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Searching for new combinations: How do academic inventors affect firms? technological recombination?

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Abstract

This paper proposes that academic inventors, who are researchers employed at universities and who are involved in the invention processes of firms, can be an important search channel for firms, and that directly involving them in firms? invention teams may increase the probability of generating technological combinations new to the firm. The hypotheses derived based on this proposition are tested on patent data between 1990 and 2005 on Swedish based R&D intensive firms in manufacturing industries, and are supported by the empirical tests. The findings demonstrate that when academic inventors join firms? inventor teams the likelihood of generating new combinations increase substantially, but only so in firms? core technologies. This paper thus contributes to the emergent microlevel theory of technological recombination and innovation search, by examining a specific type of inventor not investigated in prior studies.

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Abstract

This paper proposes that academic inventors, who are researchers employed at universities and who are involved in the invention processes of firms, can be an important search channel for firms, and that directly involving them in firms' invention teams may increase the probability of generating technological combinations new to the firm. The hypotheses derived based on this proposition are tested on patent data between 1990 and 2005 on Swedish based R&D intensive firms in manufacturing industries, and are supported by the empirical tests. The findings demonstrate that when academic inventors join firms' inventor teams the likelihood of generating new combinations increase substantially, but only so in firms' core technologies. This paper thus contributes to the emergent microlevel theory of technological recombination and innovation search, by examining a specific type of inventor not investigated in prior studies.

1. Introduction

Technological inventions are commonly conceived as created through a search process for novel recombinations of knowledge (Fleming, 2001; Nelson and Winter, 1982). In order to innovate and remain competitive, firms need to leverage their existing knowledge base by searching for and accessing new "distant" knowledge, since relying solely on their pre-existing knowledge base over time limits the choice of and opportunities for useful new combinations (Fleming, 2001; Nickerson and Zenger, 2004; Rosenkopf and Nerkar, 2001), thus limiting the chances for successful innovation.

While it is the inventors, individually or in the teams they work in, that search for and recombine knowledge into new inventions, thus rejuvenating the knowledge base of the firm, most studies of innovation search and technological recombination has been conducted at the firm level (see Gruber et al., 2013). Much attention has in line with this focus been put on investigating the external sources which firms use to search for and access distant knowledge, showing for instance the importance of inter-firm searching and learning through strategic alliances and mobility and hiring of inventors (Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011; Song et al., 2003).

Microlevel studies of technological recombination are fewer, but Fleming et al. (2007) show that inventor-level factors, such as network structure and breadth of experience, influence the creation of new technological combinations. More recently, Gruber et al. (2013) studied the difference between the two main types of inventors - scientists and engineers -regarding their ability to span technological boundaries.

In this paper, I investigate the influence of another specific type of inventor on firms' (novel) technological recombinations; Namely academic inventors, who are researchers employed at universities and who firms involve in their invention processes. While universities and academic research have been shown to be relatively important external sources of knowledge for innovation (Cohen et al., 2002; Mansfield, 1998; e.g. 1991), there have been few microlevel studies of the role and impact of academic researchers on firms' invention processes (cf. Ljungberg et al., 2013), and this type of inventor has not been the object of study in the literature on innovation search and technological recombination. This paper therefore analyses whether and to what extent involving academic researchers in firm inventions affects the probability of generating technological combinations which are new to the firm.

Drawing on literature on the role of science for innovation (Allen, 1977; Fleming and Sorenson, 2004; Gibbons and Johnston, 1974) in relation to the the work on innovation search and technological recombination (see e.g. Fleming and Sorenson, 2001; Katila and Ahuja, 2002; Laursen, 2012), I propose that directly involving academic researchers in firms' inventor teams can enhance the probability of generating technological combinations new to the firm; And hence, I suggest that academic inventors can be an important search channel for firms when attempting to rejuvenate their knowledge base through technological recombination. I test this proposition, through a set of hypotheses derived in the following section, on patent data between 1990 and 2005 on Swedish-based[1] R&D intensive firms in manufacturing industries. By using the KEINs/APE-INV database on European academic inventors (see Lissoni et al., 2006; Ljungberg et al.,

[1] This geographical limitation is due to limitations in the data used to construct the main explanatory variables, i.e. the data on academic inventors (see Section 3 on method and data).

