The Relationship between Publications and Patents by Researchers at Five Companies

Kwanghui Lim

Massachusetts Institute of Technology

Sloan Working Paper 4120 June, 2000

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Kwanghui Lim[•]
MIT Sloan School of Management,
50 Memorial Drive, E52-539
Cambridge, MA 02138, USA
Tel: 1-617-876-0041
Fax: 1-617-253-2660
Email: kwanghui@mit.edu

June 13, 2000

Abstract

This paper explores the relationship between patents and publications by researchers at five companies (IBM, AT&T, Intel, DuPont and Merck). The analysis shows that at IBM, AT&T, and Intel, researchers who published a higher fraction of their papers in basic research journals were less likely to obtain patents. This supports the theory that researchers face a tradeoff between participating in basic and applied research (Allen, 1977). The opposite relationship holds for Merck and DuPont, where scientists who published a higher fraction of papers in basic scientific journals obtained more patents. This is consistent with previous research suggesting a positive productivity impact of participating in basic research among pharmaceutical firms (Gambardella, 1992; Cockburn and Henderson, 1998; Zucker and Darby, 1995). This paper contributes by showing the effects occur at the level of the individual researcher, not just the firm as a whole. In addition, the result for Merck and DuPont is largely driven by publications in the field of *basic chemistry*. Even within the same pharmaceutical firm, the relationship between basic research and patents is stronger for chemistry than other fields; it is also stronger among researchers who work on pharmaceutical R&D than on other areas within the same firm. Apart from basic research, patents are positively related to the total number of publications by a researcher (signaling her ability), but negatively related to the fraction of articles co-authored with academic and public-sector researchers.

• I am indebted to Scott Stern, Rebecca Henderson, and Eric von Hippel for their invaluable guidance. Jeff Furman and Pierre Azoulay gave me valuable feedback. Scott Cooper provided very able editorial assistance. All errors and omissions remain my own. I thank Diana Hicks of CHI Research for data essential to this project. This paper would not have been possible without the encouragement of my wife, Seto Wai Ling.

1 Introduction

Industrial research is an important contributor to scientific progress and a major source of science-based innovations (Jewkes, Sawers and Stillerman, 1958; Mowery and Rosenberg, 1989).[1] Many scholars have studied the relationship between scientific research and patents at industrial firms (e.g., Griliches, 1984; Jaffe, 1986; Patel and Pavitt, 1994). Fewer studies have examined the relationship between patents and publications, taking the researcher — rather than the firm — as the unit of analysis.[2] This is a difficult exercise, because patent and publication databases provide incomplete information about the names and affiliation of researchers, making it harder to match individuals within and across these databases than it is to identify the firm that produced the patent or publication.

In this paper, I explore the relationship between publishing and patent production by researchers at five leading research laboratories (IBM, AT&T, Merck, DuPont, and Intel). To do so, I created a new dataset that combines patents from the U.S. Patent Office database with publications in the Science Citation Index (SCI). This relies on a new technique for matching individuals based on their names (see Appendix).

Choosing the individual researcher as the unit of analysis complements previous studies by adding another perspective. One advantage is that it allows for comparisons *of scientists within the same firm*, such as the relationship between their participation in basic research and the number of patents they produced. Comparing the participation in basic research and patents at the level of the firm does not allow us to distinguish whether an observed relationship is due to the characteristics of scientists employed by each firm, or other firm-specific effects (such as the product-markets in which the firms compete). A related benefit of individual-level data is that they allow comparisons to be made across scientific disciplines more effectively than do firm-level data, which are clouded by company-specific differences.

Adopting the individual researcher as the unit of analysis also allows us to test several important theories. In this paper, I test the following hypotheses:

- Researchers face a tradeoff between basic research and patenting, so that those who are more heavily involved in basic research are *less* likely to patent than those who are more heavily involved in applied research.
- Basic research improves the productivity of researchers, so that those who are more focused on basic research are also *more* likely to patent relative to others who do applied work. (This hypothesis is the opposite of the first hypothesis, above.)
- High-ability researchers are likely to produce more patents *and* publish more articles than are low-ability researchers.
- There is a stronger link between basic science and patents in drug discovery than in other areas.

[1] See Hounshell (1996) for a history of industrial research in the United States.
[2] For example, see Noyons, Luwel, and Moed (1998); Cockburn, Henderson and Stern (1999); and Zucker, Darby, and Armstrong (1998).

- Researchers at different firms differ in their relationship between the number of patents and publications they produce.
- Researchers who co-author with academics and scientists at public-sector laboratories are more likely to obtain patents than are those researchers who do not so co-author.

Some of these hypotheses have been tested at the firm level (for example, Cockburn and Henderson, 1998, show a positive relationship between a firm's productivity and whether its researchers co-author with universities and public-sector laboratories). It would be interesting to see whether the same effects occur at the level of the individual, as this might help us better understand the firm-level effects and offer new insights on behavior within the firm. Other hypotheses have been not formally tested against patent and publication data, such as the claim that researchers choose between participating in science and in engineering (Allen, 1977), and that the link between basic and innovation is closer in drug discovery than elsewhere (Stokes, 1997).

When choosing the individual as the unit of analysis, one should not automatically draw the same conclusions about firms (Judd, Smith and Kidder, 1991, p. 356).[3] For example, the observation of a negative relationship between participation in basic research and patent output at the level of the researcher does not necessarily imply that the same relationship holds at the firm level. In particular, some individuals may specialize in basic research and others in patent-production such that the firm benefits from knowledge-sharing among these workers. Nonetheless, if the *same* effect is observed at both levels of analysis, it is plausible that some degree of aggregation exists.

I found the following in testing the above hypotheses: given two researchers at IBM, AT&T, or Intel who published the same number of articles, the one who published a greater fraction of papers in basic research journals is *less* likely to obtain patents. This supports the view that scientists are different from engineers. However, the opposite relationship holds at Merck and DuPont: the higher the proportion of papers a researcher publishes in basic scientific journals, the *more* likely she is to obtain patents. This is consistent with prior studies that showed a positive impact on productivity of participating in basic research among firms engaged in drug discovery (Gambardella, 1992; Zucker and Darby, 1995). This paper shows that the effect also exists at the level of the individual researcher. Furthermore, I show that the result for Merck and DuPont is driven largely by publications in the field of *basic chemistry*. Even at these pharmaceutical firms, the relationship between basic research and patents is stronger for chemistry than for other fields; it is also stronger among researchers who work on pharmaceutical R&D than on other areas within the same firm.

Apart from basic research, patents are positively related to the total number of publications by a researcher, which I interpret as a signal of her ability. However, patents are related negatively to the fraction of articles co-authored with academic and public-sector researchers. The latter is surprising in view of previous research that underscored the importance of "connectedness" at the level of the firm (e.g., Cockburn and Henderson, 1998). One possible explanation is that researchers who co-author with

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[3] Using the individual rather than the firm as a the unit of analysis is neither better nor worse, only different.

outsiders may be playing the role of gatekeepers (Allen, 1977), increasing the productivity of other researchers within the firm but not necessarily adding to the number of patents they obtain.

