How does firm size mediate firms’ ability to benefit from invention? Evidence from patents and scientific publications

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Abstract

Using novel firm-level panel data, this paper investigates how firms’ ability to benefit from invention is mediated by firm size. We distinguish between output indicators of applied research using patents versus output indicators of basic research using scientific publications in “hard science” journals. Our results show that the relationship between performance and patents is stronger for small firms than for large firms. By contrast, the relationship between performance and scientific publications is stronger for large firms than for small firms. We also investigate several mechanisms that may be responsible for these firm size effects. Cost-spreading, complementary assets and especially large firm’s inertia all appear to exert a significant influence on the appropriability of patented research. Conversely, a key role of published research seems to be that of complementing large firms’ marketing and sales efforts.

Keywords: patents, publications, firm size, basic and applied research, productivity, growth

JEL Classification: O16, O32, G32, G34

1. Introduction

Following Schumpeter (1934, 1942), an extensive literature has explored the effect of firm size on innovation. Large firms have often been perceived as slow to introduce new technologies because of bureaucracy and “core rigidities” (Hannan and Freeman, 1984; Tripsas and Gavetti, 2000) and a tendency to focus on existing markets (Christensen, 1997). On the other hand, large firms may enjoy a number of advantages, such as scale and scope economies in R&D (Schumpeter, 1942; Chandler, 1962) and superior capabilities in product development, marketing, and commercialization (Teece, 1986; Mitchell, 1991; Nerkar and Roberts, 2004). However, empirical research has largely focused on which type of firms are more adept or prolific at producing inventions (e.g., Henderson and Clark, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009). Less is known about interfirm differences in the ability to
appropriate the returns from invention, and whether these differences are contingent on industry setting and the nature of the inventive activity (Cohen, 2010). Yet, appropriability is a key concern for managers, and lack of it may undermine private incentives to invest in R&D. In this paper, we examine two related research questions: To what extent do large and small firms differ in their ability to benefit from the outputs of basic and applied research? And if size matters, what are the fundamental mechanisms that drive these firm size effects?

This paper argues that the relative advantages and disadvantages of size will vary across industries and will depend on the type of inventive activities that a firm carries out. Small, entrepreneurial firms may enjoy advantages over large firms in industries where technological change is fast and opportunities are fleeting, while large firms may perform better in industries where cost-spreading advantages and complementary assets are important (Cohen and Klepper, 1996a,b; Teece, 1986). Size may also offer significant appropriability advantages when inventive activities are close to the basic-science end of the spectrum, since large firms may more easily find commercial applications for the unpredictable outcomes of basic research (Nelson, 1959), may be better able to integrate multiple research streams (Henderson and Cockburn, 1996; Pisano, 2006), and may more effectively use the published findings of basic research to market their products (Hicks, 1995).

To examine these issues, we develop a novel and comprehensive database on patents and scientific publications. We systematically match patent data from the European Patent Office (EPO) and bibliometric information from Thomson’s ISI Web of Science to all European firms. We identify about 15,000 firms that have at least one patent or scientific publication in a “hard science” journal in the period 1978–2006. Collectively, these firms hold 253,573 EPO patents and 58,025 publications. We are interested in “firm publications” – scientific articles where at least one of the coauthors is a company employee – because this should capture a type of research that is more basic (or science-based) than that captured by patents (Cockburn and Henderson, 1998). Patents are required by law to be very specific and circumscribed to well-defined commercial applications. By contrast, scientific publications are not assessed on the basis of their commercial application, but rather on their novelty and applicability to a wide range of scientific problems. Our dataset therefore allows us to distinguish between firm-level indicators of applied research using patents, and firm-level indicators of basic research using scientific publications in “hard science” journals.