2013), I can identify academic researchers named as inventors on the sampled firms' patents.

This study contributes to the existing literature in two ways. First, I contribute to the literature on technological recombination (e.g. Fleming, 2001; Fleming et al., 2007) by furthering the limited evidence existing at the microlevel (cf. Gruber et al., 2013). Second, by focusing the analysis on the role and influence of academic inventors, who is not only a specific type of inventor not addressed by prior literature on technological recombination, but per definition also is an inventor that spans the firm boundaries, the paper moreover contributes to the literature on innovation search (see Laursen, 2012).[2]

2. Theory and Hypotheses

Technological inventions are largely the outcome of a process of searching for and recombining existing components of knowledge and technology[3] (e.g. Fleming, 2001; Nelson and Winter, 1982). In this view, invention is either a new combination of technological components (Nelson and Winter, 1982) or a reconfiguration of existing combinations (Henderson and Clark, 1990). Thus, invention can be characterized as a process of search for and recombination of new or reconfigured combinations of knowledge and technologies (Fleming and Sorenson, 2001).

Due to cognitive limitations of the inventor(s), and the fundamental uncertainty inherent in invention processes, this search process is closely related to the firm's existing knowledge base. Accordingly, the literature suggests that firm inventions tend to rely on local search for knowledge (Fleming, 2001; Nelson and Winter, 1982), meaning that the firm incrementally search in its available knowledge base. Firms are, in this way, bounded by their available knowledge bases (and competencies), and their prior knowledge and experience guide the inventive search processess.

Although firms' invention activities often are highly related to the existing knowledge base, their search processes are not necessarily limited within the technological

[2] The paper, and the study reported on, is a work in progress, and as such the results provided here should be seen as tentative.

[3] I here follow Arthur (2007) in defining technology as "a means to fulfill a human purpose" (p. 276) , and that it is "put together or combined from component parts" (p. 276). A component represents any fundamental part of knowledge, physical artefact or matter used to construct an invention. Thus, knowledge is an inherent part of any technology.

boundaries of the firm. Firms tend to be technologically diversified, and increasingly broaden and deepen their technology base over time, especially larger firms (Granstrand et al., 1997). One reason or this is that while there are several advantages of local search (see Laursen, 2012), such as learning effects, overreliance on this approach over time limits the choice of and opportunities for useful new recombinations (Fleming and Sorenson, 2001; March, 1991; Rosenkopf and Nerkar, 2001). That is, relying solely on local search, i.e. the pre-existing knowledge base, in the long run constrains the ability and possibility of the firm to successfully innovate, and thereby limits its competitiveness.

In order to remain competitive, firms therefore need to leverage and rejuvenate their existing knowledge base by spanning their technological boundaries (Fleming, 2001; Nickerson and Zenger, 2004; Rosenkopf and Nerkar, 2001). Put differently, the firm must "explore new possibilities" rather than just "exploit old certainties" (March, 1991); This is often referred to as exploratory search, as opposed to exploitative or local search, meaning that the firm actively searches for knowledge outside its preexisting knowledge base or that the inventors search for knowledge outside their own technological boundaries (Katila and Ahuja, 2002; Rosenkopf and Nerkar, 2001).

This means the firm needs to not only span the technological but also the organizational boundaries of the firm (Nickerson and Zenger, 2004; Rosenkopf and Nerkar, 2001). Indeed, the literature on innovation search and technological recombination have indicated the importance of not only combining knowledge across technological domains (e.g. Rosenkopf and Nerkar, 2001; Yayavaram and Chen, 2015) but also the importance of inter-firm knowledge sourcing through strategic alliances and mobility and hiring of inventors (Rosenkopf and Almeida, 2003; Singh and Agrawal, 2011; Song et al., 2003).

While most of the studies conducted in this literature have analyzed innovation search and technological recombination at the firm level, fewer have dealt with the microlevel, i.e. the inventors and inventor teams. A notable recent exception is Dahlander et al. (2014), who analyzed the relation between individuals' external search breadth and their innovation outcomes at IBM, finding that those individuals who allocated their attention to searching inside the firm were more innovative, and that those with a high external search breadth were more innovative only when they allocated more attention to those sources.

