i) We do the proof by contradiction. Suppose that $\mu(A_i) = A_i$ and $\mu(A_{i'}) = F_j$ with $\delta_{A_{i'}} < \delta_{A_i}$. We denote $\Pi_{AF}^c \equiv \Pi_{AF}^c(x_A, \delta_A, x_F, \delta_F)$, $\pi_A^n \equiv \pi_A^n(x_A, \delta_A)$, $\pi_F^n \equiv \pi_F^n(x_F, \delta_F)$ and $\Delta_{AF} \equiv \Delta(x_A, \delta_A, x_F, \delta_F)$ for any $A \in \mathcal{A}$ and $F \in \mathcal{F}$. The efficiency of the equilibrium matching implies $\Pi_{A_i' F_j}^c + \pi_{A_i}^n \geq \Pi_{A_i F_j}^c + \pi_{A_{i'}}^n$ that, given the definition of $\Delta_{A_i F_j}$, is equivalent to $\Delta_{A_i' F_j} \geq \Delta_{A_i F_j}$. However, $\Delta_{A_i' F_j} \geq \Delta_{A_i F_j}$ is not possible under hypothesis 1a because it implies that equation (4) holds, hence the net benefits from collaboraton Δ are increasing in δ_R . (ii) The proof is similar. ■

Proof of Proposition 8. (i) The derivative of $\Delta(x_A, \delta_A, x_F, \delta_F)$ with respect to x_A coincides with the derivative of $\Pi_{AF}^c(x_A, \delta_A, x_F, \delta_F)$ with respect to x_A , which is

$$\frac{4(\delta_A + \delta_F)^2}{C} t(x_F - x_A) \frac{\lambda_A v_A \lambda_F v_F}{\lambda_A v_A + \lambda_F v_F} V_{AF}(|x_F - x_A|).$$

Therefore, $\frac{\partial \Delta}{\partial x_F}(x_A, \delta_A, x_F, \delta_F) > 0$ if and only if $x_F - x_A > 0$. (ii) The proof is similar. ■

Proof of Proposition 9. (i) Suppose, by contradiction, that $\mu(A_i) = A_i$, $x_{A_{i'}} < x_{A_i}$ and $\mu(A_{i'}) = F_j$ for some $F_j \in \mathcal{F}$. We use the same notations as in the proof of Proposition 7: Π_{AF}^c , Δ_{AF} and so on.

Under Hypothesis 1a, $x_{F_j} \geq x_{A_i} > x_{A_{i'}}$, which implies (see Proposition 8) $\Delta_{A_i F_j} > \Delta_{A_{i'} F_j}$. Therefore, $\Pi_{A_i F_j}^c + \pi_{A_{i'}}^n \geq \Pi_{A_{i'} F_j}^c + \pi_{A_i}^n$, which contradicts the fact that the equilibrium matching μ must be efficient.

Under Hypothesis 1b, we first show that $\mu(A_i) = A_i$ implies that $i < k$. Otherwise, consider the firm F_{i-k+1} , for which $x_{A_i} = x_{F_{i-k+1}}$. If $\mu(F_{i-k+1}) = A_{i''}$ for some $A_{i''}$, then for the same arguments as before, it would be more efficient that A_i is matched to F_{i-k+1} and $A_{i''}$ remains unmatched than the situation under μ . Similarly, if $\mu(F_{i-k+1}) = F_{i-k+1}$ then it would also be more efficient than $\mu(F_{i-k+1}) = A_i$ (note that the net benefits from this collaboration must be positive because they are the same as the benefits from the collaboration between $A_{i'}$ and F_j). The efficiency of μ implies that the two previous situations are not possible.

Finally, if $i < k$ then we have $x_{F_j} \geq x_{A_i} > x_{A_{i'}}$ which, by the same reasons as above, would contradict the efficiency of μ .