The paper makes three important empirical contributions. First, we demonstrate that the relationship between performance (as measured by sales and employment growth), firm size, and invention depends crucially on the type of inventive activities that a firm carries out. Large firms appear to benefit the most from the outputs of basic research (publications), while small firms appear to benefit the most from the outputs of applied research (patents). Second, in line with Levin et al. (1987) and Cohen et al. (2000), we find that multiple mechanisms exert a significant influence on appropriability; however, different mechanisms seem to play a role in applied versus basic research. Cost-spreading, complementary assets and especially large firm’s inertia all appear to have a significant effect on the appropriability of
patented research. Conversely, a key role of published research seems to be that of raising the reputation of a company and its products, thus facilitating especially large firms’ marketing and sales efforts. Finally, our results indicate that the incentives for firms to engage in basic research are quite complex. Many small firms publish a lot, despite not gaining very much out of it and actually appearing to sacrifice sales in order to publish. This indicates that there might be benefits from engaging in basic research that our performance measures do not satisfactory capture, such as a “taste” for science (Stern, 2004; Roach and Sauermann, 2010) or reputational advantages in the markets for acquisitions or partnerships (Arora and Gambardella, 1990; Higgins and Rodriguez, 2006; Higgins et al., 2011). Selection with respect to employee motives may also be an important factor determining innovative behavior in small versus large firms (Sauermann, 2012). Investigating these issues is clearly an important direction for future research.

2. Theoretical background and hypotheses

Innovation is a complex, uncertain, and highly non-linear process, shaped both by technological and economic factors. It can be understood as “an ongoing search activity – a search for products possessing new or superior combinations of performance characteristics, or for new methods of manufacturing existing products” (Kline and Rosenberg, 1986; p. 303).

In searching for new products or processes, firms must often solve scientific, technical and organizational problems. In this paper, we view inventions as new ideas or concepts generated by R&D (Khilji et al., 2006). When a new idea is put into use commercially, it becomes an innovation (Schumpeter, 1934; Damanpour, 1987). Thus, invention is just one step of the innovation process, which must be integrated with other steps such as financing, development, design, production and marketing.

For analytical purposes, it is helpful to distinguish outputs of the R&D process that are close to the basic-science end of the spectrum, from outputs of the R&D process that are close to the applied-science end of the spectrum (Ruttan, 1959; Nelson, 1959). Basic research can be defined as research directed toward “a fuller knowledge or understanding of the subject under study, rather than a practical application thereof” (National Science Foundation, 1985, p. 221). Applied research is research aimed at gaining the knowledge necessary to solve a specific practical problem, often with a commercial application in mind. Most of corporate R&D is directed toward solving specific commercial problems. Occasionally, however, corporate research leads to the creation of new scientific knowledge. Outstanding examples are the birth of radio astronomy at Bell Laboratories, and the discovery of high temperature superconductivity at IBM research labs. Less dramatic but more typical examples are industry-sponsored clinical trials. Clinical trials contribute to growth of medical knowledge; however, they also bring significant benefits to the sponsoring firms, for they play an essential role in the development, approval and marketing of new drugs. As discussed above, we use patent-based indicators to measure the outputs of applied research, and publication-based indicators to measure the outputs of basic research. Thus, we conceptualize patents as “applied inventions”, and firm publications as “basic” or “scientific” inventions". 
The distinction between basic and applied research is often fuzzy: science and technology overlap to a significant extent. Murray (2002) and Murray and Stern (2006), in particular, note that the same piece of knowledge is often inscribed both in a patent and a scientific publication. Thus, the same piece of knowledge may have a more “applied” manifestation (in a patent), and a more “basic” manifestation (in a scientific article). These different manifestations may serve different corporate objectives. Patents are typically used to enforce exclusivity and secure market access, while publications may be used to raise corporate image or create interest in a product. Thus, patents and publications, even when they incorporate the same knowledge, may have different effects on firm performance, depending on the relative importance of different corporate objectives.

2.1. Determinants of appropriability

The goal of this paper is to study how large and small firms differ in the ability to appropriate the benefits from their inventions. Our focus will be on how inventions can increase firm productivity (i.e., how they can increase sales holding capital and labor inputs fixed). Firm productivity increases when inputs are used more efficiently, or when new goods with superior characteristics are created. We also expect improvements in productivity growth to be associated with firm growth, as suggested by an influential literature in economics on industry evolution (Lucas, 1978; Jovanovic, 1982; Ericson and Pakes, 1995).\footnote{However, our discussion will largely neglect other benefits that inventions can bring about, most notably licensing revenues.}

For firms to benefit from their inventions, opportunities must be identified and commercially exploited. Traditionally, two sets of factors that can influence the appropriability of inventions have been emphasized in the literature: the inability of some firms to rapidly take advantage of new opportunities (organizational inertia) and differences in scale, scope and capabilities. The nature of the invention may also differentially affect the ability of large and small firms to benefit from their inventions. We discuss these three sets of factors in turn. Table A summarizes the discussion, and how our empirical results shed light on various theories.