The remainder of this paper is organized as follows. Section 2 reviews prior research and develops hypotheses on the relationship between patenting and publishing by researchers at industrial laboratories. Section 3 presents the empirical methodology used in the paper. Section 4 describes the datasets and algorithms used to identify the corporate affiliation of individuals and to match them based on their abbreviated names. Section 5 presents the results and discussion as well as the limitations of this study. Section 6 draws conclusions.

2 The Relationship between Publications and Patents

Researchers who work in industrial laboratories face conflicting demands. On the one hand, many would like to perform interesting research that is important to the scientific community — and thus gain peer recognition (Merton, 1973). On the other hand, such research is not necessarily in line with the firm's financial interests. Research that seeks a fundamental understanding of phenomena (which I term "basic research") is often expensive and has uncertain payoffs. Often, the only extrinsic reward is a publication in an esteemed journal (Stephan, 1996).

In theory, firms would prefer the speculative investigation of "basic research" to be done others (Nelson, 1959; Arrow, 1962).[4] In contrast, firms do support applied research and development, which is more likely to result in new commercial products and services. Applied research is also more likely to be associated with patents, since an invention must exhibit *usefulness* to be patentable.[5] While primarily a source of intellectual property protection, patents also act as a measure of a firm's innovation output.[6] From the researcher's point of the view, applying for a patent is an onerous activity that takes up time that could otherwise have been spent writing articles or on other activities.

Faced with this tension between basic and applied research, how should an industrial researcher spend her time? One solution is to choose one alternative over the other. Allen (1977) and Ritti (1971) maintain that researchers are either engineers or scientists. Whereas an engineer is most interested in career advancement within the firm, a scientist cares most about her reputation outside the company. The engineer's goals coincide with those of the firm: to develop new products and succeed commercially. In contrast, the scientist desires professional autonomy and to publish her research (Allen 1977, pp. 37-39). These preferences are due to self-selection as well as the socialization process in

[4] National Science Foundation data show that in 1997, industry 67% of U.S. applied research but only 21% of basic research (NSF, 1998, tables 4-7 and 4-11). These tables also show that private industry's share of basic research is declining, while its share of applied research is increasing.

[5] An invention must also be novel and non-obvious to be patentable.

[6] There is a well-developed literature on the strengths and weaknesses of patent analysis (see Griliches, 1990). Patents are an *imperfect* measure of innovation: they are highly skewed in their economic value (Hall, Jaffe and Trajtenberg, 1999), and not all innovations are patented.

educational institutions: engineers typically hold a bachelor's degree, while most scientists earn a Ph.D.

The distinction between scientists and engineers suggests the following hypothesis:

H1: A researcher who is heavily involved in publishing basic research articles is *less* likely to produce patents than one who is heavily involved in publishing applied research articles.

An alternative hypothesis is that there is no tradeoff between basic and applied research. Scientists who publish basic research may be better connected to external sources of knowledge. Therefore, they are more likely to have early access to new ideas that stimulate creativity. For example, Zucker and Darby (1995) show that "star" scientists who are heavily involved in public science play an important part in the productivity of biotechnology firms. Similarly, Gambardella (1992) advocates a science-friendly environment within firms that gives greater autonomy to researchers and encourages them to publish. Another source of complementarity between basic and applied research is the presence of feedback loops in the innovation process (Roberts, 1988). Thus, researchers who are more likely to perform applied research may be more likely to contribute to basic science.

If there is no tradeoff between basic and applied research, so that they are complements rather than substitutes, then Hypothesis H1 is reversed:

H1': A researcher who is heavily involved in publishing basic research articles is *more* likely to produce patents than one who is heavily involved in publishing applied research articles.

In practice, is difficult to test the above hypotheses because other factors affect the relationship between patents and publications. The most important is that people have different abilities. This ability bias may be magnified by the "Matthew Effect" (Merton, 1973), in which success breeds further success. Therefore, a successful researcher may have better opportunities to perform basic research as well as better organizational resources for obtaining patents. Hence, I hypothesize that researchers who produce a greater number of publications (basic plus applied) *are also more likely* to obtain a greater number of patents.

H2: High-ability researchers publish more articles *and* receive more patents than do low-ability researchers.

The relationship between publications and patents is also likely to depend on the scientific area under investigation. Stokes (1997) observes that the dichotomy between basic and applied research breaks down in the field of medicine: medical research is performed both in the quest for fundamental breakthroughs as well as to create practical remedies. Hence, it is likely that researchers who work to discover new drugs are more likely to obtain patents than researchers who work in other fields.[7] I therefore propose the following:

H3: In the area of drug discovery, a researcher who participates heavily in basic scientific research is *more* likely to receive patents than is a researcher less involved in basic research.

H3': In other areas, a researcher who participates heavily in basic scientific research is *less* likely to receive patents than is a researcher who is less involved in basic research.

The firm that employs a researcher also influences the extent to her which participation in basic science translates into a larger number of patents. In part, this is because firms produce different goods and services, and therefore pursue research in different scientific fields. In addition, the industries in which they compete have different degrees of appropriability (Levin *et al.*, 1987). This affects the extent to which firms rely on patents vis-à-vis secrecy and time–to–market. Furthermore, von Hippel (1988) shows that some firms play a key role in developing innovations, while others depend on users or suppliers to take the lead. Firms also vary in size and their ability to capture economies of scope with regards to knowledge spillovers. For these and other reasons, firms endogenously offer different incentives to their researchers to publish and participate in basic research. They also exert strong selection pressures on the types of researchers they attract and those they eventually employ. This leads to the following hypothesis:

H4: Firms differ in the extent to which their researchers show a positive relationship between participating in basic research and the number of patents their researchers obtain.

Apart from a preference for performing basic research, another factor that might affect a researcher's likelihood to obtain patents is the extent to which she co-authors articles with scientists at universities and other public-sector laboratories. Such co-authorship is distinct from having a preference for basic research. An industrial researcher may co-author heavily with researchers from outside her firm, but much of it could be applied research. Prior research shows a relationship between a firm's productivity and its rate of co-authorship with universities and public sector laboratories (Cockburn and Henderson, 1998). It is not known whether this relationship holds for individual researchers as well as for firms. I hypothesize that the exchange of ideas among co-authors makes these researchers better connected to sources of new technical ideas and may lead them to produce a greater number of patents.

H5: An industrial researcher who co-authors with academics and public-sector researchers is more likely to obtain patents than are industrial researchers who do not so co-author.

In the next section, I describe an empirical methodology to test these hypotheses.

[7] Allen's (1977) work on the dichotomy between scientists and engineers is based on data collected at two engineering laboratories. It is interesting to inquire whether the results apply equally well to drug discovery.

3 Methodology

Let the number of patents awarded to researcher *i* in firm *j* be denoted by Pat_{ij}. Similarly, let the number of articles published by this researcher be Pub_{ij}. The extent of her participation in basic research is reflected in the percentage of articles she published in "basic" scientific journals, $PctBas_{ij}$. The following model relates these variables:

(1) $$Pat_{ij} = \boldsymbol{a} + \boldsymbol{b} * Pub_{ij} + \boldsymbol{g}_j(\boldsymbol{d}_j * PctBas_{ij}) + \boldsymbol{f} * PctCoau_{ij} + \boldsymbol{c}_j\boldsymbol{d}_j$$

where δ_j are dummy variables for each firm, and
$PctCoau_{ij}$ is the percentage of articles co-authored with academics and other public-sector scientists

This specification was chosen because it attempts to capture the researcher's ability through the effect of Pub_{ij} on Pat_{ij}, and her participation in basic research using $PctBas_{ij}$.[8] Conditional on observing two researchers with the same number of publications, it asks whether the one who published a higher percentage of articles in basic scientific journals is more likely to obtain patents. I also added another variable, $AvgSCI_{ij}$, to control for ability bias. For a given researcher, $AvgSCI_{ij}$ is the average of the SCI impact scores of the journals in which she publishes.[9,10] Despite my attempts to control for ability bias, it is still possible that the researcher who published a higher percentage of articles in basic journals had higher ability than the other, but that remains a limitation of this study.

