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The transfer and value of academic inventions when the TTO is one option

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Abstract

Although the transfer of professors' inventions is typically performed by an intermediary set up by the university (the technology transfer office), other forms of transfer do coexist in reality. To clarify this situation and its consequences, we develop a model that endogenizes a professor's decision regarding the form of transfer for her invention in which intermediation by the transfer office is only one of two options, the other one being a transfer carried out by the professor herself. The intermediary can reach more potential licensees of the invention, whereas the professor is usually better at mitigating information asymmetry through signaling. In the semiseparating equilibrium of the game, promising technologies are likely to be cherry-picked and transferred by the professor. This prediction that the transfer mode is influenced by invention quality is tested and confirmed, as are several other predictions, on our sample of 446 UK academic inventors. Specific care is taken to control for other mechanisms of IP assignment, such as those derived from consulting and sponsored research. Insights in terms of policy are drawn from this new perspective focusing on alternative transfer channels, match quality, and information asymmetry rather than on moral hazard.

1 | INTRODUCTION

University-generated knowledge is increasingly perceived as making a decisive contribution to innovation and thus to the long-term economic growth of nations and local economies. While standard theories have traditionally focused on knowledge spillovers (Arrow, 1962; Nelson, 1959), inventions by university professors themselves and their transfer to the economic sphere have increasingly been discussed and emphasized as important. In this context, a 40-year-long policy debate has discussed the allocation of rights to those innovations (see Kenney & Patton, 2009). Should the rights be allocated to the sponsor (e.g., the government, not-for-profit entities, companies, etc.), put in the public domain, kept by the university, or even assigned to the professor-inventor? The Bayh-Dole Act, introduced in the early 1980s, granted U.S. universities the rights to inventions stemming from federally funded research. Other regulations, assigning the rights to the sponsor or to the inventor ("professor privilege"), were gradually abandoned worldwide as Bayh–Dole-equivalent legislation was adopted, owing to the alleged superiority of this model.

Accordingly, the literature has progressively conceptualized the transfer of university-generated inventions as involving three main types of actor (Siegel et al., 2007), as follows. When a professor makes a discovery which she believes has application potential, she discloses it to her university technology transfer office (TTO), which retains the intellectual property rights and performs the transfer in the form of a license to a firm seeking to commercialize the invention. There is widespread evidence, however, that this model does not tell the whole story about academic technology transfer, even in a context in which universities have residual rights to professors' inventions. For example, there are many instances where companies (or other external partners) take the initiative, collaborating with academic researchers and/or sponsoring their research so that they may claim and be contractually granted the rights to the commercial applications of the results. In continental Europe, Lissoni et al. (2008) show that most of the patents invented by employees of universities (and other not-for-profit research organizations) are owned by the business sector. Thursby et al. (2009) estimate that 26% of U.S. academic patents were (first) assigned solely to firms.

In this article, we emphasize another channel through which the rights to university inventions can end up being held by other parties: university researchers can bring their inventions directly to the marketplace, without the involvement of the TTO. Even when university-generated inventions are not funded by external private money, disclosing them to the TTO may be only one option available to the professor. Markman et al. (2008) find that 42% of respondents in a survey of academic inventors in U.S. universities report having bypassed their TTO at least once. In the U.S. medical field, Audretsch et al. (2006) document that more than 20% of professors have set up firms in their field of expertise without university licenses. Huyghe et al. (2016), surveying more than three thousand nontenured academic researchers from universities in five European countries (Belgium, Germany, Slovenia, Spain, and Sweden), find that only a minority are aware of the existence of a TTO at their university.

Even though empirical evidence shows that these forms of commercialization of university inventions coexist with traditional ones, it is not yet clear how they work, what their consequences are, and how the TTO can or should adapt to them. Our paper contributes to the growing literature on university technology transfer (Chukumba & Jensen, 2005; Dechenaux et al., 2009, 2011; Hellmann, 2007; Hoppe & Ozdenoren, 2005; Jensen & Thursby, 2001; Jensen et al., 2003; Lach & Schankerman, 2004; Macho-Stadler et al., 2007) by taking a step in this direction. We formalize a context in which upward *autonomous* transfers of academic inventions may coexist together with the more "traditional" TTO downward transfer. In our model, a professor has the opportunity to perform a technology transfer autonomously with a given probability. Certain national regulations or university employment contracts make autonomous transfer perfectly legal whereas bypassing the TTO is illegal and strictly enforced in others. Our model nests those two extreme cases and also captures mixed models in which professors may disclose their inventions to the TTO but sometimes do not. In between those extreme cases we have a situation, well known by technology transfer professionals in universities, characterized by the university formally having the rights, but professors not always disclosing their inventions to the TTO beforehand. The TTOs may then be unaware of undisclosed inventions, and even when they actually do they are either unable to prove that the invention was not performed outside the employment contract, not willing to enforce the rights of the university, or even not able to do so for internal or external reasons.

To appreciate how transfer channels may affect the matching between academic inventions and potentially interested companies, we incorporate insights from the recent literature explicitly modeling information and coordination issues in technology transfer. On the one hand, the professor/inventor has better knowledge of the invention quality, which we assume she may signal to potential partners in an *autonomous* transfer strategy. On the other hand, the model conveys the idea, often put forward in support of the university ownership regime, that the TTO can contact a larger set of potential licensees. We do not formally make the assumption that the TTO is better at finding good matches, but, as this may happen, it is one of the reasons justifying its very existence in a welfare perspective. In fact, the model highlights that the TTO plays two other crucial and non obvious roles in the transfer of academic inventions. First, it secures the rights to the invention that the professor is trying to sell upward. If knowledge leaks to the firm but no agreement is reached, the professor may then rapidly explore the standard downward transfer to protect her invention. Second, it increases the outside options of professors when an agreement is to be reached upward, and economizes on the signaling costs.

Solving the model allows us to formulate further predictions on university technology transfer. We focus on a semiseparating equilibrium of the game, in which good ideas are more likely to be transferred by the professor. The mixed transfer process leads to the quality sorting of academic inventions, as inventions of higher quality are often transferred upward to companies whereas lower-quality inventions are disclosed to the university. The model also predicts that those faculty members who can obtain a good match on their own are more likely to perform *autonomous* transfers, while they are more likely to disclose their inventions to the TTO when the TTO is more efficient or experienced.

We test the model's predictions on a sample of British professor–patent pairs. Data on the UK are particularly relevant to our setting. The UK was one of the first countries in Europe to implement the university ownership model when, in 1977, parliament approved the Patent Act which conferred to the employer (universities included) the right to employee inventions (Geuna & Rossi, 2011). In the mid-1980s, universities started to open technology transfer offices when budget cuts forced them to adopt new approaches to revenue generation (Meyer & Tang, 2007). The early establishment of TTOs, along with growing funding for research and government support for entrepreneurial activities in the mid-1990s (Smith & Ho, 2006), made the UK academic system one of the most entrepreneurial in the world. We focus on the years 1990–2001, as this period is particularly worthy of study because of its institutional heterogeneity vis-à-vis technology transfer. Some universities, like the University of Oxford, are known to strongly support the university ownership model (Smith et al., 2013). At the time, a few UK universities even had rules on IP ownership that overrode the national regulations (Smith et al., 2013). The best-known case is the University of Cambridge, which adopted an inventor ownership model and kept it until 2001 (Breznitz, 2011). In our empirical analysis we use PPPs to identify different scenarios for technology transfer. This allows us to exclude nonuniversity owned academic inventions which may not correspond to *autonomous* transfers. We regress the type of technology transfer, that is, *autonomous* versus university (or TTO) transfer, on patent, professor, and university characteristics. Probit estimates show that *autonomous* transfer by professors, as predicted by the theoretical model, favors the quality sorting of academic inventions. In line with the model, *autonomous* transfer is also associated with the professor's patenting experience and with lower TTO efficiency.

We also investigate the policy implications of autonomous transfer. As the hybrid model introduced in this paper encompasses both the TTO's monopoly over technology transfer and the situation whereby the professor always initiates an *autonomous* transfer, it provides insights to the policy literature discussing the impact of switching from one regime to the other.[1] In this respect, the closest article to ours is Hvide and Jones (2018) which shows Norway's abandonment of the "professor privilege" for a more standard university ownership regime had a negative impact on faculty inventions and start-up creations. Focusing on the moral hazard issues that arise in the joint production of two independent parties in the spirit of Holmstrom (1982), they interpret their results as the professor's contribution to technology transfer is more important than the university's one, and conclude professors should have the rights over their inventions. In our framework focusing more on match quality, a negative impact of making bypassing illegal when faculty members expect university rights to be enforced may be instead interpreted by closing efficient upward matching channels yet without having efficient, well-funded, and well-staffed TTOs in place, something which usually takes decades to be settled down. We may then refrain from concluding that the professor privilege regulation should be reintroduced but rather suggest allowing autonomous upward transfers (at least in a long transition period) and better rewarding professors for their inventions.

The remainder of the paper is organized as follows. Section 2 presents the literature on technology transfer and discusses the fundamental challenges associated with the coexistence of upward transfers together with the traditional downward transfer managed by the TTO. Section 3 sets out a theoretical model of such upward transfer in which the professor can initiate an *autonomous* transfer. It derives propositions to be tested further in the empirics. Section 4 presents the data and the different scenarios of university-industry technology transfer. Variables are presented in Section 5. The econometric model and the results are presented in Section 6. Section 7 concludes by discussing the policy implications of our approach acknowledging the potential coexistence of upward channels with downward ones.

2 | UNIVERSITY-INDUSTRY TECHNOLOGY TRANSFER: FRAMING THE ISSUES

2.1 | Literature review

Three main classes of conceptual problem have been considered in the literature on university-industry technology transfer. The first concerns the search activities required to find a match between inventors and investors; the second relates to the transaction costs associated with asymmetric information about the scientific quality of the invention and its commercial value; and the third concerns the involvement of inventors in the development stage, and the related moral hazard problem which arises once a technology transfer agreement has been signed.

2.1.1 | Matching

In the matching problem between suppliers of new knowledge (the professor) and potential buyers (the firms), the TTO has been seen as an intermediate actor providing organizational solutions to coordination failures. Searching for and identifying potential partnering firms in the market for technologies requires considerable time, effort, and competences. The TTO, characterized by a lower opportunity cost of time and better specialization than professors, is better qualified to pursue this goal (Chukumba & Jensen, 2005). Hellmann (2007) stresses how patent protection might facilitate knowledge transfer from universities to the private sector by allowing scientists to delegate the promotion of their scientific discoveries to the TTO. The author shows that inventors have incentives to delegate all search activities to the TTO if the invention is protected by a patent.[2] In our model, we focus on the matching between professors and companies and build on the idea that the TTO is better at extensively finding potentially matching companies.

2.1.2 | Information asymmetry

Information asymmetries on both sides of the match may arise. Professors know the intrinsic quality of their inventions better, given that these are usually embryonic, whereas companies can better evaluate the commercial value of the inventions (Macho-Stadler & Perez-Castrillo, 2010). The literature has investigated the former type of information asymmetry much more than it has the latter.

The high degree of uncertainty about the profitability of scientific knowledge (Arrow, 1962) paves the way for intermediaries to economize on the costs of expertise and to identify and sell profitable inventions (Hoppe & Ozdenoren, 2005; Lizzeri, 1999). Lizzeri (1999), for example, models a situation in which sellers and buyers are asymmetrically informed about the quality of a product, and then investigates the extent to which a certification intermediary may enter the market. The TTO usually assumes the role of information asymmetry reduction in university-industry technology transfer operations. Since it is not an independent certification institution, it can rely on success-based contingent payments, such as royalties (Gallini & Wright, 1990) or equity (Macho-Stadler et al., 2008), to extract private information: not only can it convince firms that it has an interest in choosing the right match, but also that it can screen the most valuable commercial projects (Savva & Taneri, 2012). These types of contracts pose other problems, however, because the firm does not have the right incentives to produce as much as it would otherwise do (Macho-Stadler & Perez-Castrillo, 2010).