2.1.1. Organizational inertia

Organizational inertia refers to the inability of organizations to change their patterns of behavior in response to changes in competitive conditions, such as changes in prices, technology, and regulation (Rumelt, 1995). The importance of overcoming inertia as a determinant of firm performance has been stressed by organizational ecologists (Hannah and Freeman, 1984; Kelly and Amburgey, 1991) and students of competitive dynamics (Chen and Hambrick, 1995; Ferrier et al., 1999; Chen et al., 2010). Dynamic capability researchers have also emphasized the importance of managers’ ability to rapidly integrate, build, and reconfigure internal and external capabilities in dynamic environments (Teece and Pisano, 1994; Teece et al., 1997).

In the context of innovation, inertia can take at least two forms. It can refer to an unwillingness to...
explore new technological paths, or it can refer to an inability to recognize or exploit new commercial opportunities arising from technological progress. In the latter case, even technological leaders may become laggards in the introduction of innovative products and processes (Teece, 2010). Business history is replete with examples. Xerox invented the graphical user interface and many other fundamental technologies in the computer industry, but other firms – most notably Apple and Microsoft – reaped most of the rewards. Fairchild invented the silicon gate process, but Intel became the leader in microprocessors. AT&T invented the transistor and cellular (wireless) phone technology, but appropriated only a negligible fraction of the associated benefits and actually had to resort to acquisitions to regain a foothold in the cellular phone market.

The strategy literature has highlighted several reasons why firms may not be able to seize commercial opportunities that were well within their technological grasp. First, because change is always risky, evolutionary forces may favor organizations whose structures are reliable and accountable (Hannan and Freeman, 1984). However, the very same processes that generate reliability and accountability, such as standardized routines, may also generate resistance to change. Second, firms with large market share may be reluctant to introduce new products for fear of cannibalizing sales of their existing products (Arrow, 1962). Third, firms may fail to perceive or exploit new opportunities because past experience affects the way in which new data is processed and interpreted (Leonard-Barton, 1992; Tripsas and Gavetti, 2000). Incumbents, in particular, may have a tendency to cater to the needs of their existing customers. This tendency, however, may hinder their attempts to serve new customers and markets (Christensen and Bower, 1996; Christensen, 1997). More generally, past commitments to customers, employees, and surrounding community may powerfully restrain a firm’s ability to change and adopt new technologies (Sull et al., 1997).

The main problem associated with inertia is that firms may forgo first-mover advantages. Lieberman and Montgomery (1988) highlight three reasons why late entry in a market may hinder a firm’s prospects: (i) learning by doing may favor early movers, (ii) valuable assets such as scarce inputs or superior locations may be preempted, and (iii) existing buyers may be reluctant to switch suppliers. Buyer switching costs may also be reinforced by network effects (Shapiro and Varian, 1999). Overall, the evidence strongly suggests that first-mover advantages and the ability to move quickly down the learning curve are very effective means of appropriating the returns to innovation (Levin et al., 1987; Cohen et al., 2000). For example, in the brewing, telecommunications, and personal computer industries, first movers and early imitators appear to enjoy systematically higher stock market returns than late imitators (Lee et al., 2000). In the medical diagnostic imaging industry, entry-order effects have also been found to be important (Mitchell, 1991). In short, organizational inertia, by making a firm forgo first-mover advantages, can seriously hinder its prospects.
2.1.2. Scale, scope, and capabilities

A firm’s ability to appropriate the returns from invention is also influenced by its size and the breadth and depth of its technical and commercial capabilities. Importantly, size (as measured by output or market share) matters because larger firms can apply the fruits of their R&D over a greater output than smaller firms. As a result, the returns from innovative efforts can be expected to be systematically higher for larger firms (Scherer, 1980; Cohen and Klepper, 1996a). This effect is likely to be important when inventions do not substantially change the scale at which the inventing firm is operating – the ex ante firm size – and when imperfections in the market for technology prevent firms from profiting from their inventions through licensing. Traditionally, this effect is termed “cost spreading” because it can alternatively be stated by saying that larger firms can average the cost of R&D over a greater level of output.