(ii) The proof is similar to the proof of (i). ■

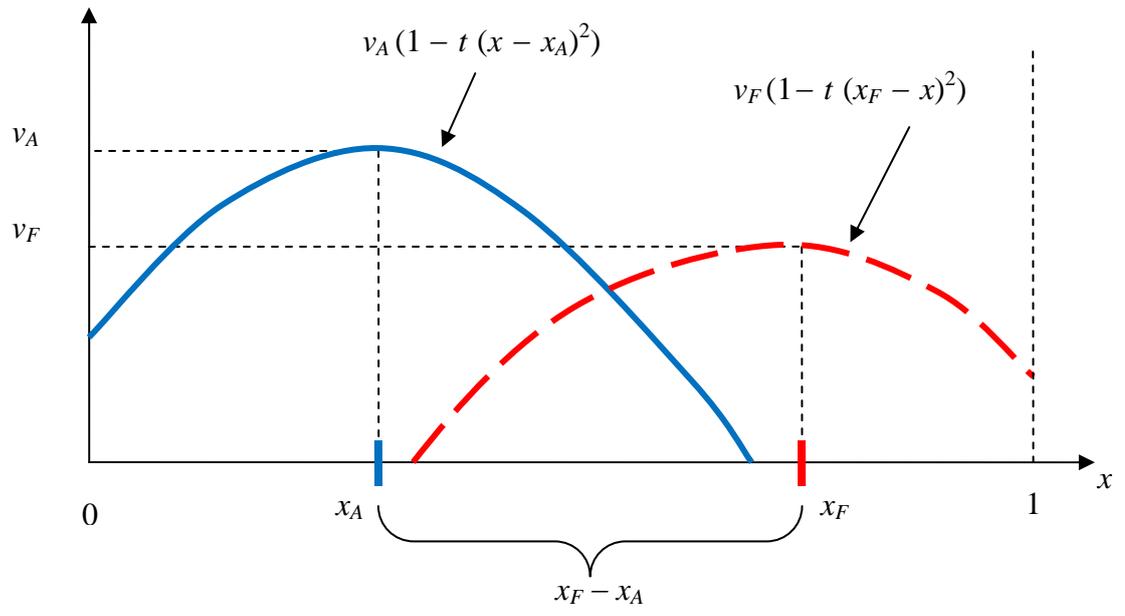


Figure 1

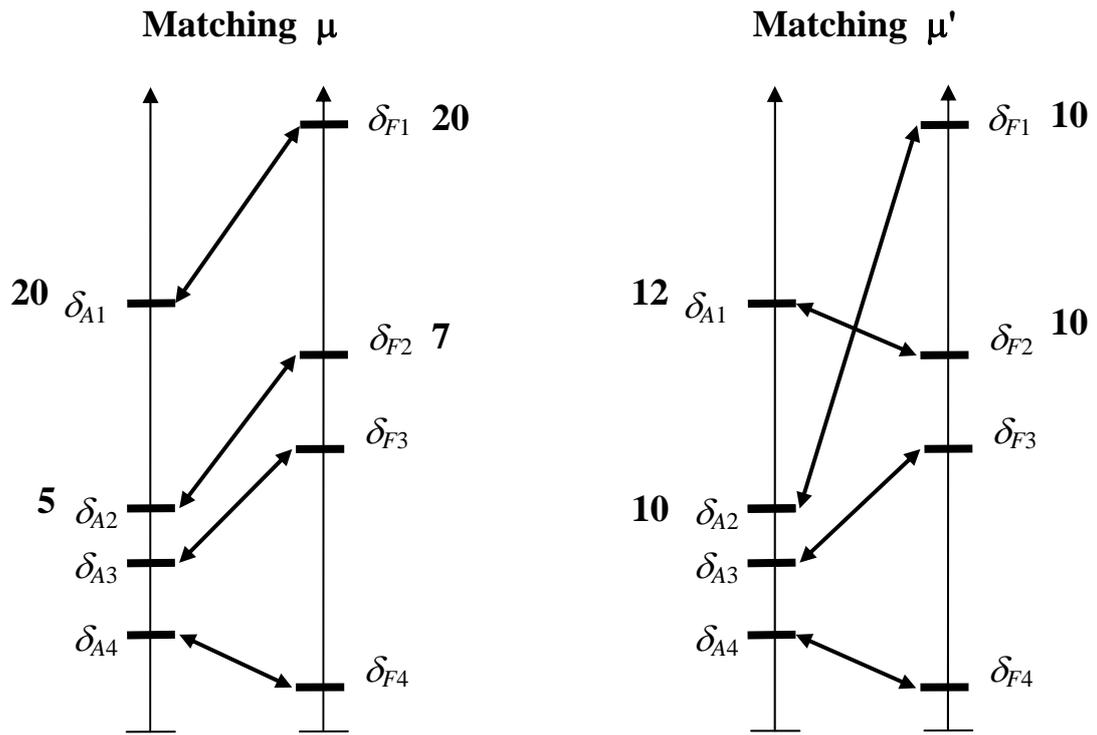
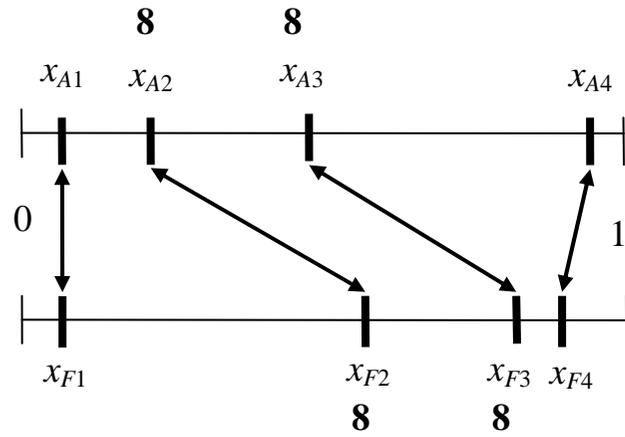