The TTO can also build a reputation by pooling innovations across departments and research units within a university and, especially in the case of a large pool of inventions (Hoppe & Ozdenoren, 2005), it can shelve certain scientific discoveries to raise the buyer's beliefs as to the expected quality, which results in higher fees and profits (Biglaiser, 1993; Lizzeri, 1999; Macho-Stadler et al., 2007). However, the prerequisite for TTO efficiency in such signaling mechanisms is that it knows the quality of the professor's invention. Surprisingly, the information asymmetry problem between the inventor and the intermediary is not discussed in the literature. Why should it be assumed that the TTO has full information about the quality of inventions? Equally, why should we assume that the TTO is aware of companies' capacity to commercially exploit university inventions? In such a context, in which the seller has limited information, auctions turn out to be a relevant allocation mechanism.

2.1.3 | Moral hazard

Jensen and Thursby (2001) highlight the fact that the inventor's involvement in the development stage is crucial for companies, since most university inventions are still at an embryonic stage and require further development efforts from their inventors. However, since the involvement of faculty in the development stage is not contractable ex ante, it is difficult for it to commit to the transfer of this expertise and know-how, especially when professors prefer research activity to development (Dechenaux et al., 2009; Jensen et al., 2003). Consequently, companies normally ask for the inventor's income to be tied in some way to licensee output, through royalties or equity (Lach & Schankerman, 2008; Macho-Stadler et al., 2008). In general, the latter mechanism is more effective (Bray & Lee, 2000; Dechenaux et al., 2009; Jensen & Thursby, 2001). Macho-Stadler and Perez-Castrillo (2010) provide a conceptual framework of the main contractual issues related to the necessity to involve faculty in the downstream development of inventions, considering and comparing licensing and start-up creation as two different transfer paths.

This stream of literature is particularly interesting because it explicitly considers the behaviors of professors as separate agents. The main difference from our approach is that it focuses on what happens after the professors have gone to the TTO, whereas we are more concerned with what happens before they go to the TTO, and with whether they actually do go to the TTO or instead find an external agreement with a firm. This literature argues that the embryonic character of academic inventions creates a moral hazard problem regarding downward faculty involvement. We are more concerned with the high uncertainty this creates on both sides of the market and the importance of highly specialized expertise. This expertise leads to information asymmetry: professors know more about the scientific value of their inventions, whereas companies know more about the economic relevance of technologies.

2.2 | Upward transfers

In this article, we explore the coexistence of upward technology transfers together with downward transfers performed by the TTO. As suggested by the literature, we view academic technology transfer (either upward or downward) as a match between a professor's embryonic technology and a firm's capacity to bring it to market.

2.2.1 | The different forms of transfers

As synthesized in Figure 1, several typical scenarios of university-industry technology transfer can occur, depending on the origin of the invention and the way the research has been funded. According to the linear model of technology transfer (Godin, 2006), the invention may originate in the university laboratory, be disclosed to the TTO, which then protects the invention via a patent assigned to the university and seeks ways to turn the invention into a viable innovation by licensing it to industry. We call this scenario *downward (or university)* transfer. The transfer may instead take other routes, which we label as *upward* transfer channels, because most of the time the TTO has residual rights. For instance, the university professor may decide not to disclose a specific invention to the TTO and she may manage the transfer directly. We call this scenario *autonomous* transfer. The transfer might equally begin with the initial involvement of the private sector. This happens whenever companies turn to universities to investigate areas outside their core strengths, and select projects to fund in the hope of finding profit opportunities, or outsource research to a university laboratory, with the contract assigning to the firm the rights to any eventual invention stemming from that research (Evans, 2010).[3] We call this scenario *outsourcing*. The professor's invention may even originate *in* the industry laboratory. This arises when a firm has a specific problem to address but does not have all the necessary competences to deal with it. In this case, the firm may make the first move, selecting and employing a professor in a consulting activity and thus retaining the patent ownership. We call this scenario *consulting*. *Shelving* arises when the TTO refrains from

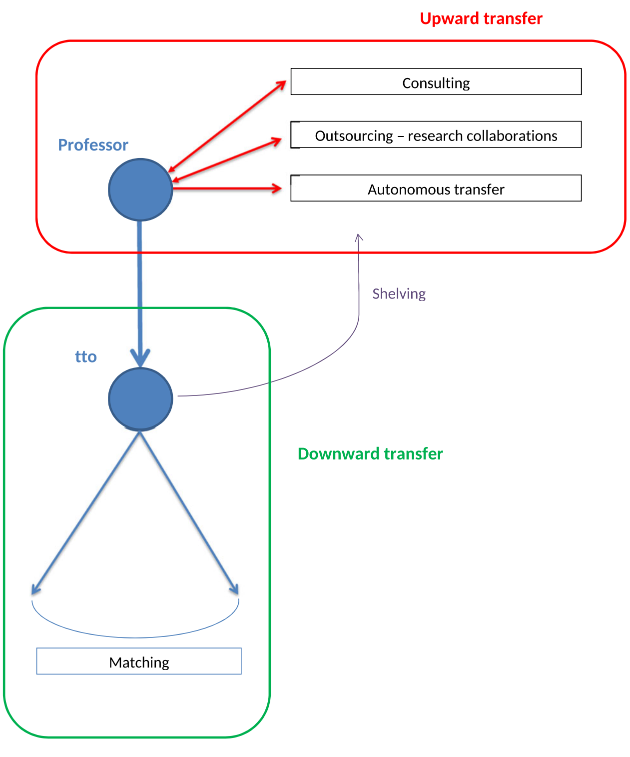

FIGURE 1 The coexistence of upward and downward transfer channels of academic inventions. TTO, technology transfer office [Color figure can be viewed at wileyonlinelibrary.com]

licensing certain inventions (Biglaiser, 1993; Lizzeri, 1999; Macho-Stadler et al., 2007). It may also result in an upward transfer, even though the invention was initially disclosed to the TTO.

2.2.2 | Modeling choices

Among the different forms of transfer, *university* and *autonomous* transfers are the core of our theoretical analysis and empirical model because we believe they are the most interesting for our purpose. But the other scenarios may occur and are thus also considered in the empirical part of this article.

As the literature reviewed above suggests, the TTO is likely to be more efficient at searching for potential partners than the professors. This transfer channel thus generates better expected matches for a given technology. The TTO, however, faces information asymmetry vis-à-vis the two sides of the market: invention qualities, of which professors are better informed, and the capacity to exploit these ideas, on which companies are themselves better informed. In this context, the TTO can advertise the technology to numerous potentially interested companies and allocate it through an auction design (Kamien, 1992). We do not claim that TTOs regularly use auctions to sell university technologies.[4] But, they do advertise their technologies to potentially interested companies and sell (exclusive or nonexclusive) licenses to the most interested ones among those which show up. An auction design thus turns out to be a convenient modeling tool to convey key ideas.

In upward transfers, experts on both sides of the market are usually more directly involved. Direct meetings and more informal relations often transmit information that reduces information asymmetry. This creates private costs (signaling costs, for instance) that may be offset by better matches. Therefore, professors can only interact with a few companies and thus obtain fewer potential matches. In the model presented in the next section, we take an extreme view for the sake of tractability: we assume that the professor meets only one firm and can observe its ability to exploit her idea. We focus on the information asymmetry concerning invention quality. The informed agent (the professor) can play first to signal this quality to the firm.

3 | AN HYBRID SIGNALING MODEL OF UNIVERSITY TECHNOLOGY TRANSFER

In this section, we introduce a theoretical model in which *university* and *autonomous* transfer channels coexist. In the *autonomous* case, the university scientist can signal the quality of her idea to a sampled firm. We show that there exists a semiseparating equilibrium of this signaling game, and fully characterize it. We focus on this equilibrium to derive predictions on the sort of inventions that are transferred upward and downward.

3.1 | The game

We model academic technology transfer as a game involving a professor, a matched firm, the university technology transfer office and the n other companies that will compete for the technology if it reaches the TTO. The game starts with a professor having an idea she believes has a potential commercial application. We assume the invention can be protected via a patent.[5] The commercial exploitation of this idea needs to be realized by a match with a firm. This match may be operated by the TTO or by the professor herself. With a nonnull probability φ, the professor is matched with a firm. If an agreement is reached with that firm, the professor hands over the property rights to the firm, and the game ends with a firm-assigned patent. If the professor does not consider the *autonomous* transfer (with probability $1-\varphi$), or if no agreement is found with the firm, the professor discloses the invention to the university TTO, which then always retains the intellectual property rights. The match is then operated by the TTO which organizes an auction to sell an exclusive license. We can view $(1-\varphi)$ as a measure of intellectual property rights enforcement in the university ownership regime. It may depend on the opacity of the legal system, the willingness of the university to enforce the law, and the capacity of the professor to bypass the TTO.

We assume that the expected commercial value of a patentable idea, noted ω, is a function of its intrinsic scientific and technological quality v, and of q, the ability of the matched firm to convert the idea into marketable technology products. The two variables are positive real numbers. The two dimensions are assumed to be complementary[6] and thus we use the following simple specification:

$$\omega = v \times q. \tag{1}$$

One of the basic premises of our model is that v is private information known only to the professor. The objective priors on the distribution of v, common to all companies, are described by the density function g, whose cumulative density is G; the mean of this distribution is noted as $\langle v \rangle$. The capacity of the firm to exploit the invention (q) is distributed according to the density function h, whose cumulative density is H and its mean $\langle q \rangle$. The capacity of the firm is a private information to all other agents and in all circumstances but to the professor if she operates the transfer. She can then contemplate the realization of q in this upward process path that we write q_0, because, from her point of view, this firm is not randomly matched to her. We assume the professor contacts a firm she knows from previous experience (which is itself not observable by other agents). The two dimensions are also assumed to be uncorrelated: $cov(v, q) = 0$.[7]

In the technology transfer operated by the professor, she can exert signaling efforts e, which produce a signal s, observed only by the matched firm. These signaling efforts consist in the professor preparing and holding several meetings to convince the firm of the quality of her idea. They have no effect on the intrinsic scientific quality v of the idea. We can equally view e as the opportunity cost of time dedicated to technology transfer as it diverts the professor from research. A natural assumption is that it is easier to signal the quality of an invention when it is of good quality. Thus, the efforts needed to provide a certain signal s, are also a function of v: $e(s, v)$. The standard and natural assumptions are that the marginal cost of signaling decreases with the quality of the idea, increases with the signal, and that the cross derivative is also negative: $e'_v < 0$, $e'_s > 0$, and $e''_{vs} < 0$. To keep the model simple, we will assume the following functional form for the signaling technology: $e(s, v) = s/v$. Assuming that signaling efforts and monetary incomes enter the utility function in a linear fashion, the net gain for the professor in the *autonomous* technology transfer is:

$$u(s, F, v) = F - e(s, v), \tag{2}$$

with F the monetary transfer. We assume that the professor makes a take-it-or-leave-it offer to the firm regarding the fixed fee F. Technically, this equates to give the professor all the bargaining power in this process but mitigating the bargaining power of the professor would not qualitatively change the results.

The matched firm's payoffs are given by:

$$\pi(F, v) = q_0 v - F, \tag{3}$$

if an agreement is concluded. These payoffs are equal to the total value of the invention minus the transfer to the professor. The model does not consider specifically faculty start-ups or, more generally, firms in which the faculty member has an equity stake. With a faculty start-up in place of the matched firm, the model would be modified but would not change fundamentally.[8]

For the sake of simplicity, we assume that the TTO organizes a Vickrey auction to sell an exclusive license of any invention that has been disclosed.[9] We use the auction design as a simplifying modeling device to capture the idea that the TTO exploits its visibility to contact a larger set of companies.