Equation (1) takes into account the difference among companies by including a fixed effect for each firm (δ_j), so that each firm has a different intercept, $\boldsymbol{a} + \boldsymbol{c}_j$. In addition, the firm dummy is interacted with $PctBas_{ij}$, so each firm has a different slope, $\boldsymbol{g}_j$. The number of patents awarded to researcher *i* is also affected by the percentage of articles she co-authors with academics and public-sector researchers ($PctCoau_{ij}$).

We can test the hypotheses in the previous section by estimating the parameters of this model. Testing the hypothesis that $\boldsymbol{g} = 0$ tells us whether researchers who participate heavily in basic research are more likely to be awarded patents than those who concentrate on applied research (hypotheses H1, H1'). Testing $\boldsymbol{b} = 0$ indicates whether researchers who publish more articles also receive more patents (hypothesis H2). To test for differences among firms (hypothesis H4), we can examine whether firms have the same intercept terms ($\boldsymbol{c}_1=\boldsymbol{c}_2=\ldots=\boldsymbol{c}_n$) and the same slope coefficients ($\boldsymbol{g}_1=\boldsymbol{g}_2=\ldots=\boldsymbol{g}_n$). We can test hypothesis H5 — that researchers who co-author with outside researchers are more likely to patent — by estimating $\boldsymbol{f}$. A value of $\boldsymbol{f} > 0$ would be consistent with this hypothesis, while a value of $\boldsymbol{f} \leq 0$ would reject the hypothesis.

8 With a Cobb-Douglas production function or log-log specification, if we observe a positive relationship between patents and basic research publications, we would not be able to distinguish ability bias from hypothesis H1.

9 Each journal's SCI impact score is published with the Science Citation Index. I used Impact scores for 1997. These scores are very stable across time (Lim 2000b)

10 The expected effect of $AvgSCI_{ij}$ on patenting is uncertain: publishing in highly cited journals signals a researcher's ability, but might also take time and effort away from creating patentable inventions.

The basic model can be modified to test Hypothesis H3, which proposes a stronger relationship between basic research publications and patents for researchers in the field of drug discovery than those in other areas. For each scientific discipline (k), a separate coefficient $\boldsymbol{g}_{ijk}$ can be estimated as follows:

$$(2) \qquad Pat_{ij} = \boldsymbol{a} + \boldsymbol{b} * Pub_{ij} + \sum_{k} \boldsymbol{g}_{jk} (\boldsymbol{d}_j * PctBas_{ijk}) + \boldsymbol{f} * PctCoau_{ij} + \boldsymbol{c}_j \boldsymbol{d}_j$$

Among the papers published by researcher *i* from firm *k*, $PctBas_{ijk}$ is the percentage of those papers that appear in basic scientific journals in scientific field *k*. It is *not* the share of basic research publications in field k by researcher *i*. The estimated value $\boldsymbol{g}_{jk}$ tells us whether a scientists who concentrates on publishing basic research in field *k* is more likely to receive patents than another researcher who concentrates less on it.[11]

<u>Basic versus Applied journals</u>

An essential ingredient in this methodology is the ability to distinguish between a “basic” and “applied” journal. This paper relies on the journal classification scheme developed by CHI research.[12] Each journal is assigned a number from zero to four, indicating increasing basicness (see Hicks, 1996 for details). In this paper, I define a journal as “basic” if it scores a four; all other journals are “applied.” Naturally, this approach ignores heterogeneity among articles within the same journal. However, it is the only tractable approach given the large number of publications in the dataset.

CHI Research also classifies journals into different scientific disciplines. The classification used is very similar to that in the Journal Citation Reports, which are published as an accompanying volume to the Science Citation Index each year.

<u>Research Setting</u>

I estimate the model for researchers at five leading companies spanning a broad range of industries: IBM, AT&T, Merck, DuPont, and Intel. IBM produces computers, microelectronics, and information services; AT&T is involved in telecommunications and microelectronics; Merck is a leading pharmaceuticals company; DuPont is involved in pharmaceuticals, chemicals, and materials science; and Intel specializes in semiconductors.

Each of these five firms is an important innovator. AT&T created the transistor (Nelson, 1962; Riordan and Hoddeson 1997); DuPont created Rayon, Nylon and Teflon (Mueller, 1962); Intel invented the microprocessor (Jackson, 1997, pp. 69-77); Merck was the first to create vaccines against mumps, measles, rubella, and hepatitis (Galambos and Sewell, 1995); and IBM has created many important computer and semiconductor technologies (Campbell-Kelly and Aspray, 1996).[13]

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[11] An alternative would be to create dummy variables to indicate the field in which a researcher works. The shortcoming of this approach, however, is that some researchers work in multiple fields. Furthermore, using percentages rather than dummies measures the *strength* of participation in a particular field of basic research.

[12] I thank Diana Hicks for sharing these valuable data.

[13] IBM’s most famous inventions include the fabled S/360 computer and Deep Blue.

While IBM, AT&T, DuPont and Merck have excellent central research laboratories, Intel was added to the analysis for its very different R&D strategy: with no central research laboratories, Intel performs R&D on the manufacturing floor and relies heavily on relationships with universities and other firms for basic scientific knowledge (Moore, 1996).

4 Data

The dataset contains U.S. Patents (1976-99) and publications in the SCI (1985-97) by these companies.[14] I used U.S. Patent data for the entire period to identify inventors within each firm. However, I used only patents between 1985 and 1997 in the regression analysis, to coincide with the period for which publication data were available in electronic format. I performed a careful search to obtain patents that list the firms in the sample as "assignees," and searched the SCI for all publications that include the name of these firms among those listed in the "author address" field.

The publication and patent record reflects the characteristics of these firms (see Table 1). The large number of patents and publications produced by IBM and AT&T reflects these companies' size.

There is a remarkable variation in the percentage of articles published in basic research journals by the five companies. About half of the DuPont and Merck articles are in basic scientific journals, while the figure is around one-third for IBM and AT&T. Only 5% of Intel's articles are published in basic journals, which is unsurprising given its R&D strategy described above.

The breakdown of publications by scientific area reflects the different product markets within which these firms compete. Most of the IBM, AT&T, and Intel publications are on physics, engineering/technology, or chemistry. Merck articles focus primarily on clinical medicine, followed by biomedical research and chemistry. DuPont's major field of publication is chemistry, but the firm also produces a large number of articles on clinical medicine, biomedical research, and physics— reflecting DuPont's diversification across a broad range of industries.

4.1 Identifying the Inventors and Authors of each Firm

Once I identified the patents and publications by each firm, my next step was to identify authors and inventors associated with each firm. An "inventor" is a researcher listed in a patent, while an "author" is one who published an article.