More in line with the purpose of this paper, Fleming et al. (2007) showed that inventor-level factors, such as network structure and breadth of experience, influence the creation of new technological combinations, which they measured as the combination of technological classes assigned to inventors' patents. More recently, Gruber et al. (2013) studied the relation between inventors' educational background and the technological breadth of their inventions, drawing on Allen's (1977) insight that there is a systematic difference between the two main types of inventors, scientists and engineers. They found that inventors with a scientific education are more likely to create patents with higher technological breadth than inventors with an engineering degree, measuring technological breadth using patent technological classes.

2.1 Hypotheses

In this paper, I am concerned with the technological combinations generated by a specific type of inventor, which has not been the focus of attention in the extant literature, namely academic inventors. By academic inventors, I will here mean researchers employed at universities, who are also named as inventors on firm inventions (patents). In so doing, I make the assumption that academic researchers named as inventors on firm-owned inventions have taken a collaborative role in the inventor team generating these inventions, that is that they actively and directly have taken part of the teams' search processes.[4]

Moreover, I am also concerned with technological combinations which are new to the firm, but not necessarily new beyond its boundaries, for the simple reason that my focus is on academic inventors as a mechanism for exploratory search and replenishment of the firm's knowledge base through the generation of new combinations. It should be noted that new technological combinations come in two types: the recombination of technological elements already present in the firm and/or the introduction of technological components new to the firm. At this stage, I however do not make this

[4] Empirically, I believe this to be a sound assumption, since the lion's share (n=292) of the firm-owned patents having academic inventors (n= 357) studied in this paper are co-invented together with non-academic firm inventors.

distinction, but only address the novelty of the combination, i.e. whether a combination is new to the firm or not.

I argue that, everything else equal, inventor teams which include one or more academic inventors have higher probability to generate new technological combinations, in comparison to teams with only firm inventors.[5] For the rest of this section, I will build up my arguments for this claim, starting from the specific characteristics of academic inventors - which include the particularities, characteristics and impact of academic knowledge and scientific training, skills and methods.

First, it has been argued that higher levels of formal education provides inventors with a more abstract understanding of technical problem-solving, more fine-tuned learning skills as well as a higher likelihood of developing a deep understanding of the learning process itself, which stimulates the ability of recombination across technological domains (Gibbons and Johnston, 1974). Moreover, since the achieved level of education is reflective of individuals' cognitive skills and structures (Pelled, 1996), inventors with higher formal education should have greater abilities of overcoming the complexity of technological recombination inherent for all inventors due to bounded rationality which constrains the cognitive abilities of recombination across domains (Simon, 1959). This means that academic inventors, all sharing the common denominator of having achieved the highest level of education - a doctoral degree -, should have an advantage in recombination across technological boundaries relative to inventors with less formal training. Indeed, the findings of Gruber et al. (2013) suggest that a doctoral degree is related to an increase in technological breadth for all types of inventors.

Scientific training is in a similar manner claimed to facilitate the inventor to access, evaluate and recombine new and old knowledge components (Gibbons and Johnston, 1974), thus providing an advantage in the search for new combinations. While not all academic inventors have scientific training in the strict sense, meaning education in natural sciences (cf. Allen, 1977), but many rather being engineers, it has also been pointed out that scientific knowledge in itself guides the inventor(s) to more useful and important inventions: Science, according to Fleming and Sorenson (2004), provides an understanding of the fundamental problem that the invention seeks to solve, by

[5] Note that I at this stage empirically make the assumption that all inventors of firm-owend patents, not identified as academic researchers, are firm employees.

predicting untried experiments and the usefulness of previously untested solutions through the generation and testing of theories. Thus, the scientific knowledge, skills and methods of academic inventors should "guide" their search towards new and useful combinations, giving them an advantage relative to inventors lacking the same scientific knowledge.[6]