Figure 2

Matching μ



Matching μ'

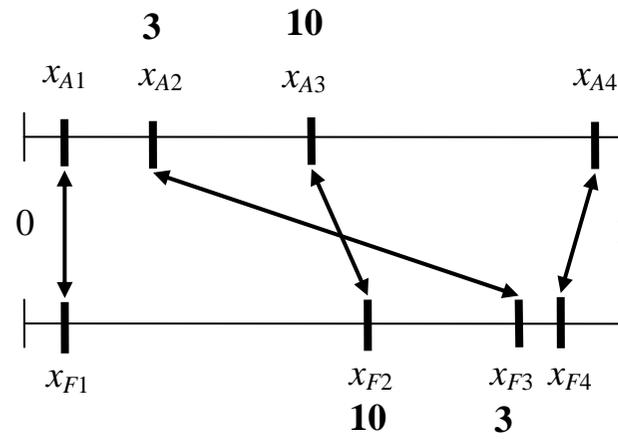


Figure 3

	Observations	Mean	St dev	Corr. academics' impact	Corr. PI's count	Corr. PI's impact	Corr. firms' count	Corr. firms' impact
Academics' count (x100)	5855	0,106	0,146	0.889***	0.562***	0.502***	0.194***	0.172***
Academics' impact (x100)	5855	0,169	0,309		0.534***	0.636***	0.223***	0.219***
PI's count (x100)	5067	0,036	0,037			0.854***	0.067***	0.058***
PI's impact (x100)	5067	0,056	0,081				0.120***	0.137***
Firms' count (x1000)	2057	0,749	1,836					0.901***
Firms' impact (x1000)	2057	1,448	5,173					

	Observations	Mean	St dev	Corr. PI's type	Corr. firms' type	Corr. respective impact
Academics' type	5519	0,653	0,328	0.938***	0.358***	-0.351***
PI's type	4674	0,666	0,343		0.343***	-0.396***
Firms' type	1563	0,579	0,284			-0.123***

Table 1. Descriptive statistics

Probit linked	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Academics' impact*Firms' impact	0.027*** [0.006]			0.023*** [0.005]	0.024*** [0.005]	0.044*** [0.008]	0.046*** [0.009]
Academics' type*Firms' type	0.167*** [0.061]	0.164*** [0.061]					0.162*** [0.060]
Academics' count*Firms' count		0.136*** [0.028]					
PI' impact*Firms' impact			0.073*** [0.026]				
PI' type*Firms' type			0.146** [0.062]				
Type distance				-0.598*** [0.070]		-0.461*** [0.074]	
Academics' impact*Type distance						-0.773*** [0.164]	
Firms' impact*Type distance						-0.033*** [0.009]	
Type distance adjusted					-0.650*** [0.073]		
Academics' impact*Firms' type							-0.418*** [0.102]
Firms' impact*Academics' type							-0.021*** [0.005]
Geographical distance	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]	0.000 [0.000]
Constant	-0.917*** [0.032]	-0.921*** [0.032]	-0.902*** [0.034]	-0.653*** [0.029]	-0.652*** [0.030]	-0.649*** [0.028]	-0.861*** [0.034]
Observations	7,323	7,323	6,426	7,323	7,323	7,323	7,323

Robust standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Probability of matching as a function of the joint characteristics of researchers and firms.