It is not easy to identify the inventors and authors of each firm. Both databases show the addresses of all authors and inventors, but neither specifies which address belongs to which person. While this is only a minor problem for the patent database because most

[14] These are the periods for which patent and publication data were available to me in electronic format.

patents are assigned to only one firm, it is a major problem with publications because of the large number of articles co-authored by researchers at these firms with outside researchers. In general, it is impossible to link a specific author with a specific firm. I used the following heuristic to identify individuals associated with each firm:

- For publication with one address (or multiple addresses that all refer to the same firm), I associated all the authors of that publication with the company listed in the address. I term these individuals "positively associated."
- For each author positively associated to a firm, I propagated the knowledge of her affiliation to other articles by the same company that list the same author.
- I used an analogous process to associate inventors of patents with firms.
- I cross-referenced the patent and publication databases to locate individuals positively identified in one database but not in the other database.

I dropped from the analysis any individuals who could not be positively identified through the process described above. It was impossible to determine whether they were individuals from other organizations who published or patented jointly with researchers from firms in the sample, or individuals from the firms in the sample who had never single-authored a paper or published one exclusively with other people from the same firm.

4.2 Matching the Abbreviated Names of Authors and Inventors

A second limitation with the data concerns the use of author abbreviations. While the patent database contains the full name of each inventor of each patent, the SCI — unfortunately — identifies authors only by abbreviation. For example, John Harry Truman is identified as Truman-JH.

This raises two issues. First, it creates a risk that several people might be confounded as a single individual because they share the same abbreviation (e.g., Smith-J could refer to John Smith or Jane Smith). Second, a systematic technique is needed to match abbreviations of authors and inventors within each company that refer to the same person (e.g., Truman-J and Truman-JH). The absence of such a technique could distort the results. For example, Willis-A might have a large number of patents but appear to have no publications, while in fact the publications are listed under Willis-AXP.

The Appendix presents an algorithm that matches individuals with similar abbreviated names who are likely to be the same person (this is a novel contribution of my paper). A manual examination of the database shows that this algorithm works very well for matching the abbreviations of inventors, for which full names are available for verification. However, there is a risk of matching *authors* with similar abbreviations but who received no patents.[15] While this remains a possibility, the risk is very low: of the 37,831 inventors positively associated with firms, only 140 had overdetermined abbreviations. It is unlikely that the rate of people with the same abbreviations is much

[15] As long as these authors are also inventors, the problem doesn't arise, since each inventor's full name is known and is assigned a unique abbreviation.

higher among authors than among inventors. Furthermore, the results are robust when I exclude individuals with common last names such as "Smith" (see section 5.2). Their common last names make these people the most likely ones to share abbreviations with others.

4.3 The Results of the Algorithms to Identify and Match Authors and Inventors

Table 2 summarizes the number of researchers identified per firm and the results of matching them using their abbreviations. The corporate affiliations of most inventors could be identified. However, only about one-third of authors could be positively identified with each company. The rest were dropped from the analysis.[16]

The lower half of Table 2 shows the results of running the matching algorithm of section 4.2. It is interesting that, with the exception of Merck, the companies have far fewer researchers who obtained patents *and* published articles than researchers who patent but *did not* publish. This suggests that, relative to Merck, there is a weaker link at the level of the individual between publications and inventions in the other companies.

5 Results and Discussion

5.1 Descriptive Statistics

Table 3 shows the variables used in the regressions. They vary considerably, as revealed by the wide standard deviations and their maximum and minimum values.

The sample contains 41,325 researchers who had published articles and/or received patents between 1985 and 1997. Each researcher was awarded an average of 1.8 patents. The average researcher published 3.9 articles, of which 1.5 were in basic science journals. Conditional on having published at least one article, a researcher published 29% of her articles in basic science journals.[17] The $PctCoau_{ij}$ variable shows that on average, each researcher co-authored one-third of her articles with scientists at academic or government laboratories. The intensity of basic research in various scientific fields is shown in the middle portion of Table 3. The fields in which the average researcher published the highest percentage of her papers in basic research journals are chemistry, biomedical research and physics

Table 4 shows pairwise correlation coefficients for the key variables. All else being equal, the number of patents awarded to a researcher has a weak negative correlation with the percentage of articles she published in basic scientific journals (Pat_{ij} with $PctBas_{ij}$). However, the number of patents is positively correlated to the total number of articles she published (Pat_{ij} with Pub_{ij}). The correlation coefficient between $PctBas_{ij}$ and $AvgSCI_{ij}$ is rather high at 0.45. This is interesting because across the entire set of journals covered by

[16] As previously mentioned, they might be co-authors from outside the firm, or people within the firm who have never published a single-authored article or published one which involves only other authors from within the firm.

[17] The number of papers published by a researcher appears in the denominator and cannot be zero.

the Science Citation Index, the correlation coefficient between a journal's SCI impact scores and its basicness is only 0.14. Therefore, researchers from these companies who published a large fraction of their papers in basic journals had published them in highly cited journals.

5.2 Regression Results

Table 5 shows ordinary least squares (OLS) regressions with the number of patents awarded to a researcher between 1985 and 1997 (Pat_{ij}) as the dependent variable. In Model I, $PctBas_{ij}$ has a negative coefficient. This is consistent with hypothesis H1', that a researcher who is heavily involved in publishing basic research articles is *less* likely to produce patents than one who is heavily involved in publishing applied research articles. The coefficient for Pub_{ij} is positive, which favors hypothesis H2 that researchers with the greatest ability publish more and receive more patents. Both coefficients are statistically significant at the 5% level.

Model II incorporates the percentage of papers a researcher co-authored with academic and public-sector scientists ($PctCoau_{ij}$) and the average SCI impact scores of the journal in which each researcher published ($AvgSCI_{ij}$). The effect of these variables is to soak up some of the variation previously explained by $PctBas_{ij}$. Surprisingly, $PctCoau_{ij}$ has a negative and significant relationship to the number of patents awarded to a researcher. This contradicts hypothesis H5 that better-connected researchers are more likely to obtain patents. One possible explanation is that better-connected researchers may be playing the role of gatekeepers (Allen, 1977) — increasing the productivity of others within the firm, but not necessarily obtaining more patents.

Model III incorporates firm dummies to test for inter-firm differences. A Wald test of the hypothesis that each firm has the same intercept is rejected with $F(4,22052)=61$. Likewise, a Wald test of the hypothesis that each firm has the same slope for $PctBas_{ij}$ is rejected with $F(4,22052) = 84$. They therefore do not reject hypothesis H4 that each firm is different in terms of the relationship between the number of patents awarded to a researcher and the extent to which she publishes basic research. The parameter estimates for IBM are given by the case where all the dummies are zero. For the remaining firms, the dummies add a component to the intercept and to slope of $PctBas_{ij}$. The dummy variables for Intel are not significantly different from zero, nor is the coefficient for $D\_ATT*PctBas_{ij}$. However, the other dummies are statistically significant, so these firms have different slopes and coefficients from IBM. The estimates for each firm (conditional on all other variables) are given by:

$$
\begin{aligned}
Pat_{i,IBM} &= 2.02 - 1.82\ PctBas_{i,IBM} + \ldots \\
Pat_{i,ATT} &= 1.17 - 1.49\ PctBas_{i,ATT} + \ldots \\
Pat_{i,Intel} &= 1.94 - 0.33\ PctBas_{i,Intel} + \ldots \\
Pat_{i,Merck} &= 0.61 + 1.56\ PctBas_{i,Merck} + \ldots \\
Pat_{i,Dupont} &= 1.04 + 0.37\ PctBas_{i,Dupont} + \ldots
\end{aligned}
$$

The key result is that the coefficient estimates for $PctBas_{ij}$ are negative for IBM, AT&T and Intel, but positive for Merck and DuPont. This supports hypothesis H3, that the connection between basic research and patents is stronger in drug discovery than in other areas. Section 5.3 explores whether this is due to the different scientific areas or to other firm-specific characteristics (this is important to investigate since DuPont is involved in many areas outside pharmaceuticals).