Apart from their high formal education and scientific knowledge, academic inventors per definition span the organizational boundaries when taking part in firms' invention processes, and such boundary spanning have been shown to be important for technological recombination at the firm level (e.g. Rosenkopf and Almeida, 2003; Rosenkopf and Nerkar, 2001; Tzabbar, 2009). If one or more academic inventors join a team of firm inventors, they bring experiences, prior knowledge and skills to that team that differ from the other members. Greater diversity of teams have been shown to be linked to increased creativity and innovativeness (cf. Dahlander et al., 2014), which by definition are important ingredients in the ability to generate new technological combinations. Similarly, the academic inventors will also increase the variety of the teams' expertise and skills, for the same reasons as outlined above regarding their scientific knowledge and differing work experience. Variety in team expertise have been linked to increased innovation outcomes (Singh and Fleming, 2010), and for this paper more importantly to higher rates of technological recombination (Fleming et al., 2007).

Taken the argument of the boundary spanning role of academic inventors, and the associated knowledge variety, together with the advantages provided by their characteristics as scientifically trained and knowledgeable researchers lead to the following hypothesis:

> Hypothesis 1*: Inventor teams which (do not) include academic researchers are more (less) likely to generate inventions with technological combinations new to the firm.*

The technological area in which firms engage academic inventors may affect their opportunities and abilities to span technological boundaries and generate new combinations. When academic inventors join teams for projects in the firm's more

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[6] An indication that academic inventors draw more on science for invention than firm inventors is provided by a study showing that firm patents involving academic inventors have a higher propensity to cite scientific literature in the prior art (Ljungberg and McKelvey, 2012).

peripheral areas, I suggest that they will not be more likely to create combinations new to the firm, since a) the firm is by definition already conducting exploratory search in this area trying to establish new fruitful combinations which could give it a competitive advantage and b) since it is not part of the core competences of the firm the opportunities for recombination should be rich. Thus, inventor teams, with our without academic researchers, will in peripheral areas be more likely to generate new combinations. Thereby, the same logical dictates that firms ought to have fewer opportunities for recombination in their core areas, and due to their tendency to local search will not venture far outside the core's technological boundaries to supplement it with new technological components. Indeed, firms allocate most of their attention and resources to core technologies (Granstrand et al., 1997), and should thereby through extensive exploitative search have to some extent started to deplete the recombination opportunities within the technological boundaries. This means that there should be many opportunities for academic inventors, in their capacity as boundary spanners, to generate new combinations, through the introduction of new technological components, and thereby that they should be more likely to generate new combinations than other types of teams in core technologies.

> Hypothesis 2: *While inventor teams with academic members are more likely to generate inventions with technological combinations new to the firm in core technologies, they are not more likely to do so in peripheral areas.*

3. Methods

3.1 Sample and data

To investigate the hypotheses, I use patent data between 1980 and 2005 on a set of sampled firms, taken from the PATSTAT database which contain information on EPO patent applications. Patent data has been used to, and proved useful for, studying technological recombination in several prior studies (Fleming et al., 2007; Gruber et al., 2013; Rosenkopf and Nerkar, 2001).

The sample used in the study consists of R&D intensive manufacturing firms based in Sweden. A first sample of manufacturing firms was drawn from the European Union (EU) industrial R&D investment scoreboard, which annually lists the 500 most R&D-

intensive firms in Europe, as well in the U.S. and Japan, across all industries. From PATSTAT, I extracted all patent applications for the firms in this original sample, limited to patent applications where the assignee was based in Sweden as indicated by the address used on the application. This limitation, as well as the limitation of only sampling Swedish based firms, was employed due to data availability for the main explanatory variable which provided the need to limit the sample geographically to Sweden as explained further below. For the sampled firms, subsidiaries (where the firm had a majority ownership) were identified through available databases, annual reports and firm web pages, and patent portfolios were constructed by aggregating all patents to the group level.

For the present study, I limited the sample used even further to include only those firms that patent regularly and have the largest patent portfolios. This was operationalized as firms applying for on average at least 10 patents annually and having at least 100 patents in their portfolio during the studied period. This provided a conservative sample of 10 firms, which are among the largest and most R&D intensive firms in Sweden. This limitation was employed since I believe it provides a more conservative sample for estimating the issues at hand; In this way, I have assured that the patent data provides a fairly accurate picture of the sampled firms' activities.