Probit linked	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Both above median in impact	0.014 [0.010]						
Both below median in impact	0.015 [0.013]						
Both above median in type	0.066*** [0.012]	0.063*** [0.012]					
Both below median in type	0.077*** [0.011]	0.073*** [0.011]					
Both in top 25% in impact		0.059*** [0.017]					
Both in bottom 75% in impact		0.021** [0.011]					
Distance of quartiles in impact			-0.015*** [0.005]				
Distance of quartiles in types			-0.040*** [0.005]				
Distance in rank of impact				-0.023** [0.011]			
Distance in rank of types				-0.100*** [0.012]			
Rank academics' impact*Rank firms' impact					0.062*** [0.020]	0.071*** [0.021]	0.150*** [0.024]
Rank academics' type*Rank firms' type					0.086*** [0.027]	0.021 [0.027]	0.259*** [0.034]
Rank firms' impact*Distance in rank of types						-0.157*** [0.035]	
Rank academics' impact*Distance in rank of types						-0.210*** [0.041]	
Rank academics' type*Rank firms' impact							-0.159*** [0.026]
Rank academics' type*Rank firms' type							-0.219*** [0.033]
Geographical distance	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]	-0.000 [0.000]
Constant					-0.988*** [0.045]	-0.729*** [0.054]	-0.872*** [0.049]
Observations	7,323	7,323	7,323	7,323	7,323	7,323	7,323

Standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Probability of matching as a function of the joint characteristics of researchers and firms based on discrete variables. Columns 1 to 4 display the marginal effects.

Probit linked	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Unis' top papers*Firms' impact	0.000 [0.000]									
Unis' res funds*Firms' impact		0.001** [0.000]	-0.000 [0.000]				-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]	0.000 [0.000]
Unis' priv funds*Firms' impact				0.002* [0.001]	-0.001 [0.001]					
Academics' impacts*Firms' impact			0.029*** [0.007]		0.030*** [0.007]					
Unis' income*Firms' impact						0.006 [0.004]				
Academics' impacts*Firms' employees										
Academics' impacts*Firms' profits							0.001 [0.001]			
Unis' res funds*Firms' employees								0.008 [0.010]		
Unis' priv funds*Firms' profits									0.000 [0.000]	
Geographical distance	-0.000 [0.000]	0.000 [0.000]	-0.000 [0.000]	0.001 [0.001]						
Constant	-0.839*** [0.018]	-0.841*** [0.018]	-0.838*** [0.018]	-0.840*** [0.018]	-0.838*** [0.018]	-0.834*** [0.018]	-0.838*** [0.020]	-0.834*** [0.022]	-0.845*** [0.021]	-0.837*** [0.022]
Observations	10,178	10,178	10,108	10,178	10,108	9,187	7,673	6,464	7,719	6,503

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Probability of matching as a function of joint measures of universities/researchers and firms.

Probit collaborate	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Academics' impact	0.130** [0.061]						0.263*** [0.074]
Academics' type	0.635*** [0.061]	0.640*** [0.059]					0.698*** [0.065]
Academics' count		0.515*** [0.123]					
PI's impact			0.092 [0.269]				
PI's type			0.555*** [0.066]	0.605*** [0.062]			
PI's count				2.278*** [0.554]			
Academics above median in impact					0.032** [0.014]		
Academics above median in type					0.138*** [0.014]		
Rank academics' impact						0.100*** [0.024]	
Rank academics' type						0.250*** [0.024]	
University's number of projects							0.051*** [0.013]
University's number of high-impact papers							0.009 [0.006]
University's "active" academic engineers							-0.001 [0.001]
Other university controls	No	No	No	No	No	No	Yes
University Dummies	Yes	Yes	Yes	Yes	Yes	Yes	No
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1.037*** [0.181]	-1.072*** [0.182]	-0.913*** [0.187]	-1.032*** [0.188]			-0.955*** [0.139]
Observations	5,513	5,513	4,671	4,671	5,513	5,513	4,793

Robust standard errors in brackets
 *** p<0.01, ** p<0.05, * p<0.1

Table 5: Probability of collaboration as a function of the type and ability of researchers and control variables. Columns 5 and 6 display marginal effects