Model IV eliminates all researchers who have common last names such as Smith, Chen, Lee, Jones, and so on. This reduces the likelihood of confounding authors who share the same abbreviations, as discussed in section 4.2. This makes no significant difference to the results of Model III.

Model V re-estimates the regression using Huber-White robust standard errors. I did this because a plot of the residuals revealed some heteroscedasticity in the data. The results remain unchanged, except that the coefficient for $D\_ATT*PctBas_{ij}$ becomes statistically significant at the 5% level.

5.3 Firm Effects and Scientific Disciplines

As the previous section shows, researchers at DuPont and Merck who publish a large fraction of their papers in basic research were *more* likely to obtain patents than other researchers who published more heavily in applied journals; the reverse is true at IBM, AT&T, & Intel. Is this because the firms have different incentive structures and organizations to support basic research (H4), or because the researchers were in different scientific fields (H3)? To address this question, I performed a separate regression for each firm and included the percentage of basic articles by each researcher in each scientific area. Table 6 displays the results,[18] with Huber-White standard errors shown in parentheses.

Table 6 reveals that researchers at IBM, Intel, and AT&T who published a higher percentage of basic research in *any scientific field* produced fewer patents. Thus, for these companies, there is a distinction between scientists and engineers regardless of scientific discipline. The disparity appears greater in basic biology, physics, and mathematics than in other fields.

At Merck and DuPont, researchers with a preference for *basic chemistry* were more likely to obtain patents. A Merck scientist who published only in basic chemistry obtained 3.3 more patents than another researcher who published no basic research articles in chemistry. The corresponding figure for DuPont is 1.6. These coefficients are large relative to the average number of patents produced per researcher, which is only 1.8 (Table 3). At Merck, basic research in biology also had a positive relationship with patents, while at DuPont it was negative. The result for DuPont is surprising, since one would expect a strong link between pharmaceutical patents and basic biology. Another unexpected finding is the negative relationship between patents and basic biomedical

[18] Several parameters could not be estimated for Intel because the firm did not publish basic research in those areas.

research. For the other scientific fields, the coefficient estimates for basic research were imprecisely estimated, and sometimes even negative.

The overall implication of the results for Merck and DuPont is that the positive relationship between basic research and patents observed in the previous section is *driven largely by publications in basic chemistry*. Thus, the dominant effect is that of scientific discipline, rather than the firm per se: even at Merck and DuPont, there is a weak relationship between basic research and patents outside basic chemistry. Yet, the coefficient for basic chemistry for DuPont is much less than for Merck. Could this be because DuPont is more diversified than Merck, which is primarily a pharmaceutical company?

To answer this question, I repeated the analysis but included only researchers who obtained patents in U.S. Patent Classes 424 and 514 (drugs, bio-affecting and body treating compositions). This subset of researchers definitely performed pharmaceutical R&D.[19] As shown in Table 7, the results for Merck are qualitatively the same as before.[20] This is important because it suggests that researchers who received patents in the aforementioned patent classes are representative of Merck (and presumably of pharmaceutical research).

For DuPont, the results are now very similar to those for Merck. A typical DuPont researcher who published articles only on basic chemistry obtained 4.1 more patents than another who performed no basic chemistry research, *ceteris paribus*. This is much higher than before, and close to the corresponding estimate for Merck, which is 5.8.[21] This means that a stronger relationship between basic chemistry research and patents in pharmaceutical R&D than in other areas, even within the same firm (DuPont).

The rest of the parameter estimates for DuPont in Table 7, where precisely estimated, are qualitatively similar to those for Merck. Basic biological research again exhibits a surprising negative relationship to patents, although this time it is not statistically significant.

Apart from the results for basic research, Tables 6 and 7 reconfirm the positive relationship uncovered in section 5.2 between patents and the total number of publications by a researcher. As before, co-authorship with outside researchers is negatively related to patents.[22] And publishing in highly cited journals is negatively associated with patents, as previously shown.

[19] Pharmaceutical researchers also obtain patents in other U.S. patent classes, including 435, 436, 530-570, and 585. However, these patent classes overlap with various fields of chemistry unrelated to pharmaceuticals.

[20] Due to the small sample size, some of the parameter estimates are now imprecise.

[21] The average number of patents per researcher at Merck and DuPont are 1.6 and 1.7, respectively.

[22] For DuPont, the coefficient estimate for $PctCoau_{ij}$ is positive and significant in Table 6, but becomes negative and significant in Table 7, which only includes researchers who worked on pharmaceutical R&D.

5.4 Limitations and Sources of Bias

The regression analysis explains only 6-9% of the variance in the data, as evident from the low R-squared values in Tables 5, 6 and 7. The exception is Merck, which has an R-squared of around 0.2 (see tables 6 and 7). The poor overall fit is unsurprising, given that many other factors affect the relationship between patents and publications, including individual preferences for leisure and other activities, occupational and educational background, demographics, and so on. Despite this shortcoming, the variables included in the table have low standard errors and are stable across models. They have statistically significant implications for the theories tested.

Another limitation of this study is that it includes researchers from only five companies. These companies are interesting and important in themselves, but much work remains to expand the sample to other firms.

There are also data limitations arising from the use of the Science Citation Index database. I overcame several of these limitations by using the algorithms to identify the authors of each firm and match them using their abbreviated names. Nonetheless, a large number of authors listed in the publications by these firms could not be positively identified with the firms. In contrast, recall that almost all inventors are included in the analysis (see Table 2). Therefore, the missing data creates a *downward bias*, since it mainly contains researchers who have publications (including basic research articles) but no patents.

A separate source of bias arises from researchers who patented inventions but did not publish anything. These individuals are automatically dropped because the number of publications appears as the denominator of $PctBas_{ij}$. In this case, the direction of bias is *upwards*: these individuals were able to obtain patents without even publishing anything (let alone publishing basic research), meaning that the link between research and innovation may be weaker than I measured it to be.

6 Conclusions

A comparison of two researchers at IBM, AT&T, or Intel who published the same number of papers reveals that the one who published a higher proportion of her research in basic scientific journals obtained fewer patents. The opposite was true for Merck and DuPont, but this was largely driven by a positive relationship between *basic chemistry* research and patents. The link is weaker between patents and other areas of research, even within these two pharmaceutical firms. In the case of DuPont, the relationship between basic chemistry and patents was stronger for researchers working on drug discovery than for the firm as a whole.