From PATSTAT, I extracted all information regarding the sampled firms EPO patent applications needed for this study, including inventors, applicant firms, and the technology classes the patented inventions are associated with. The main interest for this paper is inventor information and the technology classes assigned to the patents. In order to construct some of the inventor-level control variables used in this study (see below), I used information from the EP-INV-PatStat database, which contains disambiguated inventor data providing a unique key identifying each individual named as inventor on PATSTAT patents, thus making it possible to trace all patents invented by the same person. This key was produced using an inventor-matching technique, for which further details are found in Den Besten et al. (2012).

In order to identify academic inventors, i.e. inventors employed at universities and named as inventors on patents, I used the KEINS/APE-INV database: This database contains information on all inventors of EPO patents which have been identified as academics employed at a university, and can through the unique inventor key provided by EP-INV-PatStat be combined with PATSTAT data. In this way, it is possible to identify all academic inventors, and not only those who are named on patents owned by universities (Lissoni et al., 2008). For this paper, I used the Swedish version of this database, which is why the study is geographically limited to Sweden. This database was created in two steps, the first one in 2004 by identifying all academic researchers working at Swedish universities, and matching this list with inventors of EPO patents through an inventor-matching procedure similar to the one used to construct EP-INV-PatStat (see Lissoni et al. 2006 for details on this procedure). The original database was expanded during the APE-INV project during which a new updated list of all Swedish academics employed in Sweden was collected in 2001, and subsequently matched with EPO inventors using a method which largely corresponds to the one employed for constructing the KEINS database (see Ljungberg et al., 2013). Due to this method, the database cannot identify those academic inventors who retired or changed profession before 2004.

While I gathered patent data on these firms starting from 1980, I only analyze patents applied for between 1990 and 2005. The period up to 1990 is used to construct some of the variables. The final data set includes data on 7 558 patents, by 8 169 inventors, out of which 114 are identified as academic inventors, involved in a total of 357 patents during the studied period.

3.3 Dependent variable: New technological combinations

The dependent variable used to examine the hypotheses is a binary variable which indicates whether a patent (invention) is based on the recombination of technological components already present in the firm. Following previous studies (e.g. Fleming et al., 2007; Gruber et al., 2013) I used the technological classes associated with each patent as a proxy for technological components to construct the variable.

At the EPO, patents are assigned technological classes according to the "International Patent Classification" (IPC). The procedure conducted to classify patents at the EPO are carefully conducted, commonly based on careful scrutiny of the application document and the description and details regarding the invention which are provided there. Moreover, there are strict guidelines to be followed, which makes these patent classifications trustworthy, and thereby they serve as a good proxy for technological components.

I constructed the dependent variable by, on a firm by firm basis, going through all sampled patents, identifying the first incidence of a combination of patent classes, not previously assigned to the focal firm's patents. Thus the constricted measure indicated a new combination for the firm, and not for the world, in accordance with the purpose of the paper. For this measure, I used the four-digit level provided by the IPC.

3.4 Explanatory variables

The explanatory variables used in this paper are a set of measures indicating that academic researchers were named as inventors on the focal patent. To examine all the different hypotheses, I created four different, but similar, indicators.

To examine Hypothesis 1, which postulates that an invention created by a team with one or more academic inventors has a higher likelihood of being based on a new technological combination, I constructed a binary variable indicating whether the focal patent was generated by one or more academic inventor (1) or not (0). This indicator (*"Academic inventor(s) (1/0)")* is included in the analysis because it is the most conservative measure of academic involvement in firm patenting.

To test the second hypothesis, I also control for the position of the patented invention in relation to the firms' knowledge base, by identifying those patents belonging to the *Core* technologies. I do this since the final hypothesis postulates that the technological area can mitigate the effect of academic inventors on the generation of new combinations. I construct this measure as a binary variable identifying those patents whose main technological class account for the highest share of all firm patents. To calculate this indicator, I use the firm's patents applied for during the five years prior to the application of the focal patent to account for knowledge depreciation and shifts in technological focus over time.