The number of companies that the TTO is able to convince to participate in the auction (without the help of the professor) is equal to n. The abilities of such companies to exploit the invention are independently drawn from the same distribution as that of the initially sampled firm. These companies do not observe the capacity of the matched firm, nor the previous experience of the professor. They even ignore whether the invention came directly or was unsuccessfully transferred upward. However, they do know that, with probability φ, academic inventions are matched with one random quality firm. Therefore, R, the expected seller revenue of the auction, is not a parameter but needs to be determined in the equilibrium of the TTO auction, even if the TTO auction is not in the equilibrium path of the game. We will see that, in the separating equilibrium, since inventions that reach the TTO either came directly or are those ones that have not been cherry-picked through the initial upward match, companies participating in the auction should update their beliefs accordingly. Let α denote the share of the expected revenue which is allocated to the professor.

The timing of the game is as follows:

1. A professor has an invention and observes its quality $v \in V$. With probability $1 - \varphi$, the professor goes directly to the TTO (then go to step 3 below) and, with probability φ, the professor is matched with a firm of quality q_0 from previous experience (then go to step 2 below).

2. The professor exerts a degree of personal effort e with the intention of convincing that firm of the quality of her idea. The signal s is observed only by that firm. Simultaneously, the professor makes a final offer to the firm in the form of a monetary compensation F to be paid by the firm in exchange for the property rights. If an agreement is reached by the two parties, the game ends. Otherwise, the invention is disclosed to the TTO and the game moves to step 3.
3. The TTO retains the property rights and organizes a Vickrey auction in which n companies participate to sell an exclusive license. The TTO gives the professor a share α of the auction revenue R.

3.2 | The (semi-) separating equilibrium

The game described above nests a signaling game (stage 2 of the game) in which the informed agent typically plays first and has the opportunity to send a (costly) message, which may or may not reveal its type (v). A professor's strategy is a function σ: $V \to S$, which attributes a signal s for each type v. A firm's strategy is a function γ: $S \to \mathbb{R}^{+}$, which attributes the largest acceptable monetary transfer F to be paid for an observed signal s. There is no need to formalize the final offer of the professor because it is uninformative and will always be equal to F. σ is an equilibrium strategy of the signaling game if $u(\sigma(v), \gamma(\sigma(v)), v) \geq u(s, \gamma(s), v), \forall\, s \in S$. This condition ensures incentive compatibility.

We focus on pure strategies and on equilibria that incorporate a separating part for (and only for) some interior segment of invention quality, that is when $v \in [\underline{v}, \bar{v}]$. A strategy σ is such a mixed separating equilibrium strategy if it respects incentive compatibility and if it is one-to-one for all $v \in [\underline{v}, \bar{v}]$. For other values of v, the equilibrium is pooling (and efficient): $\sigma(v) = 0$ for all $v < \underline{v}$ and, $(v) = \sigma(\bar{v})$ for all $v > \bar{v}$. Here the upper bound $\bar{v}$ equals the maximal value in the support of v so that there is no upper pooling part in the equilibrium (it goes to infinity if the support has no upper bound). There is a natural candidate for the lower bound, which is $\underline{v} = \alpha R/q_0$. If $v \leq \alpha R/q_0$, that is if the expected return from the TTO is larger than the total value of the innovation for the matched faculty–firm pair, a revealing mutually profitable contract is not feasible. Thus, the professor never signals herself so that the proposed payment is null and the invention is disclosed to the TTO.

When $v > \underline{v} = \alpha R/q_0$, and given that a strictly positive signal is sent, the firm is advised of the invention by the professor and informed of its quality. Via the take-it-or-leave-it offer set to the largest acceptable amount in the eyes of the firm F, the professor can extract all the value of the match ω in the (interior) separating part of the equilibrium.[10] When $v \in [\underline{v}, \bar{v}]$, provided that the relation $\sigma(v)$ is one-to-one, the firm can infer v from $\sigma(v)$, and the payment to the professor is

$$\gamma(\sigma(v)) = q_0 v, \tag{4}$$

where $\sigma(v)$ solves the first-order condition of the professor program, given by

$$\gamma'(\sigma(v)) = 1/v. \tag{5}$$

Differentiating both sides of Equation (4) with respect to v, arranging terms and using Equation (5), we obtain:

$$\sigma'(v) = q_0 v. \tag{6}$$

Integrating both sides of Equation (6) from $\underline{v}$ to v, and using the fact that the signaling strategy of the professor at the lower bound is is such that $\sigma(\underline{v}) = 0$, we obtain the interior equilibrium signaling strategy of the professor:

$$\sigma^*(v) = \frac{1}{2}(q_0 v^2 - (\alpha R)^2). \tag{7}$$

It is easy to show that $\sigma^*(v)$ respects the incentive compatibility condition when $v \geq \underline{v}$. The interior firm's equilibrium response to a given signal can be explicitly calculated by inverting Equation (4) to obtain the (expected) quality v given the observed $\sigma(v)$ and multiplying it by q as follows:

$$\gamma^*(\sigma) = q_0\, \mathrm{E}(v|\sigma) = \sqrt{2\sigma q_0 + (\alpha R)^2}, \tag{8}$$

when $\sigma > 0$. Equations (7) and (8) define agents' strategies in the separating part of the mixed equilibrium of the signaling game. The pooling part is given by

$$\sigma^*(v) = 0, \quad \forall\, v \leq \alpha R/q_0, \quad \text{and} \quad \gamma^*(0) = 0, \tag{9}$$

3.2.1 | The TTO auction

We now consider the stage 3 of the game, that is the downward second price auction organized by the TTO. The auction set up is standard (see for instance Krishna, 2009). The only originality is that the participating companies update their beliefs on the expected quality of the invention consistently with the considered equilibrium of the signaling game (stage 2). At equilibrium defined by Equations (7)–(9), R incorporates those updated beliefs in a classical subgame perfection argument. The consistency of this equilibrium relies upon the fact that R is well-defined, unique, and positive. Moreover, it is crucial to know whether R is strictly positive or null. If strictly positive, the equilibrium of the signaling game leads to the conclusion that the best inventions are more likely to be cherry-picked by initially matched companies. If R is null, any initial match leads to an agreement, and inventions never reach the TTO when a match occurs.

In the semiseparating equilibrium, the inventions that reach the TTO are not completely random: with probability φ, the inventions are matched with a firm which may cherry-pick the best ideas. Therefore, the (equilibrium consistent) expected quality of an invention that reaches the TTO, noted $\hat{v}$, is given by:

$$\hat{v} = \varphi E(v|v < \alpha R/q) + (1-\varphi)\langle v\rangle, \tag{10}$$

that is, with probability $(1-\varphi)$ the invention is a selection-free randomly drawn invention of mean quality $\langle v\rangle$, and, with probability φ, its expected quality is conditioned on the product of the random invention quality and the matched firm capacity being less than the expected return of the faculty from the TTO auction αR.

The expected return from the TTO auction (from the point of view of the seller) when the matched firm does not observe the idea, or when the professor goes directly to the TTO, is obtained by the following equation:

$$R = n\int_0^{\infty} r(x\hat{v})h(x)dx, \tag{11}$$

where $r(x\hat{v})$ is the expected payment of one of the n agents participating in the auction, having capacity x, and the posterior belief expected quality of the invention is $\hat{v}$ (and, thus, bidding $x\hat{v}$).

Therefore, $\hat{v}$ and R are intimately related by the system of Equations (10) and (11). We show, in Appendix A, that those two equations define one single solution couple that we calculate explicitly for specific density functions of v and q ($v \sim U(1/2; 3/2)$ and $q \sim U(0; 1)$):

$$R = \frac{(n-1)}{(n+1)}\hat{v}, \tag{12}$$

$$\hat{v} = (1-\varphi)\triangle(\alpha, \varphi, n), \tag{13}$$

with $\triangle(\alpha, \varphi, n) = \left(1 - \varphi^{\frac{\alpha(n-1)\ln 3}{2(n+1)}}\right)^{-1}$. It is obvious from Equations (12) and (13) that there are two necessary and sufficient conditions to have strictly positive R and $\hat{v}$: $\varphi < 1$ and $n \geq 2$. If all academic inventions are matched upward ($\varphi = 1$) then the downward market simply collapses, as in the "market for lemons," because the expected quality of the invention becomes null. If the TTO is so inefficient or the invention is so embryonic that there is no interested firm downward,[11] the expected revenue R is obviously null. Then, all inventions that have the opportunity to be matched upward, lead to a deal.

3.3 | Empirical implications

We have analysed in detail the game above and showed there exists a semiseparating equilibrium that we fully characterize. We now formulate a series of predictions of the model focusing on the stage 2 (conditional on a match) of the semiseparating equilibrium exposed above. We know that when $q_0 v \geq \alpha R$, that is when the gain of the professor in the *autonomous* transfer is greater than its expected share of the seller revenue in the downward auction, an agreement is made, and the ownership is retained by the matched firm. Otherwise, it is disclosed to the TTO. Replacing the revenue from the downward auction (R) by its endogenous value (using Equations 12 and 13), the above inequality can be rewritten as $v \geq \alpha R(\alpha, \varphi, n)/q_0$, so that the right-hand side of this inequality appears clearly as a function of the parameters of the model, noted $\Gamma(\alpha, \varphi, n, q_0)$. Thus, if $v \geq \Gamma(\alpha, \varphi, n, q_0)$, then the equilibrium path leads to *autonomous* transfer and firm assignment of the patent. If $v < \Gamma(\alpha, \varphi, n, q_0)$, the invention is disclosed to the TTO and the university retains the rights. The predictions of the model are based on comparative statics performed with respect to this inequality.

The first and most obvious result is related to ν. Note Γ is independent of ν. Therefore the larger ν is, the more likely it is greater than Γ, and, thus, of having *autonomous* transfer instead of TTO transfer. Proposition 1 follows immediately.

Proposition 1. *In the semiseparating equilibrium of the game (defined by 7, 8, and 9) higher quality ideas are more likely to be transferred through* autonomous *transfer and the rights over academic inventions are thus more likely to be assigned to companies (rather than to TTOs).*

Inventors with high quality ideas have incentives to signal their quality and to establish an agreement with the sampled firm, since their returns in the *autonomous* transfer path increase with idea quality, while their returns in the TTO transfer are invariant with respect to ν. In other words, as the information on invention quality is more efficiently revealed upward in the process operated by the professor, higher quality inventions are better sold in this transfer channel.

We now investigate how parameters α, φ, n, and q_0 affect the type of transfer. Our results are synthesized in Proposition 2.

Proposition 2. *In the semiseparating equilibrium of the game (defined by 7, 8, and 9), professors' ideas are more likely to be transferred through* autonomous *transfer, and the patents, in consequence, are more likely to be assigned to a firm (i) when the professor is matched initially with a high capacity firm (high q_0); (ii) when the invention is less likely to be matched with a firm upward (φ small); (iii) when the share of the price paid back by the TTO is low (α small), and; (iv) when the TTO is less efficient in attracting companies (n small).*

This proposition derives from the fact that $\Gamma(\alpha, \varphi, n, q_0)$ decreases with q_0 and φ, and increases in α and n (see comparative statics in Appendix A).

Inventors matched with a "good" firm (large q_0) are more likely to establish an agreement upward and thus not to disclose the invention to the TTO. When professors have strong connections with industry, they find better partners on their own and are thus less likely to be using the TTO transfer channel.

Moreover, the higher the share α of the revenue generated by TTO auction that is paid back to the professor, the higher the chance she will choose the TTO transfer process. This is due to two reinforcing but distinct effects. Raising α has a direct impact on what the professor obtains from the TTO (taking R constant). It also has an indirect effect through R, since it increases $\hat{\nu}$, the posterior belief of the companies about the quality of the invention in the auction organized by the TTO (which in turn increases R).