Large, diversified firms may also enjoy appropriability advantages thanks to scope economies in product development and commercialization. Inventions are more likely to achieve their full potential if the sponsoring firm provides an environment conducive to further development. The diversity of a firm’s technological base and product-market experience can provide such an environment by facilitating knowledge spillovers and the discovery of new commercial applications (Henderson and Cockburn, 1996; Hargadon, 2003; Nerkar and Roberts, 2004; Leiponen and Helfat, 2010). Thus, the value of an innovative idea may be enhanced by the opportunities for cross-fertilization that larger firms typically provide.

Finally, large size may be associated with attributes such as superior capabilities in product development, marketing, and commercialization. Capabilities can be defined as resources that firms can draw upon to accomplish their aims (Helfat et al., 2007). The capabilities necessary to successfully commercialize an innovation are often related to the possession of complementary assets (Teece, 1986). These assets include pre-existing knowledge stocks, relational capabilities, manufacturing and distribution assets, and firm reputation. Complementary assets are said to be generic if they are not tailored to a specific invention; assets which exhibit unilateral (bilateral) dependence with the innovation are termed specialized (cospecialized). Because generic assets are easy to replicate, only specialized and cospecialized assets are typically viewed as a source of competitive advantage (Barney, 1991).

Complementary assets have been shown to be important determinants of the probability and timing of entry (Mitchell, 1989, 1991), the decision to invest in R&D (Henderson and Cockburn, 1996), and the ability of incumbents to survive and prosper in the face of technological change (Tripsas, 1997; Rothaermel, 2001). In his study of the medical diagnostic imaging industry, for instance, Mitchell (1991, 1992) finds that when innovation does not significantly change the identity of the individuals that use a product (so that incumbents’ complementary assets such as sales and service systems remain important), incumbents typically outperform industry newcomers. Clearly the possession of complementary assets can increase a firm’s ability to profit from innovation.
2.1.3. Industry characteristics

The above discussion suggests that small firms are nimbler and more agile at exploiting the outputs of their R&D, while large firms may enjoy scale and scope economies in the development and commercialization of their inventions (Schumpeter, 1934, 1942). We argue that the magnitude of these effects is likely to be contingent on industry setting.

First, the costs of inertia are likely to be particularly large in industries where the rate of technical progress is fast. Dynamic capability researchers emphasize the benefits of quickly creating and reconfiguring capabilities in dynamic environments (Teece et al., 1997). Speed has been described as a key source of competitive advantage in high-velocity, “hypercompetitive” environments (Eisenhardt, 1989; D’Aveni, 1994). Speed is likely to matter the most when opportunities are fleeting, competitive advantage is temporary, and there is a limited temporal window for exploitation (Roberts and Eisenhardt, 2003). Thus, we expect the appropriability disadvantages of inertia (typically associated with large firm size) to be prominent especially in technologically dynamic industries.

The appropriability advantages of large size are also likely to vary across industries. A point strongly emphasized by Cohen and Klepper (1996b) is that the benefits of cost spreading are likely to be much larger for process innovations than for product innovations. By reducing costs by a given percentage margin, in fact, process innovations tend to yield larger total savings to companies that produce more output (Scherer, 1980). Product innovations, by contrast, may be easier to license and may spawn more rapid growth in output than process innovations (Cohen and Klepper, 1996b). Thus, ex ante firm size may matter less for process than product innovation. As a consequence, we may expect the cost-spreading advantages of large size to be prominent especially in industries where process innovations are common.

Lastly, because large firms are more likely to possess the complementary assets required to successfully commercialize innovation than small firms (Teece, 1986), we can expect the appropriability advantages of large size to be prominent especially in industries where complementary assets are important.

Hypothesis 1. The effect of firm size on a firm’s ability to appropriate the benefits from invention is contingent on industry setting. Small firms should enjoy greater appropriability advantages in dynamic, high-velocity industries. Large firms should enjoy greater appropriability advantages in industries where process innovations are common and complementary assets are important.