Further research is required to learn whether these findings can be generalized. If so, it means that while scientists and engineers are inherently different, there is a special role in drug discovery played by scientists who perform basic research. In particular, participation in basic chemistry research by these individuals is strongly associated with the production of new, patentable ideas. While a relationship between public science and productivity has been reported before for pharmaceutical firms, it is remarkable that it occurs at the level of the individual researcher.

Apart from these results, I also found a positive correlation between the number of patents obtained by a researcher and the total number of articles (basic plus applied) that she published. This most probably reflects the heterogeneity in the ability of individual researchers. The results for co-authorship revealed a surprise: there is a negative correlation between the number of patents obtained by a researcher and the percentage of her publications that are co-authored with academics and public-sector researchers. Further work will be required to gain a full understanding of this result.

While this study suffers from the limitations discussed above, it presents several important contributions. It is one of the few attempts to develop a systematic understanding of the relationship between patents and publications by researchers at leading industrial firms. It tests the implications of several competing theories on the relationship between basic research and patents and shows how applicability of such theories depends upon the scientific discipline in which a researcher is engaged. Finally, the technique developed for matching inventors, authors, and firms may have other potentially useful applications.

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Appendix: Algorithm for Matching Authors and Inventors

The U.S. patent database contains the full name of each inventor of each patent, but the Science Citation Index (SCI) identifies authors only by abbreviation. For example, John Harry Truman is identified as Truman-JH. I designed the following algorithm to match authors of publications in the SCI to inventors of U.S. patents, based on each researcher's abbreviated names.

Steps:

- First, I corrected misspellings in the patent and publication datasets.
- Next, I assigned a unique abbreviation that *maximally differentiates* each inventor in the patent database. For example, Ron Willis, Ron M. Willis, and Ronald Willis were abbreviated as Willis-RM, not Willis-R (note that Willis-R would not maximally differentiate this individual if the database also included a Rachel V. Willis, who would be Willis-RV).
- I marked abbreviations that refer to more than one individual as "overdetermined" (e.g., Smith-J, which refers to John Smith and Jack Smith).
- For each company, I created a tree structure from the abbreviated names of all authors and inventors (see Figure 1). Each last name is a "root" of the tree. I then classified each node of the tree into one of four types (L, B, I or P) as described below. The purpose is to identify nodes that can be combined with other nodes because they refer to the same individual. L, B and I nodes cannot be combined, while P nodes must be checked to see if they can be combined, or "promoted."
    - L-nodes: A *leaf* node refers to an abbreviation that is not part of another, longer, abbreviation (e.g., Willis-AXP, Willis-RV).
    - P-nodes: The remaining nodes are *promotable*.[23] They must be checked to see whether they refer to the same person as the one referred to by a longer abbreviation along the same arc. For example, Willis-A is likely to be the same person as Willis-AXP, since there are no obstacles on the arc between the two nodes.[24]
    - B- nodes: A *branch* node is part of several longer abbreviations along *divergent* arcs. For example, Willis-R is a branch node because both Willis-RM and Willis-RV exist and diverge into separate paths. Unlike P-nodes, the B-nodes cannot be matched to longer abbreviations because of the ambiguity caused by branching. Thus, Willis-R cannot be matched to Willis-RM or Willis-RV.
    - I-nodes: An *invariant inventor* node refers to an inventor whose abbreviated name is part of another inventor's with a longer abbreviation.[25] In Figure 1, Willis-SL and Willis-SLA refer to "Samuel Lee Willis" and "Sandra Lauren A. Willis," respectively. Therefore, Willis-SL is an I-node. I-nodes cannot be matched to longer abbreviations because they refer to different inventors.

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23 By "promotable" I mean that the node must be tested to see whether it can be merged into another node that is further from the root and closer to a leaf.

24 The fact that Willis-A is a "P-node" means that there cannot be another inventor with the abbreviation Willis-AXP. Otherwise Willis-A would have been classified as an "I-node."

25 It is impossible to do this for authors because their full names are unavailable.

- After each node has been classified, the entire tree is traversed along each arc starting from the root. Each P-node is matched to the next node along its arc until reaching a leaf node or until a B-node or an I-node blocks the path. The result is shown as dashed lines in Figure 1. Willis-A is matched to Willis-AXP and Willis-RM is matched to Willis-RMU. However, Willis-SL is not matched to Willis-SLA because they refer to different inventors (Samuel and Sandra).

Figure 1: Matching Authors to Inventors

Shown is a hypothetical case for individuals who share the last name "Willis":

- Each node is the abbreviated name of an author or inventor.
- The "Willis" node is the root of the tree; each line is called an "arc".
- The node are classified into four types: (L)=leaf, (B)=branch, (I)=invariant, and (P)=promotable.
- The dashed arrows show abbreviations matched by running the algorithm. Willis-A is matched to Willis-AXP, Willis-RM is matched to Willis-RMU, and Willis-S is matched to Willis-SL. Observe that Willis-SL is not matched to Willis-SLA because they refer to different inventors, Samuel Lee Willis and Sandra Lauren A. Willis.