By assumption, φ clearly increases the probability that ideas are matched upward. Besides, φ also plays a role at equilibrium in the subgame where it eventually matches with a firm because it affects the beliefs downward of companies participating in the auction. Their managers know that the upward channel exists, and that it is quality sorting. In consequence, their beliefs concerning the quality of inventions that come out along the TTO channel increase when the probability that inventions go directly to the TTO $(1 - \varphi)$ increases. It follows directly, that the downward revenue from the auction, R, decreases with φ.[12] This involves a reduced revenue of the professors involved in those transfers (αR) who are then more likely to reach an agreement when matched upward.

Lastly, the higher the number of companies a TTO is able to attract to the auction (n), the higher the expected returns from the auction and, thus, the more the professor is likely to disclose the invention to the TTO.

To sum up, these arguments suggest that academic patents are likely to be assigned to companies when such inventions are of higher quality (high ν), when they are invented by professors with more connections with industry (high q_0), when professors inventions are more likely to match upward because of a weak enforcement of university rights (high φ), when professors are employed by universities whose TTO is less experienced in technology transfer (low n) and which offer inventors lower royalty share (low α). Most of these propositions will be tested empirically in Section 6. Their policy implications are discussed in Section 7.

4 | DATA

In this section we present the data and variables for the empirical estimation of the theoretical model, according to which a university scientist may opt for disclosure of her invention to the TTO or transfer it directly to a firm. In our estimation, we exploit detailed information on patents from a sample of 446 UK academic inventors. The sample of UK academic patents is presented in Section 4.1; the methodology for the identification of the different scenarios of technology transfer is described in Section 4.2.

4.1 | Sample of UK academic patents

Original data on UK academic patents come from the CID-KEINS database and were collected by Sterzi (2013), to whom we refer for in-depth descriptive statistics. The database contains detailed information on faculty members of UK institutions who appear as inventors in one or more patent applications filed at the European Patent Office (EPO) between 1990 and 2001.

The database is obtained by merging the patent data from the PATSTAT database (Version 2009), containing information on all EPO applications and their respective inventors, with the Review of Research Assessment (RAE) 2001 database,[13] containing data on 60,672 academic researchers active at March 31, 2001 and 173 institutions. By considering only researchers in research in scientific/technical disciplines,[14] RAE 2001 contains data on 29,362 research staff. Academic research active staff do include both full time and part time researchers, but do not include casual/hourly paid staff, or individuals employed under consultancy contracts or on the basis of payment of fees for services, without a contract of employment (RAE 2001, Guidance on Submissions, Section 3).

In the RAE database, individual information includes only the name of the university department (or research center) of affiliation, the discipline, complete surnames and first (and middle) name initials. In PATSTAT, individual information includes complete inventors' names and surnames and personal addresses (country, city, province, region, street, and zip code). The "Massacrator" algorithm[15] allows us to identify when two (or more) inventors listed in two (or more) patent applications are the same person.

Academic inventors are identified in four stages.

First, we select inventors at the EPO having British addresses, whose last patenting year is not before 1994 and not later than 2002.[16]

Second, we match the list of UK inventors' names with the list of UK academic researchers, by surname and first name initials. This matching procedure gives a total of 9009 potential British academic inventors. However, given that the match has not been done on the basis of complete names, the probability of false matches is very high.

Third, we perform web searches to retrieve information on complete names (first names included) of UK academic researchers and to collect their email addresses. By comparing the complete names and surnames from the list of UK inventors with those from the restricted list of UK academic researchers, we are now able to eliminate 5005 false matches when the two names do not fully correspond.[17] Moreover, in the web search we find 2588 professors' email addresses.

Fourth, these professors are then asked by email to confirm or refute their inventor status, using a web interface. We received 998 answers (response rate of 38.5%). Out of the 998 inventors who replied, 625 confirmed at least one invention. Altogether, these 625 inventors reported 1376 academic patent applications which were filed with the EPO when they were working in a UK university and represent 2.1% of all UK academic scientists.

As a final step, we collect personal information from CVs that professors have been asked to upload during the email survey or through internet searches. This includes time-invariant (such as gender, PhD institution, and PhD year) and time-variant information (such as the university affiliation at the time of the patent filing).

Looking at the distribution of the professors by discipline, T-tests reveal no statistically significant differences between respondents and nonrespondents in terms of discipline.[18] At the same time, we also suspect that academic inventors who may prefer to keep their patenting activity hidden or those for whom patenting has been a very marginal activity may be underrepresented. However, we do not think that this would influence the econometric results since we believe that the way patent and inventor's characteristics correlate with the invention assignment is orthogonal to the sample selection.[19]

It is possible that the applicant of the first filing may differ from the data from the applicant reported in the PATSTAT database, in the event of a subsequent change of ownership. So we manually checked[20] all patent applications assigned to companies according to the PATSTAT database. We found that approximately 5% of these were originally owned by universities, and so we categorized them as university-owned academic patents.

Since our focus is on the allocation of ownership rights between universities and companies, we consider the following major categories: "firm," "University," "University and firm," and "Others." The "firm" category consists of patents with at least one firm as first applicant, to the exclusion of patents coapplied for with other types of applicant.

Despite this conservative rule, Table 1 shows that almost 50% of academic patents in the sample are owned by firms. Patents coapplied for by companies and universities are counted in the "University and firm" category, representing 3.5% of the sample. Patents applied for by universities, alone or with other types of applicant excluding companies, represent about 38% of the sample. Finally, patents applied for by professors[21], public research organizations, and the British Technology Group (BTG)[22] are counted in the residual category ("Others").

These figures situate the UK somewhere between continental European countries—which usually report more than 70% of firm-owned academic patents (see Czarnitzki et al., 2012; Lissoni et al., 2008)—and the United States, in which about 25% of academic patents are assigned to companies (Thursby et al., 2009). It should be noted that, in the UK, with a few exceptions, professors have legally been obligated to disclose their inventions to the TTO since 1977 (Geuna & Rossi, 2011).

Since our aim is to explain why certain academic patents are assigned to firms while others are assigned to universities, patents assigned to the "Others" and "University and firm" categories are excluded from the analysis,[23] so that the final data set consists of 1186 patent applications filed by 518 academic inventors.

4.2 | The identification of different scenarios for the university-industry technology transfer

As discussed in Section 2.2, upward and downward technology transfers may coexist and there are four typical scenarios of university-industry technology transfer (*university*, *autonomous*, *outsourcing*, and *consulting*) which depend on the origin of the invention, the way the research has been funded and the academic inventor's disclosure strategy.

To identify the scenario each academic patent belongs to, we start by looking at the type of first applicant of academic patents. Whenever a patent has been assigned to the university in the first instance—that is, when the first patent applicant is a university—we assume that it is associated with the *university* transfer scenario: a professor has disclosed the invention she made in the university laboratory to the TTO, which has then managed the patent application.

4.2.1 | Upward transfers

The presence of a firm as patent applicant is consistent with all the remaining scenarios: *autonomous*, *outsourcing*, and *consulting*.

To identify these three scenarios, we exploit the fact that patents filed by academics are often science-based and linked to scientific discoveries, especially when they are based on inventions originating from university laboratories. In such cases, the same idea is recorded in both a patent and a publication, thus creating a patent-publication pair (PPP) (Ducor, 2000; Murray, 2002). More precisely, a patent and a paper form a pair when the same idea is described to some extent in both documents, and the academic inventor is also one of the authors of the paper.

We thus search for publication(s) linked to the patents assigned to companies out of all the articles by the academic inventor published in the year of the patent and in the following 4 years,[24] and we consider that a

TABLE 1 Frequency and number of academic patents by type of ownership

	%	Number
Firm	48.1	662
University	38.1	524
University and Firm	3.5	48
Others	10.3	142
Total	100	1376

Note: The category "Others" includes patents assigned to government institutions and PROs (74 cases), to physical persons (20 cases), or to the British Technology Group (48 cases).

patent and a publication form a pair when the same idea is given, for the most part, in both documents. By applying the *bag of words* method to the abstracts (the methodology is described in Appendix B.3) we are able to assign an index of similarity (cosine similarity measure) to each potential PPP and to select the closest publication for each patent.

Theoretical values of the similarity index are in the continuous $[0, 1]$ range. In our sample, as expected, the similarity index is higher for university-assigned academic patents than it is for firm-assigned ones, with an average of 0.15 and 0.13, respectively (the difference is statistically significant at the 95% level).

Scenario (a): Consulting transfer

We identify and define patents based on consulting activities as those for which we do not observe a twin scientific publication, which corresponds to a low index of similarity. We interpret the lack of complementarity (closeness) between the technological and scientific research of the professor as a sign of consultancy activity. In the absence of a clearly established threshold, we consider firm-owned academic patents as deriving from consulting activities when their index of similarity falls in the bottom 50% of the distribution of firm-owned patents. Results do not change significantly when we change the threshold (see Section 6.4). According to this selection rule, we consider 345 patents as being consulting-based, corresponding to 29% of the initial sample of 1186 academic patents.

Scenario (b): Outsourcing transfer

To differentiate between the two remaining scenarios, we use the information in the PPPs. In particular, we compare the names of the patent assignees with the names of the companies[25] which appear in the authors' affiliation and in the acknowledgments of the paper. A patent is thus considered to be based on the *outsourcing* transfer scenario when the firm that appears as patent applicant also appears in the publication linked to the patent.[26]

Out of the 317 firm-owned academic patents which are not associated with the *consulting* scenario, we identify and download the twin publications for 301 patents: we do not find the complete document for 16 publications listed in ISI-WoS.[27] We find 91 cases (30.3%) in which the firm listed as patent applicant is also reported in the publication pair, either in the affiliation of one or more authors or in the acknowledgments, or both. These patents are associated with the *outsourcing* transfer scenario.

Scenario (c): Autonomous transfer

In the remaining cases (210 patents, corresponding to 70% of the firm-owned academic patents that are not associated with the *consulting* transfer scenario and for which we are able to identify and download the twin publication), we do not find any firm in the scientific publication, or else the institution (firm) in the publication is different from the patent assignee. We thus categorize these inventions as being in the *autonomous* transfer scenario, according to which the academic inventor does not disclose the invention to the TTO and manages the transfer alone.[28] A variant of the *autonomous* transfer scenario is the case in which the professor discloses the invention to TTO that, however, decides to shelve it. Unfortunately, we cannot distinguish this last case from the *autonomous* transfer scenario in the data. However, a TTO may decide to shelve academic inventions either when it is unable to find a firm willing to buy the technology (Chukumba & Jensen, 2005) or to maintain quality and to build reputation (Macho-Stadler et al., 2007), or for budget-related reasons; in all these cases we would expect that, on average, inventions that are given back to the professors are of low value, leading to the opposite result to the one expected by the theoretical model.

Table 2 presents the frequency of academic patents for the different scenarios.

5 | VARIABLES AND DESCRIPTIVE STATISTICS

In this section, we present the variables used to proxy parameters of the theoretical model and present the descriptive statistics. In accordance with the theoretical model presented in Section 3, we focus only on the inventions generated in the university laboratory, without the initial involvement of the private sector, and that can be transferred either according to the *university* or the *autonomous* transfer scenario. Our final sample consists thus of 837 patents–professors pairs, for a total of 734 patents, corresponding to 210 patents following the *autonomous* transfer scenario and 524 the *university* transfer scenario.

TABLE 2 Upward and downward transfer of academic patents

	Number of patents	%
Consulting transfer	345	29.5
Outsourcing transfer	91	7.8
Autonomous transfer	210	17.9
Upward transfer (total)	*646*	*55.2*
University transfer	524	44.8
Total	1170	100

Note: Only "Firm" and "University" patents are considered. We could not find and download the twin publication of 16 academic patents assigned to companies.