2.1.4. The “basicness” of research

The ability of a firm to appropriate the benefits from its inventive activities is also influenced by the nature of these efforts. A characteristic that has received substantial attention is the “basicness” of research. Although all forms of R&D are subject to appropriability problems, more basic inventions – where basic is usually defined in terms of originality, closeness to science, breadth, etc. – have generally been regarded as possessing a lower degree of appropriability, despite their often great social value (Arrow, 1962; Trajtenberg et al. 1997; Salter and Martin, 1991).
To be sure, scholars have identified several ways through which investments in basic research can benefit the sponsoring firm (Rosenberg, 1990). On relatively rare occasions, basic research leads directly to the discovery of new processes or products, as DuPont’s nylon showed. More commonly, however, basic research simply plays an intermediate role in the invention of a final good (Mowery and Rosenberg, 1989; David et al., 1992). For instance, basic research can help guide and evaluate the sponsoring firm’s more applied research efforts (Cohen and Levinthal, 1990; Fleming and Sorenson, 2004). Basic research can also benefit the sponsoring firm by allowing it to signal its scientific and technical capabilities to prospective customers, employees, or financiers (Hicks, 1995; Azoulay, 2002; Stephan et al., 2007). But despite these indirect benefits, basic research has generally been viewed as plagued by severe appropriability problems.

The key reason why profiting from basic research is difficult is that its payoffs are often uncertain and distant. Even in industries where science is an important component of the innovation process, it usually takes a substantial amount of time, investment, and effort before basic research results can come to fruition – if they ever do. Compounding this problem, is the fact that product development in science-based industries typically requires the integration of multiple knowledge streams and capabilities. In the pharmaceutical industry, for instance, drug discovery necessitates tight integration between scientific subfields such as cell biology, genetics, and bioinformatics, and technical, commercial, clinical, and regulatory capabilities (Pisano, 2006; Swan et al., 2007). Profiting from basic research can be difficult if a firm cannot master all the necessary competencies. Indeed, Pisano (2006) argues that the fragmentation of the biopharmaceutical industry, by impairing the ability of biotech firms to learn and integrate multiple knowledge streams, may in part be responsible for the poor financial performance of the sector.

Another significant risk associated with basic research is that valuable information may leak out to competitors. This risk is particularly severe for basic research because scientific discoveries often do not fit the criteria for patentability, thus legal protection may not be available (Nelson, 1959; Arrow, 1962). Secrecy may also not be particularly effective or possible as an appropriability mechanism for basic research, since scientists’ internalized norms of science may conflict with firms’ confidentiality necessities (Dasgupta and David, 1994).

Because of these problems, scholars have suggested that large firms may be better positioned than small firms to profit from the outcomes of basic research. Nelson (1959) was arguably the first to make this point. He noted that, as one moves from the applied-science end to the basic-science end of the spectrum, the unpredictability about the outcomes of a specific research project rises, as the goals become less clearly defined and less closely tied to the solution of a specific practical problem. This unpredictability hinders appropriability because organizational search is typically local (March and Simon, 1958; Stuart and Podolny, 1996; Ahuja and Lampert, 2001). Firms often search locally because their knowledge is embedded in firm-specific, path-dependent capabilities and routines, which shape and constrain the further evolution of their knowledge (Nelson and Winter, 1982; Teece et al., 1997; Leonard-Barton, 1992). Thus, if the commercial applications of a basic research result lie outside the sponsoring firm’s area of expertise, the returns from that basic research investment may be limited. This problem is arguably
most relevant for small firms, as large firms often have a broad technological base which can ensure that, “whatever direction the path of research may take, the results are likely to be of value to the sponsoring firm” (Nelson, 1959, p. 302). Thus, large, diversified firms might be the ones best positioned to exploit the results of basic research.

The logic of the resource-based view (RBV) also suggests a link between superior performance and the breath of a firm’s technical and commercial resources. The RBV views the firm as a bundle of resources (Penrose, 1959). These resources can produce supernormal profits only to the extent to which they are unique and inimitable. Given the causal ambiguity and the path-dependent nature of the resource development process (Nelson and Winter, 1982; Dierickx and Cool, 1989), however, the uniqueness and inimitability of a collection of resources is likely to be greater than the uniqueness and inimitability of each individual resource. Thus the breadth of technical resources may be an antecedent of rent generation (Sampson, 2007; Ndofor et al., 2011), particularly in environments where absorptive capacity and complementarities between knowledge streams are important (Henderson and Cockburn, 1996; Argyres, 1996; Rosenkopf and Nerkar, 2001).