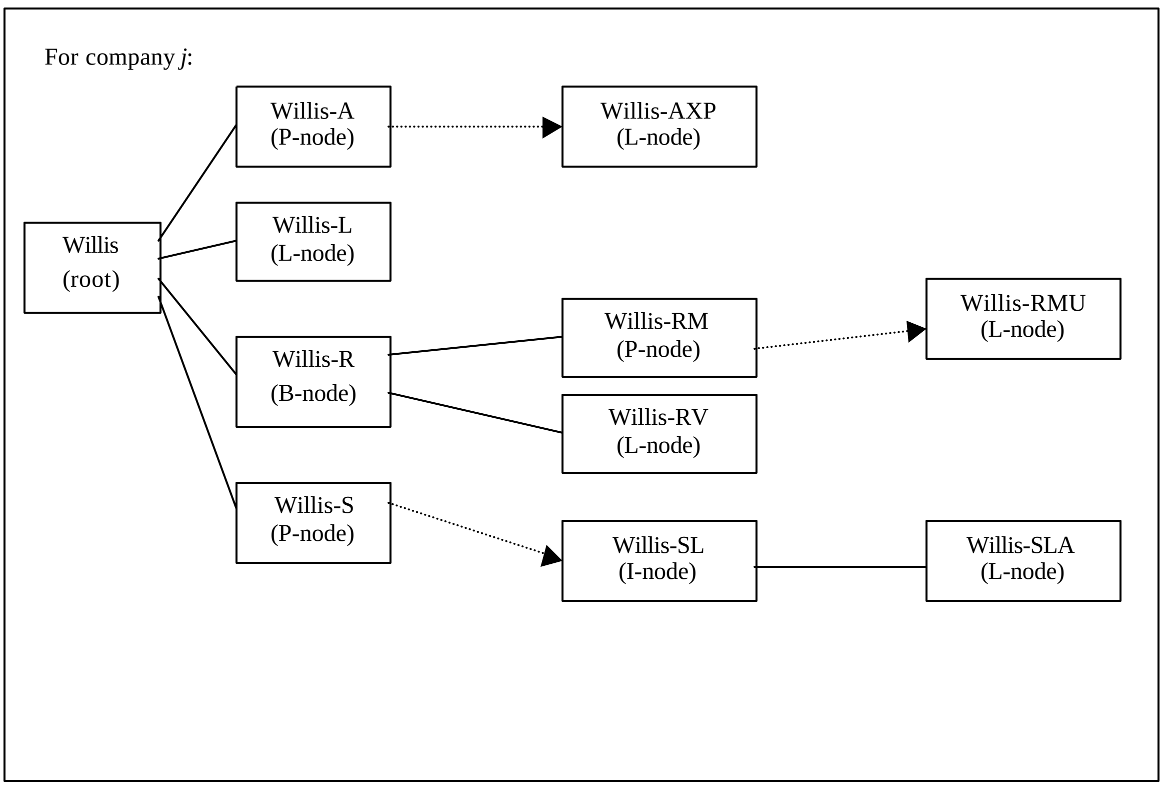

Table 1: Summary Statistics for Each Company

	DuPont	Merck	AT&T	IBM	Intel
Patents					
Number of Patents (1976-1999)	9938	4974	12364	22078	3330
Number of Patents (1985-1997)	6007	2822	6930	12452	1752
Publications in SCI Journals (1985-1997)					
Total Number	8428	10443	19724	20049	665
Articles Published in Basic Journals	4466	5080	6698	7072	31
Percentage Basic Research	53%	49%	34%	35%	5%
Publications in SCI Journals (1985-1997) by Scientific Area					
- Biology	357	375	24	15	1
- Biomedical Research	1141	2801	387	371	5
- Chemistry	3715	2160	2463	3368	70
- Clinical Medicine	1284	4855	143	200	3
- Engineering & Technology	746	41	5011	4752	370
- Mathematics	20	40	699	496	7
- Physics	918	24	10289	10340	198
- Multidisciplinary	124	90	274	213	4
- Other	123	57	434	294	7

Note: Patents and publications by the Dupont-Merck subsidiary (which existed from 1991) are excluded, because they would have introduced ambiguity when trying to identify the affiliations of authors and inventors. The numbers involved were small: Dupont-Merck obtained 208 patents (1976-1999) and published 1,219 articles (1985-1997).

Note: The multidisciplinary journals are: *Science*, *Nature*, *Recherche*, and *Search*.

Table 2: Inventors and Authors Identified and Matched in Each Firm

	DuPont	Merck	AT&T	IBM	Intel
Inventors (1976-1999)					
Number of inventors in each company's patents†	5456	2767	9133	19057	2309
Number of inventors positively identified with each firm*	5294	2697	8740	18837	2263
Authors (1985-97)					
Number of authors in each company's publications†	11269	17250	16540	19097	1463
Number of authors positively identified with each firm	4012	5996	6603	8163	471
Researchers Positively Identified with Each Firm After Matching by Abbreviation					
Total number of researchers positively identified with this firm	7771	6233	12006	22470	2465
Of which:					
▪ Researchers who only patent	3958	1149	5725	14752	1997
▪ Researchers who patent and publish	1336	1548	3015	4085	266
▪ Researchers who only publish$^{\Psi}$	2477	3536	3266	3633	202

Notes:

* Of the 37,831 inventors positively associated with these firms, only 140 inventors had overdetermined abbreviations (e.g., Larry Smith and Laura Smith are both Smith-L). These were subsequently dropped.

† Includes individuals from universities and other firms that co-authored or co-invented with researchers within these firms

Ψ This is a lower bound for the total number of researchers who published but did not patent, since some authors could not be positively identified with each firm.

Table 3: Variables

Variable	Description	N	Mean	StdDev	Min	Max
Main Variables						
Pat_{ij}	Number of patents by this researcher (1985-1997)	41325	1.8	3.6	0	94
Pub_{ij}	Number of publications by this researcher (1985-1997)	41325	3.9	11.4	0	429
$PubBas_{ij}$	Number of publications by this researcher in "basic" journals	41325	1.5	6.3	0	202
$PctBas_{ij}$	Percentage of publications by this researcher in "basic" journals	23279	0.29	0.39	0	1
$PctCoau_{ij}$	Percentage of publications by this researcher coauthored with academic institutions and public-sector laboratories	23279	0.23	0.32	0	1
$AvgSci_{ij}$	Average SCI Impact Scores of the journals in which this researcher publishes.	22065	2.4	2.4	0.08	38.9
Percentage Basic Research by Scientific Area						
Pc_bas_biol	Percentage of publications by this researcher in basic biology journals	23279	0.09	0.07	0	1
Pc_bas_biomed	Percentage of publications by this researcher in basic biomedical journals	23279	0.07	0.22	0	1
Pc_bas_chem	Percentage of publications by this researcher in basic chemistry journals	23279	0.12	0.27	0	1
Pc_bas_clinical	Percentage of publications by this researcher in basic clinical medical journals	23279	0.01	0.09	0	1
Pc_bas_engtech	Percentage of publications by this researcher in basic engineering and technological journals	23279	0.0004	0.01	0	1
Pc_bas_math	Percentage of publications by this researcher in basic mathematics journals	23279	0.002	0.04	0	1
Pc_bas_physics	Percentage of publications by this researcher in basic physics journals	23279	0.07	0.20	0	1
Control Variables						
Comn_lastnam	Dummy for researchers with common last names	1898			0	1
D_Merck	Dummy for researchers positively identified with Merck	41325			0	1
D_Dupont	Dummy for researchers positively identified with DuPont	41325			0	1
D_ATT	Dummy for researchers positively identified with AT&T	41325			0	1
D_Intel	Dummy for researchers positively identified with Intel	41325			0	1

Notes: The subscripts refer to researcher *i* in company *j*.
For the company dummies, IBM is the base case.
140 inventors with overdetermined abbreviations were dropped

Table 4: Pairwise Correlation Coefficients

	Pat_{ij}	Pub_{ij}	$PubBas_{ij}$	$PctBas_{ij}$	$PctCoau_{ij}$	$AvgSci_{ij}$
Pat_{ij}	1.00					
Pub_{ij}	0.16*	1.00				
$PubBas_{ij}$	0.11*	0.79*	1.00			
$PctBas_{ij}$	-0.02*	0.13*	0.35*	1.00		
$PctCoau_{ij}$	-0.01	0.11*	0.11*	0.06*	1.00	
$AvgSci_{ij}$	-0.05*	0.13*	0.22*	0.45*	0.11*	1.00

Note: * = significant at the 5% level.