5.1 | Variables

5.1.1 | The invention quality

Bessen (2008) suggests distinguishing the value of patent rents from the quality of the underlying technology. He argues that, as the former is generally linked to the quality of one or more products to be protected in the market (and to the position of the firm in the market), it is thus correlated to its ability to generate profits; the quality of the technology is far removed from the specificities of the market. This view is fully consistent with the theoretical model presented above, in which the total expected commercial value ω encompasses both the technical and the scientific part, captured by v, the quality of the invention, and the ability of the firm to translate it into commercial returns, captured by q_0.

In this section, we intend to find the most appropriate proxy for v. A useful way of thinking of v here is that it should reflect the quality of the patented invention *regardless of* the characteristics and ability of the applicant to convert it into a commercial product. In our view, the variable which best meets these requirements is the number of forward citations received by the patent (Jaffe & de Rassenfosse, 2019). Since Trajtenberg (1990), forward patent citations have often been used as an indicator of the technological importance of the patent. Albert et al. (1991) are among the first to provide a validation study of the use of forward citations as an indicator of technological impact. In their study, the authors report a strong correlation between the citations received by 77 Kodak silver halide patents and expert evaluations of technical importance of the patented inventions. Moreover, other authors also find that patent citations are highly correlated with the perceived importance of the invention by the inventors themselves (Harhoff & Reitzig, 2004; Harhoff et al., 1999; Harhoff et al., 2003; Jaffe et al., 2000).

Although counts of forward citations are an indicator of subsequent technological (Jaffe & de Rassenfosse, 2019), it turns out that forward citations might be also correlated with commercial value, although this usually happens with substantial noise (Abrams et al., 2013; Bessen, 2008; Gambardella et al., 2008). For example, Bessen (2008) finds that patent citations explain only little variance in patent value and that, among very highly cited patents, a significant fraction appears to be of little value.

As regards the requirement that the chosen proxy for v should be independent from the characteristics of the firm that exploits the patent, forward citations seem to be quite well suited. The number of times a patent is cited is not directly influenced by patent applicants and patent attorneys, and the exclusion of self-citations at the applicant level when counting forward citations can further help to mitigate possible reverse causality.[29] Other possible proxies sometimes used in the patent literature, such as the number of patent offices in which the patent has been filed (family size) and the number of years the patent was renewed for, are more likely to be correlated with the patent commercial value and more influenced by the characteristics of the applicant since they directly, or at least partly, result from decisions made by the applicant (de Rassenfosse & Jaffe, 2018).

More specifically, in the empirical analysis, patent quality is proxied by the number of forward citations in the first three years after the patent priority date (PatQual). We use a moving fixed-period time-window to control for the fact that, because of truncation, older patents receive on average more citations than more recent ones. We consider a 3-year window, because later citations are mostly seen as an indication of the science-basedness of patents (Czarnitzki et al., 2012; Lach & Schankerman, 2004; Sampat et al., 2003). However, to test for robustness, we also consider different citation lags (see Section 6.2).

Finally, we consider alternative measures of invention quality and propose, in Section 6.2, a composite index based on a common factor model encompassing different proxies for invention quality often used in the literature.[30]

5.1.2 | The expected returns from TTO transfer and the capacity of the sampled firm

The capacity of the firm to exploit the professor's idea (q_0) is approximated by the patenting experience of the focal professor, assuming that the capacity to find a good match on one's own is grounded in previous invention experiences. For each patent–professor pair, the focal professor's patenting experience ($\mathrm{ProfExp}$) is measured by the number of EPO patent applications she filed before the priority date of the focal patent. The idea is that the greater the professor's experience, the higher her capacity to contact a firm able to convert the idea into a product with high returns.[31]

The efficiency of the TTO (scaled by n in the theoretical model) is related to its ability to search for potential buyers of the technology. In doing so, the TTO should be effective in filing patent applications that are actually used and commercialized. Filing applications that are eventually not granted or that are not used actually represents a pure cost for the TTO. Without shelving certain inventions the TTO cannot raise the buyer's beliefs as to the expected quality of the patented inventions (Hoppe & Ozdenoren, 2005). Since only valid and (often) licensed patents are renewed, we proxy the efficiency of the TTO with the share of university patents managed by the TTO (or university) that have been renewed at least once. For each university and for each year, we compute the cumulative number of patent applications filed by the university and the subsample of them that have subsequently been granted and renewed at least once. Our proxy of TTO efficiency is thus the ratio of the two sums (TTOEff).

Unfortunately, we do not have data on φ, that is, the (ex ante) probability of the professor being matched with a firm of random quality rather than assigning the rights of her invention directly to the TTO. We argue that this probability reflects the opacity of the legal system, the willingness of the university (or the TTO) to enforce the law and the capacity of the professor to bypass the TTO. In the former case, the omission of φ does not lead to biased and inconsistent coefficient estimates: all professors face the same probability regardless of the quality of their invention. In the remaining cases, its omission does not cause problem when φ does not change over time and we control for university fixed effects and professor fixed effects. Nevertheless, when φ is a university or professor's characteristic which varies over time, its omission may lead to biased estimates. On the one hand, it is in fact reasonable to think that φ and TTOEff are negatively correlated since a university (TTO) investing in IP management might have more incentive to enforce the law. In this case, professors in universities investing in IP management have a higher likelihood of assigning their inventions to the TTO, not only because the latter provides them with a larger profit with respect to the *autonomous* transfer (through n), but also because it has a greater incentive to oversee and enforce the law. On the other hand, we might also expect that φ and $\mathrm{ProfExp}$ are positively correlated since more experienced professors have more power over the university administration (or TTO). In this case, experienced professors have a higher likelihood of transferring their inventions autonomously, not only because they know better companies to exploit their ideas (through q_0), but also because they can easily bypass the TTO.

Similarly, we do not have data on the revenue-sharing policies of UK universities, which could have been used to estimate the effect of the share (α) of the price paid back by the TTO on the patent assignment outcome. In most universities, in the years covered by the sample patent-related policies did not exist in written form and universities generally show limited interest in IP issues (Gazzard & Brown, 2012). This leads us to believe that universities, especially in the years covered by the analysis, did not often change policy regarding the royalty shares for their faculty. Thus, we are confident that, by considering university dummies, we can control for any nonobservable university technology transfer policy, such as revenue-sharing and incentive payments for technology licensing officials (Belenzon & Schankerman, 2009).

5.2 | Descriptive statistics

Since single patent applications may appear more than once if the invention was made by more than one academic inventor in the sample, the unit of observation in the analysis consists of patent–professor pairs, giving a result of 837 observations comprising 734 patent applications and 446 UK academic inventors.

Table 3 presents summary statistics for the previously described explanatory variables, reporting them separately for 600 academic patent–professor pairs transferred to the private sector through the TTO (*university* transfer) and 237

TABLE 3 Summary statistics on the sample of academic patent–professor pairs

	University transfer					Autonomous transfer					*T*-test	
	Obs.	Oean	*SD*	Min	Max	Obs.	Mean	*SD*	Min	Max	Diff.	*t*-value
PatQual	600	1.76	3.12	0	33	237	2.81	5.25	0	65	1.05	3.57
ProfExp	600	3.37	5.19	0	29	237	4.80	6.24	0	26	1.43	3.38
TTOEff	600	0.37	0.31	0	1	237	0.30	0.30	0	1	−0.07	−2.80

Note: Patents following the *consulting* and *outsourcing* scenarios are not considered. For a definition of the *university* and *autonomous* transfer scenarios, see Section 4.2.

academic patent–professor pairs transferred by university scientists without the involvement of the TTO (*autonomous* transfer).

A simple *t*-test for the comparison of means reveals that the two groups are significantly different in terms of invention quality (PatQual) as measured by forward patent citations (*t*-value = 3.57): patents transferred through the *autonomous* transfer channel have, on average, 60% more citations than those transferred through the TTO. In terms of patenting experience (ProfExp), more experienced professors are, on average, associated with the *autonomous* transfer scenario, and this difference is statistically significant (*t*-value = 3.38). Finally, the share of granted and renewed patents (TTOEff) is on average higher (*t*-value = 2.80) in cases of patents associated with the *university* transfer scenario, suggesting that professors in universities with high-quality TTOs are more likely to assign their patents to the university.

6 | ESTIMATION RESULTS

In this section, we test the implications of the theoretical model summarized in Propositions 1 and 2. In the first section, we propose baseline estimations. The other sections provide robustness checks that those main results hold under various specifications. In the second section, we control for the robustness of the results by considering alternative proxies for the computation of patent quality. In the third section, we account for unobserved heterogeneity. In the last section, we examine different ways for identifying technology transfer scenarios and excluding inventions resulting from faculty consulting.

6.1 | Baseline estimations

In accordance with the theoretical model, we regress the binary assignment variable y_i that indicates whether the patent has been transferred to the private sector according to the *autonomous* transfer scenario ($y_i = 1$) or according to the *university* transfer scenario ($y_i = 0$) on patent, professor, and university characteristics:

$$\Pr(y_i = 1) = F(\beta_1 \text{PatQual}_i + \beta_2 \text{ProfExp}_i + \beta_3 \text{TTOEff}_i + \mathbf{D}_i \boldsymbol{\beta}_4), \tag{14}$$

where i refers to the patent–professor pair and $\mathbf{D}_i$ stands for the matrix of control variables. Table 4 presents the coefficient estimates for probit models. In all models, we include year dummies, while we also add technological dummies, classification in 30 classes) in models II and III to account for the fact that academic patents in some fields are more likely to be transferred through one particular scenario. We also introduce university dummies (we include dummies for the Top 10 universities[32] according to the number of the patents in the sample) in model III to control for (time-invariant) specificities of the professor's university as regards technology transfer, such as royalty shares. Since the observations in the model consist of patent–professor pairs and academic inventors may appear several times in the data, we use standard errors clustered by academic inventor to control for potential dependence among the error terms. All explanatory variables, with the exception of the share of renewed patents at the university level (TTOEff), are expressed as their logarithm plus one, to avoid the nuisance of a null value.[33]

In all three models, the signs of the coefficient estimates are in line with the theoretical discussion. The quality of the invention is positively correlated to the *autonomous* transfer scenario, and the effect of patent quality is always significant at the 99% confidence level. Moreover, in line with the predictions of the model, we find that the higher the

TABLE 4 Baseline models: Probit model for the autonomous transfer scenario

	(I) Probit	(II) Probit	(III) Probit
PatQual	0.238***	0.238***	0.265***
	(0.066)	(0.071)	(0.069)
ProfExp	0.130*	0.138*	0.212***
	(0.071)	(0.071)	(0.072)
TTOEff	−0.373	−0.362	−0.775***
	(0.229)	(0.223)	(0.264)
Professor's university			
Imperial College			0.264
			(0.305)
UCL			0.324
			(0.313)
Bristol			−0.590
			(0.477)
Cambridge			0.124
			(0.219)
Durham			−0.511
			(0.614)
Manchester			−0.821**
			(0.381)
Nottingham			0.254
			(0.350)
Oxford			−0.867***
			(0.262)
Sheffield			0.0159
			(0.382)
Southampton			−0619.610
			(0.425)
Priority Year FE	Yes	Yes	Yes
Field FE	No	Yes	Yes
Observations	837	837	837
Pseudo R^2	0.056	0.097	0.142

Note: The dependent variable is equal to one if the transfer follows the *autonomous* transfer scenario; zero in case of *university* transfer scenario. PatQual is the (log of the) number of forward citations within the first 3 years after the patent priority date. Standard errors clustered by academic inventor in parentheses:

*$p < .10$.

**$p < .05$.

***$p < .01$.

professor's patenting experience, the greater the probability of the patent being transferred without the involvement of the TTO, and that the higher the efficiency of the TTO the lower the probability of observing an *autonomous* transfer.