3.5 Control variables

I include a set of variables in my models to control for various factors at the patent, team and organization level. First of all, I controlled for *Patent scope*, indicated by the total numbers of technological classes assigned to the focal patent (at the IPC4 level), due to the fact that the probability that a combination of patent classes is new to the firm technological increase with the total number of classes assigned to the patent. This measure has also been used as a proxy for the scope of the invention (Lerner, 1994), and the complexity of the patent (Harhoff and Wagner, 2009), and can thereby be used as an indicator for specific invention characteristics related to technological recombination.

Since scientific knowledge is argued to guide inventors to more useful solutions and combinations (Fleming and Sorenson, 2004), I also control for the number of references to non-patent literature added to the focal patent's search report, since this proxies the scientific linkage of the patent (Callaert et al., 2006).

Moreover, I include a variable measuring *Number of inventors* named on a focal patent, as this is commonly used as a control for the R&D input of the firm to that specific invention.

At the firm level, I control for the *Technological diversity of the firm*. Technological diversity can have both positive and negative impact on exploratory search. Firms with high technological diversity have more opportunities for internal use of new (external) knowledge. At the same time, they also have more opportunities to find useful new knowledge combinations internally through local search.. This measures is based on the technology classes of the firm patents applied for during the 5 years prior to year of the focal, using an adjusted Herfindahl index:

$$Technological\ Diversity_{i\,t} = \left(1 - \sum_{j=1}^{K} \left(\frac{P_{jit}}{P_{it}}\right)^2 x\right)\left(\frac{P_{it}}{P_{it} - 1}\right)$$

Where P_{jit} is the number of patents in class j applied for by firm/inventor *i* in the prior 5 years, and P_{it} is the total number of patents applied for during the same period.

At the team level, I control for *Average team experience* by including a measure of the mean number of patents generated by each inventor up to the priority year of the focal patent. I also control for the *Average technological diversity of the inventor team*, which is calculated the same way for each inventor on a focal patent as done at the firm level, detailed above.

For calculating this measure at the level of team, I take the average of all inventors' diversity.

Finally, I included time dummies (1991-2005) to control for unobserved period effects, as well as technology dummies, to control for heterogeneity across different technological areas in terms of opportunities for innovation and recombination.

The descriptive statistics and correlation matrix of the variables used in the paper are presented in Table 1. Correlations between independent variables are rather low, indicating that collinearity should not be a problem.

3.6 Estimation method

The unit of analysis in this study is the patent.[7] To estimate the likelihood of patents being based on technological combinations new to the firm, I employ probit models, the results of which are presented in Table 2. I report the average marginal effects (AMEs) of the model, since the coefficient of probit estimations are difficult to interpret and AMEs are commonly seen as the preferred choice for estimating marginal effects (Hoetker, 2007). I also ran regressions using the marginal effects at the mean, which provided highly similar results. The coefficients of the probit models are reported in Table A1 in the Appendix.

[7] Tentative results from analysis of the inventor shows similar results as those reported here.

Table 1. Descriptive statistics and correlation matrix

	Variable	Mean	Stand. dev	Min.	Max.	1.	2.	3.	4.	5.	6.	7.	8.	9.
1.	New combinations	0.236	0.424	0	1									
2.	Academic inventors (1/0)	0.0472	0.212	0	1	0.010								
3.	Core technologies	0.603	0.489	0	1	0.275	0.010							
4.	Patent scope	1.839	1.000	0	10	0.485	0.002	0.074						
5.	# inventors	2.204	1.405	1	16	0.031	0.128	0.036	0.063					
6.	Avg team patenting experience	1.859	3.324	0	48	0.098	0.114	0.085	0.003	0.029				
7.	Avg team technological diversity	0.0866	0.200	0	1	0.080	0.014	0.141	0.066	0.039	0.265			
8.	# Non-patent references	0.961	0.630	0	12	0.004	0.046	0.010	0.034	0.045	0.002	0.012		
9.	# Co-assignees	0.00939	0.114	0	4	0.034	0.004	0.038	0.031	0.161	0.022	0.032	0.001	
10.	Firm technological diversity	0.587	0.154	0.156	0.896	0.247	0.027	0.328	0.052	0.025	0.079	0.082	0.060	0.047

Note: All correlations over 0.2 statistically significant at the 5 % level

4. Results

The results, in terms of average marginal effects, from the estimations are presented in Table 2. The estimation in Model 1 is employed to test Hypothesis 1, that inventor teams which include academic researchers are more likely to generate technological combinations which are new to the firm, and therefore includes the binary explanatory variable *Academic inventor(s)*. The estimation shows that the average marginal effect of this dummy variable is positive and statistically significant ($p<0.001$). This indicates that patents generated by teams involving academic inventors are more likely to be based on technological combinations new to the firm, relative to other types of inventor teams, thus lending support to the hypothesis.