Table 5: OLS with Number of Patents Awarded to a Researcher as the Dependent Variable

Independent Variables	Dependent Variable = Pat_{ij} (1985-97)				
	(I) Base Model	(II) Coauthorship and SCI Impact	(III) With Firm Effects	(IV) Eliminate Common Last Names	(V) Huber-White Robust Std. Errors
Main Variables					
Pub_{ij}	0.069* (0.002)	0.071* (0.002)	0.075* (0.002)	0.075* (0.002)	0.075* (0.005)
$PctBas_{ij}$	-0.59* (0.07)	-0.18* (0.08)	-1.82* (0.15)	-1.85* (0.15)	-1.85* (0.11)
$PctCoau_{ij}$		-0.44* (0.08)	-0.22* (0.09)	-0.22* (0.09)	-0.22* (0.08)
$AvgSci_{ij}$		-0.13* (0.01)	-0.11* (0.01)	-0.11* (0.01)	-0.11* (0.01)
Intercept	1.2* (0.03)	1.5* (0.04)	2.02* (0.06)	2.0* (0.06)	2.0* (0.06)
Firm Effects					
D_Merck			-1.41* (0.12)	-1.38* (0.11)	-1.38* (0.10)
D_Dupont			-0.98* (0.11)	-0.96* (0.11)	-0.96* (0.09)
D_ATT			-0.85* (0.08)	-0.84* (0.08)	-0.84* (0.07)
D_Intel			-0.08 (0.20)	0.02 (0.21)	0.02 (0.23)
D_Merck*$PctBas_{ij}$			3.38* (0.21)	3.40* (0.21)	3.40* (0.19)
D_Dupont*$PctBas_{ij}$			2.19* (0.22)	2.20* (0.22)	2.20* (0.17)
D_ATT*$PctBas_{ij}$			0.33 (0.22)	0.32 (0.22)	0.32* (0.14)
D_Intel*$PctBas_{ij}$			1.49 (1.92)	1.40 (1.92)	1.40 (1.01)
Regression Statistics					
N	23279	22065	22065	21045	21045
Adj R-quared	0.06	0.07	0.09	0.09	0.09

Note: Standard errors are shown in parentheses
* = significant at 5%
140 inventors with overdetermined abbreviations were dropped
When firm dummies are used, IBM is the base case.

Table 6: OLS of Patents per Researcher by Firm and Scientific Area (Robust Standard Errors)

Independent Variables	Dependent Variable = Pat_{ij} (1985-97)				
	Merck	DuPont	AT&T	IBM	Intel
Percentage of Research Published in basic Journals in each Field:					
Pc_bas_biol	0.5* (0.2)	-0.8* (0.2)	-2.8* (0.8)	-2.1* (0.8)	NA
Pc_bas_biomed	-0.5* (0.1)	-0.6* (0.1)	-0.7 (0.4)	-0.5 (0.9)	-4.9* (1.2)
Pc_bas_chem	3.3* (2.6)	1.6* (0.2)	-1.1* (0.2)	-1.0* (0.2)	-1.7* (0.8)
Pc_bas_clinical	1.5* (0.4)	-1.0* (0.1)	-1.1* (0.3)	-1.1 (0.9)	2.5 (3.4)
Pc_bas_engtech	NA	4.5 (4.9)	-0.6 (0.6)	-2.4 (2.7)	NA
Pc_bas_math	NA	NA	-1.6* (0.2)	-2.2* (0.3)	NA
Pc_bas_physics	8.8 (6.2)	-0.7 (0.5)	-1.9* (0.1)	-2.3* (0.1)	NA
Other Variables					
Pub_{ij}	0.15* (0.02)	0.04* (0.01)	0.06* (0.006)	0.07* (0.007)	0.10 (0.07)
$PctCoau_{ij}$	-0.38* (0.19)	0.48* (0.18)	-0.12 (0.09)	-0.21 (0.12)	0.19 (0.54)
$AvgSci_{ij}$	-0.07* (0.01)	-0.04* (0.02)	-0.05* (0.02)	-0.09* (0.02)	-0.31* (0.13)
Intercept	0.04 (0.11)	0.85* (0.08)	1.20* (0.05)	2.03* (0.07)	2.02* (0.32)
Regression Statistics					
N	4839	3363	6101	7333	429
R-Squared	0.19	0.06	0.13	0.05	0.01

Note: Robust standard errors are shown in parentheses
* = significant at 5%
140 inventors with overdetermined abbreviations were dropped
NA denotes a scientific area in which researchers from a firm did not publish in any basic journals.

Table 7:OLS for Researchers who Received Patents in U.S. Patent Classes 424 and 514 (drugs, bio-affecting and body treating compositions).

Independent Variables	**Dependent Variable = Pat_{ij} (1985-1997)**	
	Merck	**DuPont**
Percentage Basic Research in Each Field		
Pc_bas_biol	-0.8 (1.2)	-2.7 (1.9)
Pc_bas_biomed	-3.5* (0.9)	0.1 (1.1)
Pc_bas_chem	5.8* (1.0)	4.1* (2.1)
Pc_bas_clinical	3.4* (1.4)	-3.8 (2.6)
Pc_bas_engtech	NA	NA
Pc_bas_math	NA	NA
Pc_bas_physics	54 (51)	-4.1 (4.0)
Other Variables		
Pub_{ij}	0.17* (0.03)	0.02 (0.02)
$PctCoau_{ij}$	-1.61* (0.69)	-0.10 (0.81)
$AvgSci_{ij}$	-0.19* (0.09)	-0.28* (0.13)
Intercept	3.52* (0.66)	4.29* (0.89)
Regression Statistics		
N	859	151
R-Squared	0.21	0.09

Note: Pat_{ij} refers to the number of patents obtained by these researchers in *all patent classes*.
Robust standard errors are shown in parentheses
* = significant at 5%
NA denotes a scientific area in which researchers from a firm did not publish in any basic journals.

8. The challenging relationship between patents and standards. 9. The role of SDOs and their IPR policies. 10. The growing tension between patents and standards. 11. Specific concerns and issues with patents in standards. 12. Overview of governments and courtsâ€™ perspectives on SEPs. Part IV â€“ A closer look at ITUâ€™s standardization activities and its patent policy. 13. ITU and its role in international standards development. 14. ITU-T standardization process.Â This publication is owing to the collaborative spirit of several intellectual property, competition and standardization experts. For their generous contribution of time and expertise, ITU is thankful to the following principal authors, in alphabetical order: Rudi Bekkers, Matthew Dalais, Antoine Dore and Nikolaos Volanis. Moreover companies need to distinguish between individual patent and a patent portfolio. Firstly, company should determine the quality of the underlying invention outlined in the patent. Secondly, it should check how the patent is constructed.Â where CITi,T is the number of forward citations received by patent application i published in year Pi within T years from its publication (in the present case, within five years). Cj,i is a dummy variable that gets value 1 if the patent document j is citing patent document i, and 0 otherwise.Â So the researcher can decide how many dimensions of patentsâ€™ underlying value (forward citations; patent family size; number of claims; generality index; backward citations or grant lag) to include in the index depending on the aim of the research. When U.S. researchers collaborate with researchers at foreign institutions, determining the appropriate review type and method depends on whether the collaborating institution is engaged in the research. The other responses are incorrect because they do not help the IRB determine where the research should be reviewed.Â Correct Answer : Receiving stock in a company funding your research.Â Question 1 Question : If a researcher creates the idea for a project and is not listed in the preferred author order position on resulting publications, is this considered to be research misconduct under federal policy? Your answer : Yes because it involves a form of falsification.Â Your answer : The relationship includes clear discussions about each person's expectations. In other words, the relationship between patents and â€œideasâ€ may itself not be stable over time, making this evidence hard to interpret, a point made by Lanjouw and Schankerman (2004). Our paper focuses on Ânonpatent Âmeasures. 4 See also Evenson (1984, 1991, 1993) and Lanjouw and Schankerman (2004).Â In this interpretation, At represents the number of product varieties and St is the aggre-gate number of researchers. Even with no ability to improve productivity within each variety, a constant number of researchers can sustain exponential growth if the Âvariety-discovery function exhibits constant research productivity.