University fixed effects control for time-invariant university technology transfer policies, including the willingness of universities to enforce the law (φ) and the revenue-sharing policies (α). Dummy coefficients for University of Oxford and University of Manchester are negative and significant, suggesting that academic researchers in these institutions are less likely to assign the invention to the private sector without involving the TTO. The University of Oxford is notoriously associated with the university ownership model (Smith et al., 2013) and its TTO (Isis Innovation, now renamed Oxford University Innovation) had the largest number of commercialization staff of UK universities during the first half of 2000s (Minshall & Wicksteed, 2005).[34] The University of Manchester has traditionally established rules that require faculty to disclose all inventions that may be patentable and provide strong financial incentives (up to 85% of the return to the IP during the 2000s) (HE-BCI Survey 2004–2014; Kalantaridis, 2019). The results show that, on average, researchers at the University of Oxford or University of Manchester have about 20% less probability to assign autonomously the invention to the firm (*autonomous* transfer) than an otherwise-comparable researcher in other universities.

6.2 | Alternative measurements of the invention quality

In this section, we investigate the robustness of the results by using different measures based on forward citations and by using a composite indicator which encompasses various proxies of the quality of the invention usually used in the literature.

As mentioned in the previous section, we have chosen to consider a 3-year window fixed-time interval to control for the fact that the number of citations received by a patent increases over time. However, by considering different citation lags, we show that measurements of invention quality computed by considering citations made during the first 5 years following the priority date are always significant, and are positively correlated with corporate patent ownership (see Table 5, columns I–V). In addition, results are also robust to the exclusion of self-citations at the applicant level (column VI).

To deal with the skewed distribution of patent quality we also used dummies for patents in the top of the distribution of citations (Gambardella et al., 2008). In particular, we considered seven main technological classes and, for each of them, we computed the distribution of 3-year patent citations. Then we approximated the quality of the invention with dummies for patents in the top 5% and 10% of this distribution. Results (Table 5, columns VII and VIII) show that patents in the top of the distribution are more likely to be assigned to companies. In terms of marginal effect this means that, for a patent with average characteristics, being in the top 5% increases the likelihood of observing a firm as assignee by about 24%.

While forward citations are extensively used as a proxy for invention quality, alternative indicators are also considered in the literature. Accordingly, we consider three alternative indicators which, following the approach suggested by Lach and Schankerman (2004), are combined into a synthetic indicator of invention quality: the number of backward citations, the number of claims and the number of technological classes.[35] The methodology used to construct the composite indicator of invention quality ($\mathrm{CompositeIndex}$) is presented in Appendix B.2. Results, shown in column IX of Table 5, are in line with previous findings: academic inventions of higher quality, as proxied by the composite indicator, are more likely to be assigned to companies.

6.3 | Unobserved heterogeneity

Our cross-section models may not account properly for unobserved heterogeneity characterizing academic professors. First of all, we do not observe the capacity of the professor to bypass the TTO: it could be the case, for example, that brilliant and productive scientists have more bargaining power over the university administration (or TTO) and come up with high-quality inventions. That would lead to upwardly biased estimates of patent quality on the likelihood of observing *autonomous* transfers. It could also be the case that professors have different opportunity costs of time spent in transferring technology. More productive scientists may then be more reluctant to be diverted from research and prefer the process managed by the TTO which is costless for them. That would lead to a (likely downward) bias of our estimates of patent quality if correlated with scientific productivity. to address this issue, we propose two solutions.

TABLE 5 Alternative measurements of invention value

	(I) Probit	(II) Probit	(III) Probit	(IV) Probit	(V) Probit	(VI) Probit	(VII) Probit	(VIII) Probit	(IX)
PatQual (1 year)	0.212**								
	(0.096)								
PatQual (2 years)		0.237***							
		(0.077)							
PatQual (3 years)			0.265***						
			(0.069)						
PatQual (4 years)				0.237***					
				(0.065)					
PatQual (5 years)					0.156**				
					(0.0610)				
PatQual Noself (3 years)						0.264***			
						(0.069)			
TOP 5%							0.818***		
							(0.243)		
TOP 10%								0.522***	
								(0.189)	
CompositeIndex									0.690***
									(0.386)
ProfExp	0.214***	0.211***	0.212***	0.206***	0.215***	0.230***	0.225***	0.223***	0.218***
	(0.071)	(0.071)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)	(0.072)
TTOEff	−0.760***	−0.770***	−0.775***	−0.764***	−0.750***	−0.767***	−0.764***	−0.744***	−0.748***
	(0.265)	(0.264)	(0.264)	(0.264)	(0.264)	(0.263)	(0.265)	(0.268)	(0.263)
Priority year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Top 10 University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	837	837	837	837	837	837	837	837	837
Pseudo R^2	0.132	0.136	0.142	0.141	0.134	0.140	0.134	0.130	0.141

Note: The dependent variable is equal to one if the transfer follows the *autonomous* transfer scenario, and to zero if it follows the *university* transfer scenario. CompositeIndex is a synthetic indicator of patent quality different citation lags based on the number of backward citations, claims and the number of 9-digit IPC technological classes (see Appendix B.2, for further details). Standard errors clustered by academic inventor in parentheses:

*$p < 0.10$.

**$p < .05$.

***$p < .01$.

First, we control for the scientific reputation of the academic inventor in our model. For each scientist we build a measure of scientific quality (SciRep) by considering the four articles, published in the years between 1996 and 2000,[36] that the academic inventor sent to the RAE 2001. These were then weighted by the ISI journal impact factor in which they appear. The average weighted sum is 5.06 in the sample.

Second, we exploit the variation in the quality of the inventions for a given inventor. To do so, in the case of prolific inventors, we exploit the fact that we may observe the characteristics of patents based on inventions made by the same professor but which are associated with different scenarios. We thus include inventor fixed effects in the probit estimations which control for unobservable and time-invariant characteristics of the professors. However, this procedure necessarily drops all inventors with only one patent, or with more than one patent but with only one type of patent applicant (i.e., no variation in the type of technology transfer chosen by the professor), resulting in a sample of 39 academic inventors and 173 patent applications (corresponding to 180 observations).

Results that control for unobserved heterogeneity are shown in Table 6. In columns I–II we control for SciRep, along with year, field and university fixed effects (only in column II); in column III–IV individual fixed effects replace SciRep.

In both cases, in line with the previous results and with the theoretical model, invention quality remains positive and significant: professors are more likely to bypass the TTO when they come up with high-quality inventions. Moreover, as with the baseline cases, when we control for SciRep, highly experienced professors and those working in universities with less efficient TTOs are more likely to transfer the patent autonomously. However, scientific reputation is not significant, which might be a signal of the fact that, if it exists, unobserved heterogeneity is not connected to the scientific reputation of the professors.

6.4 | Different identification of technology transfer scenarios

As explained in Section 4.2, we have developed strategies to identify unobservable upward transfer scenarios. In the baseline results, we consider (and thus exclude from the analysis) firm-owned academic patents as deriving from faculty consulting when their index of PPP similarity falls in the bottom 50% of the distribution of firm-owned patents. We now wonder to what extent the main empirical results of the paper are tied to this strategy.

To provide a first answer to this question, we run the same main regressions on samples obtained by relying alternative thresholds (10%, 25%, 75%, and 90%) of the same indicator (PPP similarity). Econometric results (see Table B3 in the appendix) show that the coefficient of invention quality remains positive and significant at the 99% level when relying on thresholds 10%, 25%, and 75%. It is only when we use the 90% threshold that it becomes non significant, that is when we consider that nine firm-owned academic patents out of ten result from faculty consulting.[37]

TABLE 6 Unobserved heterogeneity

	(I) Probit	(II) Probit	(III) Probit	(IV) Probit
PatQual	0.242***	0.267***	0.511**	0.565**
	(0.071)	(0.069)	(0.217)	(0.252)
ProfExp	0.137*	0.211***	−0.290	−0.650
	(0.072)	(0.072)	(0.527)	(0.551)
TTOEff	−0.371*	−0.775***	−1.089	−0.327
	(0.224)	(0.263)	(1.423)	(1.435)
SciRep	−0.006	−0.004		
	(0.015)	(0.016)		
Priority year FE	Yes	Yes	Yes	Yes
Field FE	Yes	Yes	Yes	Yes
Top 10 university FE	No	Yes	No	Yes
Professor FE	No	No	Yes	Yes
Observations	837	837	180	180
Pseudo R^2	0.097	0.142	0.324	0.393

Note: The dependent variable is equal to one if the transfer follows the *autonomous* transfer scenario; zero in case of *university* transfer scenario. PatQual is the (log of the) number of forward citations within the first 3 years after the patent priority date. Standard errors clustered by academic inventor in parentheses.

*$p < .10$.

**$p < .05$.

***$p < .01$.

If this threshold reduces the risk of false positives, it however leaves us with only 38 academic patents based on *autonomous* transfer, representing only 3% of our sample of UK academic patents. This percentage is very low and unrealistic, especially for the years covered by sample when some UK universities did not fully enforce university ownership right—as it was the case of University of Cambridge, that had assigned very few patents till 2006 (Geuna & Rossi, 2011).

We also use an alternative strategy to identify patents resulting from faculty consulting. Building upon Mansfield (1995) and Thursby et al. (2009), we consider that consulting projects are generally less original (and more incremental) than those originating in university laboratories. We rely on patent originality indicator (Hall et al., 2001; Trajtenberg et al., 1997), a measurement of the breadth of technology fields on which a given patent relies.[38] Inventions building on more diverse knowledge sources are here implicitly assumed be more original (Squicciarini et al., 2013). Academic patents are identified as resulting from faculty consulting (and excluded) when their originality index is either in the bottom 10%, 25%, 50%, 75%, or 90% of the distribution. The same econometric regressions as in the baseline estimation on the five samples obtained show that invention quality is always positively correlated with firm ownership (see Table B4 in the appendix).

7 | CONCLUSION AND DISCUSSION

While many scholars in the fields of law, sociology, and economics explore which entities could and should optimally own inventions that arise from government-funded academic research (Kenney & Patton, 2009, 2011), in this article we highlight the strategic behavior of academic inventors toward technology transfer. More specifically, we theoretically and empirically investigate the transfer of academic inventions by considering TTOs as facilities constituting only one way of commercializing university inventions. In this perspective, university researchers may not be willing to disclose their inventions to the TTO, but may instead choose to commercialize them on their own. We call this *autonomous* transfer.

On a sample of more than 800 pairs of British university professors and their patent applications (for their inventions) between 1990 and 2001 with the European Patent Office, we have shown that *autonomous* transfer is clearly associated with higher invention quality: professors opt to transfer the invention autonomously, rather than disclosing it to their TTO, when it is of high quality. Results are robust to the inclusion of various controls (such as the technological class, university, and individual fixed effects), and to the use of various proxies of the quality of the invention (different time windows for recording forward citations and the use of a composite indicator).

We conclude this paper by examining policy implications of acknowledging quality sorting upward transfer channels may coexist with the downward one, as suggested by our empirical results.

If the goal of the university is to maximize its revenues, our model leads to essentially two series of actions. First, the university may fight for enforcing its rights on the technology (decreasing φ) because autonomous transfer is a direct loss of revenue and because it decreases the priors on the expected value of its technologies commercialized downward. This policy may however be costly and may not please professors the university would like to keep from leaving to a more conciliating university. Second, TTOs may consider to incentivize professors to chose the downward transfer path essentially via inflating revenue shares for inventors (increase α). They may develop specific strategies towards professors with high levels of experience in patenting because they are more likely to have interesting autonomous transfer alternatives, offering them higher shares or an improved service for instance. The TTO could also allow personal financial returns to decrease less strongly with total income generated by the invention.[39] Late-entrant universities in technology transfer activity would more likely raise professors returns to compensate for their lack of experience in commercialization.