To test the second hypothesis, postulating that the invention's position relative the firm's technology base moderates the effect of academic inventors on the generation of new combinations, I split the sample into two, running one regression on patents belonging to firms' core technologies (Model 2) and one on patents belonging to their non-core technologies (Model 3). I employ this approach since it has been suggested that it is not appropriate to interact explanatory variables with dummies indicating groups when running probit regressions (Hoetker, 2007).

The estimation in Model 2 shows that the involvement of one or more academic inventors on a team does not have statistically significant effect on the likelihood of new combinations in firms' non-core technologies, while Model 3 shows a highly statically significant effect on the same in core technologies ($p<0.001$).This result lends support to Hypothesis 2.

Table 2. Probit models of New combinations (Average marginal effects)

	Model 1	Model 2 (Core=0)	Model 3 (Core=1)
Explanatory variables			
Academic inventors (1/0)	0.074***	0.038	0.075***
	(0.019)	(0.039)	(0.019)
Core technologies	-0.126***		
	(0.008)		
Control variables			
Patent scope	0.164***	0.216***	0.133***
	(0.003)	(0.006)	(0.004)
# inventors	-0.014***	-0.020***	-0.010**
	(0.003)	(0.006)	(0.003)
Avg team patenting experience	-0.015***	-0.026***	-0.009***
	(0.002)	(0.004)	(0.002)
Avg team technological diversity	0.074***	0.077*	0.085***
	(0.019)	(0.034)	(0.022)
# Non-patent references	-0.003	0.000	-0.007
	(0.006)	(0.010)	(0.008)
# Co-assignees	0.004	-0.032	0.070**
	(0.041)	(0.062)	(0.027)
Firm technological diversity	0.279***	0.260***	0.331***
	(0.035)	(0.066)	(0.037)
Technological areas	Included	Included	
Priority years	Included	Included	
Observations	7548	2988	4560
Pseudo R-squared (McFadden)	0.344	0.257	0.369
Wald/LR Chi2	1743.32***	642.82***	861.64***

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

Turning to the control variables, Table 2 shows that the technological diversity of the firm, the scope of the patent, and the core technology dummy have the highest average marginal effect on new combinations across all models. The highest effect on new combinations seems to come from the technological diversity of the firm, which was to be expected.

The core technologies dummy have a negative and highly statistically significant effect, indicating that firms have a lower probability of generating new combinations in their core technologies relative to in their more peripheral areas. This finding lends further support for the second hypothesis, by corroborating the argument provided in section 2 that firms ought to have fewer opportunities for recombination in their core areas. Finally, I conducted some robustness checks to control the validity of the estimations provided by the models reported in Table 2. First, I ran regressions including firm fixed effects, to account for unobserved heterogeneity across firms. The results remained largely the same, with the only substantial difference being that the effect of firms' technological diversity changed signs and became statistically insignificant.

Second, the positive and statistically significant effect of the Patent scope variable, together with the fact that the variable acts as a proxy for the scope and complexity of the invention, may invoke suspicions about selection bias; In other words, is the esitmated effect of academic inventors on new combinations to some extent the result of academic inventors being involved in specific types of projects, leading to higher patent scope and greater likelihood of combinations new to the firm? Looking into this, I performed a Mann-Whitney U test, and found no statistically significant difference in terms of patent scope between patents generated by teams involving academic inventors and teams without academics ($z=0.44$, $p=0.66$). This suggests that patents co-invented by academic researchers are not resulting from a specific type of invention project, as far as patent scope indicates, and thus that the results provided in the estimations do not suffer from any apparent selection bias in this regard.