In terms of welfare, the most interesting implications of upward transfers concern match quality.[40] Even though the TTO may be able to contact more companies, this does not necessarily imply that the downward match is preferable to the one the professor would make on her own. It depends on how the quality of the firm sampled upward compares to the quality of the best firm downward. Certain professors' high-quality networks with industry likely attract better companies than inefficient TTOs would. Therefore, the nice consequence of the upward transfer channel is that it offers an opportunity for the invention to take a transfer channel that leads to a better match. Therefore, universities willing to maximize social welfare rather than their own revenues may establish TTOs but may refrain from strongly enforcing their rights, letting faculty members take the upward channel when they believe that represents a better route for their inventions. TTOs may focus on earning professors' inventions by offering efficient transfer management rather than by simply exerting a monopoly power on transfer.

An issue may however arise as the professor may care more about her revenues and not directly about finding the best match for her invention. The coordination problem manifests itself however only when the quality of the matched firm upward is large enough to justify upward transfer in a professor's eyes, whereas it is not welfare-improving. One way of reducing such miscoordination would be to increase the professor's share of revenue in the downward process so that the decision to transfer upward are as consistent as possible with welfare. It would not, however, be fully implementable under budget balance constraints since the expected revenue is lower than the total social value of the invention.

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ENDNOTES

[1]See, for example, Czarnitzki et al. (2016), Ejermo and Toivanen (2018), Hvide and Jones (2018), and Martínez and Sterzi (2020).

[2]This relies on the assumption that the TTO is more efficient than the professor at searching. However, when relaxing this assumption, the author shows that delegation to the TTO is inefficient, and that the optimal outcome is for the TTO to transfer the intellectual property rights back to the professor. Note that, in the paper, the TTO maximizes the returns of its owner, the university, and does not take into account any benefit to the professor.

[3]For example, Wright et al. (2014) report that BP supported research at Berkeley with a $500-million grant to explore biofuels from cellulose in plants or crop residuals, which was an area outside of BP's core strengths.

[4]Some universities, like Pennsylvania State University, actually did this though (Cahoy et al., 2016).

[5]Although we acknowledge that not all the inventions are patented, in this article we focus on IP rights assignment.

[6]We believe the complementarity assumption is the most realistic one. A high quality invention which does not find demand through an innovation has no commercial value. However, have we chosen to model the two dimensions of quality as perfect substitutes (for instance as $w = v + q$), the results would remain essentially the same.

[7]If v and q were correlated, then the firm sampled upward could use its q to form beliefs about the v. If correlation is not perfect, then the same results would qualitatively remain essentially the same.

[8]The start-up would need to signal to VCs that the whole project is valuable (ω), that is the technology is of good quality (v) and the business plan is convincing (q). As higher v and q are still likely to be more easily signaled, equilibrium characterization is very similar. Besides, professor rewards in the upward process may more likely take the form of equities in the start-up firm instead of an upfront payment, but this is equivalent here.

[9]The matched firm upward is assumed to not participate in the auction the TTO runs selling that same invention in case it deviates. In a previous version of the model, we allow the upward matched firm to also participate to the downward TTO auction, in the no-deal scenario. This feature is interesting as it limits the bargaining power of the professor. Indeed, in a revealing separating equilibrium, the firm can improve its bidding strategies in the downward auction because it observed the invention quality. Thus, any feasible agreement with the professor should give the firm at least that amount (to the extent that this is less than the value of the invention for the firm). Though it is an interesting feature, it complexifies significantly the exposure of the model without changing significantly the results. The interested reader may refer to the working paper version of this article (see Carayol & Sterzi, 2018).

[10]Had the professor not been given all the bargaining power, she would obtain only a strictly positive share of that value. The lower bound $\underline{v}$ would raise and thus the professor would be less likely to transfer upward, but the equilibrium would remain qualitatively similar.

[11]The situation in which $n = 1$ also brings a null revenue because of the second price auction design.

[12]R, which is equal to $\Gamma(\alpha, \varphi, n, q_0)/q_0$, decreases with φ.

[13]The RAE was established in 1986, when the UK government introduced the policy of selective funding and consists in a peer-review evaluation process.

[14]The exclusion of researchers in nonscientific/technical disciplines is due to the low probability of observing academic inventors in these fields; we select the following disciplines: Medicine, Biological Sciences, Pharmacy, Chemistry, Physics, Mathematics, Engineering Sciences, and Electronics.

[15]The Massacrator algorithm compares biographical information on each inventor, as well as on the technological contents (IPC code) and applicant of each inventor's patents (see Lissoni et al., 2008).

[16]Academic inventions filed at the UK patent office are excluded from the sample. Since inventions filed at the national level are in general of lower quality than those applied for with the EPO, our feeling is that we are under-representing university-owned academic patents.

[17]For example: inventor Lineker Jacob (EPO data) might be associated with professors Lineker J. from University of Oxford, Lineker J. from University of Liverpool and Lineker J. from University of Manchester (RAE data). After the web searches we were able to find the complete names of the professors in the three universities, so that we know that the professors' first names are respectively Jacob, James, and Jack and we then may eliminate the last two matches from the list of potential UK academic inventors.

[18]Statistics are displayed in Appendix B.1.

[19]Moreover, if any correlation does ever exist, we expect that inventors with high-quality patents transferred to companies are those who prefer to avoid answering the questionnaire, so we would expect a negative bias for the estimated relationship between *autonomous* transfer and patent quality.

[20]We searched for patent applications in Espacenet and Google Patents.

[21]Only 20 patents report the professor herself as unique applicant.

[22]The British Technology Group was a public organization operating as a brokerage agency in support of universities until its privatization in 1993. For robustness, BTG patents have also been recategorized as university-owned patents. The econometric results do not change much, with the exception of the effect of the TTO which becomes more significant, and are available on request.

[23]When we include in the analysis patents belonging to the "University and firm" category—assuming they follow the "university-transfer" mode—we obtain similar results.

[24]We exclude previous years since, if publication precedes the patent application filing, then it is considered to be prior art. In addition, we consider four years after the priority year of the patent to control for a potential publication lag.

[25]We search on the Internet to control for business groups and R&D agreements.

[26]We argue that when a firm sponsors the research carried out in the university's lab the freedom of the professor to choose how to assign the IP rights is limited. However, since the private sponsor may predict only marginally IPRs assignment (at least for the UK context, as shown by Lawson, 2013), it is possible that the professor may avoid to disclose the invention to the TTO and transfers autonomously the idea to the firm. The inclusion of these patents in the *autonomous* transfer scenario does not however change significantly the results.

[27]This is the case of publications without a digital object identifier. These patents are excluded from the analysis.

[28]We acknowledge that some of these patents may still be based on research originally funded by the private sector. However, we believe that only a small proportion of them are in fact based on the research sponsored by the private sector given that the firm owning the patent does not appear in the related publication pair.

[29]However, patents that are successively cited by other patents of the same applicant are, on average, of higher technological importance (Hall et al., 2005), suggesting that the applicant keeps exploiting the original patented idea.

[30]See Squicciarini et al. (2013) and Jaffe and de Rassenfosse (2019) for a recent discussion on definitions and measurements of invention quality.

[31]As alternative measure we also consider the inventor's professional network proxied by the number of interactions the professor had at the time of the focal patent. For each professor, and for each year, we build a variable which counts the cumulative number of unique collaborators/coinventors she had in the past (till year $t-1$). This variable is highly correlated with patenting experience (0.59) and results do not change significantly if we replace the professor's patenting experience with her professional network.

[32]Several universities do appear in the sample only once or few times, causing a problem of collinearity with technology and priority year fixed effects when all university dummies are included in the model. In the specifications we thus control only for large universities fixed effects (universities with at least 20 patent applications in the years covered by the sample).

[33]Results do not change when the variables are not log-transformed.

[34]Isis Innovation was a wholly owned subsidiary of the university. Researchers at University of Oxford were supposed to assign their IP to Isis, unless there were other pre-existing arrangements for exploitation. Isis Innovation was then responsible for evaluating, protecting and marketing the IP (Minshall & Wicksteed, 2005).

[35]In the literature, other indicators based on legal actions are also used to assess the economic importance of patented inventions. This is the case, for example, of changes of patent ownership and oppositions. Both are a signal of the economic importance of the patent in the market as perceived by a third party. Nevertheless, we think that these measures are related more to the value of patent rents than to the quality of

the underlying technology and, for this reason, they depend on the characteristics of the applicant. Harhoff and Reitzig (2004) found, for example, that patents of firms with strong patent portfolios are attacked less often than the patents of their competitors. Moreover, oppositions are often related to incremental than to radical innovations and, more generally, to highly attractive technical fields, which are not typical of academic inventions (this is confirmed in our sample, where only 6.7% of granted patents are opposed while at the EPO this was about 8% in a similar period, according to Harhoff et al. (2003). We tested these measures as proxies of the quality of the invention and found a positive and significant effect only for change of ownership.

[36]The time window reflects the submission period of the RAE 2001.

[37]As for the baseline model, we also exclude patents that are based on the Outsourcing scenario. The inclusion of those patents does not significantly change the results.

[38]Formally, $\text{Originality}_p = 1 - \sum_j s_{pj}^2$, where s_{pj} is the percentage of citations made by patent p to patents in class j (IPC 4-digit).

[39]Most universities significantly decrease the share given to the professor when the total licensing returns become large.

[40]We could also discuss how the transfer channels affect transfer costs. Upward transfers involve signaling efforts (which can be interpreted as opportunity costs as they divert her from research) that are obvious social loss. However, had we introduced transfer cost in the downward process, signaling costs would be counterbalanced by economized downward transfer costs.

[41]We use the "SEM" routine in Stata.

[42]We used the python library pattern, developed at CLIPS (see http://www.clips.ua.ac.be/pattern), as described in De Smedt and Daelemans (2012).

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APPENDIX A: THEORETICAL MODEL CALCULATIONS

A.1 The expected quality $\hat{v}$ and expected payment R

In Equation (10), the conditional expectation can be computed by taking the expectation operator twice: with respect to q (E_q), and with respect to v (E_v), as follows:

$$E(v|q<\theta(v)) = E_v E_q(v|vq<\alpha R) = \int_0^\infty \frac{1}{H(\alpha R/v)} \int_0^{\alpha R/v} x h(x) dx g(v) dv.$$

Assuming specific density functions for v and q ($v \sim U(1/2, 3/2)$, and $q \sim U(0,1)$) we can explicitly calculate the conditional expectation:

$$E(v|q<\theta(v)) = \int_{1/2}^{3/2} \frac{\alpha R}{2v} dv = \frac{ln3}{2}\alpha R.$$

Introducing the right hand side of this equation in Equation (10), the equilibrium beliefs of the companies are:

$$\hat{v} = \varphi \frac{\alpha R}{2} \ln 3 + (1 - \varphi). \tag{A1}$$

We can observe that, if the professor is never matched with a firm (i.e., if $\varphi = 0$), then the expected quality is equal to the mean: $\hat{v} = \langle v \rangle = 1$. If the professors are always matched with a firm ($\varphi = 1$), the expected quality linearly increases with αR, the threshold on the total value above which the professor does not disclose the invention to the TTO.

Equation (A1) is the first equation of the system that will lead us to the simultaneous determination of $\hat{v}$ and R. The second equation of the system basically derives from Equation (11), in which we need first to compute $r(x\hat{v})$, the expected payment of an agent participating in the auction, having capacity x, provided that there are $n-1$ other competitors. This expected payment is given by:

$$r(x\hat{v}) = \hat{v} E(Z | Z < x) \times P(Z < x) = \hat{v} \int_0^x z(n-1)h(z)H(z)^{n-2} dz,$$

with random variable Z being the maximum offer among the $n-1$ other competitors: $Z = \max_{j=1,\ldots,n-1} q_j$. Assuming that capacities are uniformly distributed again between zero and one, we obtain:

$$r(x\hat{v}) = \hat{v}(n-1) \int_0^x z^{n-1} dz = \hat{v} \frac{(n-1)}{n} x^n.$$

Replacing $r(x\hat{v})$ by its above expression in Equation (11), we obtain:

$$R = n\hat{v} \frac{(n-1)}{n} \int_0^\infty x^n h(x) dx$$

which, after some computations, gives:

$$R = \hat{v} \frac{(n-1)}{(n+1)}. \tag{A2}$$

The equilibrium beliefs on invention quality $\hat{v}$, and the expected return from the TTO auction R are, thus, related in this system of two equations, composed of Equations (A1) and (A2). We can observe that we always obtain an equilibrium since $\varphi \frac{\alpha}{2} \ln 3 < \frac{(n+1)}{(n-1)}$, because α, φ, and $\ln(3)/2$ are each less than the unity. The equilibrium solutions are given by Equations (12) and (13).