5. Discussion and conclusion

This paper has contributed to the emergent microlevel theory of technological recombination, by examining a specific type of inventor not investigated in prior works, namely academic inventors. While not investigated by extant literature, I proposed that academic researchers, when involved directly in firms' invention processes, can be an important external source of knowledge, and thus one potentially important search mechanisms for firms to introduce new knowledge (and combinations) into their knowledge base. In so doing, I derived two hypotheses, which was tested on patent data between 1990 and 2005 on Swedish-based R&D intensive firms in manufacturing industries. To test the hypotheses, I employed as proxy for technological combination the combinations of technological classes assigned to a patent by the patent office, as have been done in several prior studies.

The findings of the empirical examinations provided support for the hypotheses derived and tested in the paper. The results of the probit estimations conducted in the paper demonstrated that when academic inventors join firms' inventor teams the likelihood of generating combinations new to firm increases substantially, thus corroborating the initial proposition. This finding, however, holds only true for patents belonging to firms' core technologies and when academic inventors team up with firm inventors.

While the few existing microlevel studies of technological recombination has focused on the influence of characteristics of inventors in general (Fleming et al., 2007), and the difference between inventors with scientific respectively engineering education (Gruber et al., 2013), this paper has not only investigated an overlooked type of inventor, but one that by definition span the boundaries of the firm; Thus, this paper does also contribute to the literature on innovation search (Laursen, 2012), by demonstrating that academic inventors can be employed as a search channel for firms in order to rejuvenate their knowledge base through technological recombination. This is a topic that have been overlooked so far in this literature, except for firm level studies of the effect of university interaction on firms' innovation performance and similar subjects (Soh and Subramanian, 2014)

This study has only been a first attempt to examine the issue of academic inventors' influence on new combinations, and as such it has its limitations. First, while I have framed the academic inventor in relation to the inventor team, I have not studied several of the important characteristics commonly associated and studied on the team and individual level, such as network structure (e.g. Fleming et al., 2007; Dahlander et al., 2014). To include such factors would be a fruitful next step in the research on this topic, in order to further our understanding of the conditions under which academic inventors can contribute to technological recombination.

While I have controlled and tested for a set of invention and firm characteristics, as well as limited by sample, I have in this paper not been fully able to disentangle the effect of academic inventors on new combinations from potential issues of self-selection of academics and of firms' innovation strategies. I have investigated the possibility of employing an instrumental variable approach, but have as of writing not found an appropriate instrument. For the present study, I however do not think this constitutes a major limitation, since the purpose was only to investigate whether firms' inventor teams including academic inventors contributes to technological recombination, and not why or how this comes about. This is an area of examination for further research on the topic.

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Appendix

Table A1. Probit models of New combinations (Coefficients)

	Model 1	Model 2 (Core=0)	Model 3 (Core=1)
Explanatory variables			
Academic inventors (1/0)	0.371***	0.138	0.536***
	(0.097)	(0.141)	(0.135)
Core technologies	-0.636***		
	(0.043)		
Control variables			
Patent scope	0.827***	0.775***	0.945***
	(0.024)	(0.033)	(0.036)
# inventors	-0.070***	-0.073***	-0.071**
	(0.015)	(0.022)	(0.022)
Avg team patenting experience	-0.076***	-0.094***	-0.062***
	(0.009)	(0.014)	(0.012)
Avg team technological diversity	0.373***	0.278*	0.610***
	(0.096)	(0.121)	(0.156)
# Non-patent references	-0.015	0.001	-0.049
	(0.029)	(0.035)	(0.054)
# Co-assignees	0.021	-0.115	0.500**
	(0.208)	(0.222)	(0.190)
Firm technological diversity	1.410***	0.935***	2.358***
	(0.176)	(0.237)	(0.260)
Constant	-2.925***	-2.382***	-4.372***
	(0.139)	(0.182)	(0.209)
Technological areas	Included	Included	Included
Priority years	Included	Included	Included
Observations	7548	2988	4560
Pseudo R-squared (McFadden)	0.344	0.257	0.369
Wald/LR Chi2	1743.32***	642.82***	861.64***

Robust standard errors in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$