A.2 Comparative statics

Replacing R by the right-hand side of Equation (12), we obtain:

$$\Gamma(\alpha, \varphi, n, q_0) = \frac{\alpha}{q_0}(1-\varphi)\frac{(n-1)}{(n+1)}\left(\frac{2(n+1)}{2(n+1) - \varphi\alpha(n-1)ln3}\right). \tag{A3}$$

The comparative statics follow:

- $\frac{\partial \Gamma(\alpha, \varphi, n, q_0)}{\partial q_0} < 0$ because q_0 is at the denominator of $\Gamma(\alpha, \varphi, n, q_0)$ which is positive since $\alpha\varphi ln3 < 2$.
- $\frac{\partial \Gamma(\alpha, \varphi, n, q_0)}{\partial \alpha} = \frac{\varphi(\ln 3)(1-\varphi)(2n+2)(n-1)^2}{q_0(n+1)(2n - \alpha\varphi(\ln 3)(n-1) + 2)^2} > 0$
- $\frac{\partial \Gamma(\alpha, \varphi, n, q_0)}{\partial n} = \frac{((1-\varphi)(2n+2)(n-1))}{q_0(n+1)^2(2n - \alpha\varphi(\ln 3)(n-1) + 2))} + \frac{(2(1-\varphi)(n-1) + (1-\varphi)(2n+2)}{q_0(n+1)(2n - \alpha\varphi(\ln 3)(n-1) + 2))} + \frac{((1-\varphi)(2n+2)(\alpha\varphi \ln 3 - 2)(n-1)}{q_0(n+1)(2n - \alpha\varphi(\ln 3)(n-1) + 2)^2)}$, which becomes, after some recombination, $\frac{\partial \Gamma(\alpha, \varphi, n, q_0)}{\partial n} = \frac{4(1-\varphi)(2n(1 + 2n^2 + \alpha\varphi \ln 3) - (\alpha\varphi \ln 3 + n^2\alpha\varphi \ln 3))}{q_0(n+1)((n\alpha\varphi \ln 3 - 2) - 2n - \alpha\varphi \ln 3)^2}$, which is strictly positive, since $\alpha\varphi ln3 < 2$.
- $\frac{\partial \Gamma(\alpha, \varphi, n, q_0)}{\partial \varphi} = \frac{2(n-1)(-2 - 2n - \alpha \ln 3 + n\alpha \ln 3)}{q_0(-2n - \alpha\varphi \ln 3 + n\alpha\varphi \ln 3 - 2)^2} < 0.$

APPENDIX B: EMPIRICAL COMPLEMENTS

B.1 Sample selection bias

B.2 A composite invention quality index

As alternative to the use of forward citations, we consider three alternative indicators which are combined into a synthetic indicator of invention quality: the number of claims, the number of backward citations, and the number of technological classes. By controlling for certain observed patent characteristics, such as the technological class and the priority year, we derive the common factor as the unobserved characteristic of a patent that influences the three indicators. As discussed by Lanjouw and Schankerman (2004), this composite indicator might reduce the variance in invention quality compared to employing only one of the proposed indicators.

As the first indicator of the quality of the invention, we consider the number of claims in the patent application, which determines the breadth of the rights conferred by a patent and reflects its technology value (Lanjouw & Schankerman, 2004).

The second indicator is the number of backward citations, that is, citations to prior art listed in the patent document, which are checked by the patent examiner during the technical examination at the EPO (Squicciarini et al., 2013). Formally, backward citations are used to define the validity of the claims stated in the patent application (OECD, 2009). Lanjouw and Schankerman (2001) suggest that backward citations are a sign that a patent belongs to a relatively well-developed technology area and Harhoff et al. (2003) find them positively related to the value of the patent.

Finally, the third indicator is the patent scope (Lerner, 1994), defined as the number of 8-digit International Patent Classification (IPC) technology classes. A large number of technological classes should reflect the diversity and the scope of the patented invention and should be positively correlated to the quality of the invention.

We consider the sample of all European patent applications between 1990 and 2001, with at least one inventor residing in the UK (58,572 observations), to retrieve the parameter estimates and construct the composite indicator of patent quality (CompositeIndex).

The composite quality index is a linear combination of observed indicators. Following the approach suggested by Lanjouw and Schankerman (2004), we use a multiple indicator model with an unobserved common factor:

$$x_{i,n} = \gamma_i s_i + e_{i,n} \tag{B1}$$

where $x_{i,n}$ is the value of the ith patent indicator for the nth patent observation (in log); s_i is the common factor, with factor loading $\gamma_{i,}$ and normally distributed.

The common factor is the unobserved characteristic of a patent that positively influences the "quality" indicators. We consider the following indicators:

1. Claims: Number of claims listed in the patent application (Source: OECD Patent Quality Data set, Squicciarini et al. (2013);
2. Backward citations: Number of backward citations (Source: CRIOS-PATSTAT);
3. Patent Scope: Number of 8-digit IPC technology fields (Source: CRIOS-PATSTAT).

Like Lach and Schankerman (2004), we call "quality" the unobserved common factor because we think it is the only characteristic common to all three indicators.

The present analysis is based on the total number of European patent applications between 1990 and 2001, with at least one inventor residing in the UK (58,572 observations). We estimate s_i by a two-step procedure. We first regress the three observed patent quality indicators against two observable patent characteristics: the priority year and the technological class of

TABLE B1 Disciplines: Sample versus nonrespondents (%)

Aggregated units	Respondents	Nonrespondents
Medicine	278 (27.86)	438 (27.55)
Biological Science	166 (16.63)	272 (17.11)
Pharma and Chemistry	145 (14.53)	240 (15.09)
Physics and Math	102 (10.22)	166 (10.44)
Engineering and Electronics	307 (30.76)	474 (29.81)

the patent according to the OST30 classification. The residuals of such equations are the indicator values that are not explained by these observable characteristics. In the second step, we use the residuals from the first step, as determined by the common factor. From the matrix of variance-covariance of error terms of the three equations we derive the parameter estimates (shown in Table 8) of the common factor model.[41] Finally, from these estimates we derive the weights we use for the quality index.

B.3 PPP identification

We apply established methods of data mining to identify PPPs, as follows:

1. From our sample of 625 UK academic inventors we collected their publication data from the Clarivate-*Web of Science*. This procedure has been done by searching for the academic inventor's last name and first name initial. We also considered the scientific domain to impose a restriction. To identify potential pairs, we selected only scientific documents published in the year of the patent and in the following four years. In addition, we selected only articles and discarded all other types of documents (such as Meeting abstract and Book Review). According to this rule we did not find any scientific articles for ten academic inventors and ended up with 58,060 distinct articles, which gives a ratio of 94 articles per inventor. We acknowledge we might have some false-positives, but this is not a problem since we only use these publications to select the potential pair of the sample of UK academic patents, identified as being the most similar in terms of abstract content. In particular, once all potential scientific articles were identified, we then matched them with the selected academic inventors' patents, thus obtaining a pool of patent-PPPs. Thus, for all PPPs, we examined the abstracts and transformed them into comparable sets. We removed uninformative terms such as conjunctions, pronouns and most frequent nouns and verbs from abstracts.
2. In the second step, we applied the *bag of words* method (Leopold & Kindermann, 2002; Salton & McGill, 1983) to compute a similarity index among all potential PPPs. The algorithm, built in python, consists in building a list with all the words existing for each disciplinary field. Then each document (patents and scientific articles) is described by a vector, where the value of each dimension corresponds to the number of times that term appears in the document. The similarity value is given by cosin similarity, defined as the inner product space that measures the cosine of the angle between them. If x_{ij} is the value of the binary variable for word i and document j, S measures the similarity between two documents, k and s, as follows:

$$S(k,s) = \frac{\sum x_{ki} x_{si}}{\sqrt{\sum x_{ki}^2}\sqrt{\sum x_{si}^2}}.$$

Since the cosine of 0 is 1, the value ranges between 0 and 1, where 1 is a perfect similarity.[42] In our application, by considering all potential PPPs, this index takes values comprised between 0 and 0.62.

3. In the third step, for each patent, we presumed a one-to-one match between patent and publications and selected the closest publication in terms of cosin similarity. The index of similarity for the patent–professor pairs has a mean of 0.14 and a median of 0.11.

TABLE B2 Parameter estimates of the common factor model

Backward citations	0.29***
	(0.013)
Claims	0.18***
	(0.009)
Patent scope	0.43***
	(0.019)
Observations	58,572

Note: The explanatory variables are the standardized residuals of regressions of the three patent quality indicators against year and technological field dummies. Standard errors in parentheses:

*$p < .10$.

**$p < .05$.

***$p < .01$.

B.4 Robustness check

TABLE B3 Alternative thresholds to exclude Consulting based patents (probit models)

	(I) Exclusion rule: Proximity <0.02 (10th percentile)	(II) Exclusion rule: Proximity <0.05 (25th percentile)	(III) Exclusion rule: Proximity <0.19 (75th percentile)	(IV) Exclusion rule: Proximity <0.28 (90th percentile)
PatQual	0.198***	0.250***	0.279***	0.062
	(0.059)	(0.061)	(0.087)	(0.110)
Priority year	Yes	Yes	Yes	Yes
Field	Yes	Yes	Yes	Yes
Top 10 university	Yes	Yes	Yes	Yes
Observations	1096	989	716	646
Patents	975	874	626	562
Aut. transfers	451	350	102	38
Univ. transfers	524	524	524	524
Pseudo R^2	0.111	0.123	0.172	0.243

Note: The dependent variable is equal to one if the transfer follows the *autonomous* transfer scenario; zero in case of *university* transfer scenario. PatQual is the (log of the) number of forward citations within the first 3 years since the patent priority date. TTO efficiency and professor's experience are included in all specifications and are always significant. Patents based on the *outsourcing* transfer scenario are excluded from the models. Standard errors clustered by academic inventor in parentheses.

*$p < .10$.
**$p < .05$.
***$p < .01$.

TABLE B4 Alternative indicator to individuate consulting-based patents: Patent Originality (probit models)

	(I) Exclusion rule: Originality <0.38 (25th percentile)	(II) Exclusion rule: Originality <0.50 (50th percentile)	(III) Exclusion rule: Originality <0.67 (75th percentile)	(IV) Exclusion rule: Originality <0.74 (90th percentile)
PatQual	0.242***	0.276***	0.314***	0.262**
	(0.064)	(0.070)	(0.098)	(0.112)
Priority Year	Yes	Yes	Yes	Yes
Field	Yes	Yes	Yes	Yes
Top 10 University	Yes	Yes	Yes	Yes
Observations	1008	855	715	656
Patents	899	759	629	573
Aut. Transfers	375	235	102	49
Univ. Transfers	524	524	524	524
Pseudo R^2	0.139	0.169	0.258	0.335

Note: The dependent variable is equal to one if the transfer follows the *autonomous* transfer scenario; zero in case of *university* transfer scenario. PatQual is the (log of the) number of forward citations within the first 3 years since the patent priority date. TTO efficiency and professor's experience are included in all specifications and are always significant. Patents based on the *outsourcing* transfer scenario are excluded from the models. Standard errors clustered by academic inventor in parentheses.

*$p < .10$.
**$p < .05$.
***$p < .01$.