The difficulty to identify and patent all the potential applications of basic research may also confer appropriability advantages to large firms. Nelson’s (1959) conjecture assumes that small firms are unable to exploit their basic inventions, not only by developing new product lines, but also through licensing to others (Kamien and Schwartz, 1975). Indeed, if licensing was easy, small firms could reap the benefits of basic research simply by contracting with larger firms. We envisage at least two reasons why licensing may be difficult for basic research outcomes. First, because often scientific results cannot be patented, the risk of expropriation is higher. Second, the uncertainty surrounding the potential applications of basic research may be a source of bargaining frictions (Akerlof, 1970; Arora et al., 2001). As a result, licensing may be difficult and commercial applications may have to be developed in-house. Larger firms with the complementary capabilities in product development, marketing, and commercialization may thus enjoy significant advantages over smaller firms in appropriating the returns from basic research.

Finally, basic research can raise the reputation of a company and its products, thereby increasing sales. In the context of procurement, Lichtenberg (1986, 1988) notes that private investments in R&D are often used by firms to signal ability to perform certain government contracts, particularly those for major weapons systems. In the prescription-drug industry, much advertising is based on and driven by clinical-research outputs (Azoulay, 2002; Goldacre, 2012). Thus, published research can complement and lend credibility to a firm’s marketing efforts. To the extent that these marketing efforts are mainly undertaken by large firms, published research might benefit chiefly those firms.²

Together, these arguments suggest that large firms may be best positioned to exploit the outputs of basic research.

**Hypothesis 2.** The relationship between performance and basic research outputs is stronger for large

²However, it is also possible that reputation may be particularly valuable to small firms that do not have an established brand name or track record.
firms than for small firms.

Two important remarks are in order. First, it should be noted that Hypothesis 2 refers to the exploitation of basic research results. Thus, it does not rule out the possibility that small firms may have advantages over large firms in the generation or exploration of new ideas, as some scholars have suggested (Abernathy, 1978; Henderson, 1993).

Second, although the discussion leading to Hypothesis 1 arguably applies most directly to applied research, some of those arguments may also apply to basic research. In particular, it is plausible that complementary assets may be important to appropriate the benefits from basic research. In the empirical section, we will thus also examine the impact of industry characteristics (including the importance of firm reputation) on firms’ ability to appropriate the benefits from basic research.

3. Data

This paper combines data from three main sources: (i) patents from the European Patent Office (EPO), (ii) scientific publications from the Web of Knowledge database, and (iii) financial information from Amadeus. Of the firms in our final sample, 27% are German, 20% French, 16% Italian, and 11% British. The remaining 26% are from the other eleven Western European countries. In this section, we explain the methodology for constructing the data, and describe our sample.

**Patents.** To generate a firm-level output measure of applied research, we follow the large literature that uses patent data (see Griliches, 1990, for a survey). We construct a unique dataset of European patents by matching all granted patent applications from the EPO to the complete list of Amadeus firms (about 8 million firm names) for the period 1978–2006. Details on the matching procedure are available upon request.

**Scientific Publications.** Our output measure of basic research is the number of publications in academic journals. We develop systematic data on firm publications to proxy for science-based inventive activity by firms. The world’s largest source of information on scientific publications is Thomson’s ISI Web of Knowledge (WOK), which includes publication records on thousands of international journals in “hard” sciences (such as natural or physical sciences). Each publication has an address field that contains the authors’ affiliation. We match all firms by name to the complete ISI database, taking special care to exclude research and non-profit institutions that are also included in Amadeus.

Using bibliometric data raises a number of issues. First, a key concern is heterogeneity in the quality of publications. To mitigate this concern, for each article we collect information on the number of citations it receives, as well as the quality of the journal where it was published, as measured by the impact factor from the Journal Citations Report. A second concern relates to whether the knowledge incorporated into a firm publication was actually generated within the firm. Hypothetically, a new hire might publish the results of her dissertation, thus bringing external knowledge to the firm. While we cannot rule out this possibility, it is important to note that in most “hard” sciences publication lags tend to be very short –
typically a few months.\textsuperscript{3} We mitigate this early-publication concern by showing that our results are not sensitive to removing firms whose publications are concentrated very early in their life-cycle - a pattern that may suggest that publications were not generated within the firm. Lastly, our matching procedure assigns a publication to a firm if at least one of its coauthors is a company scientist. We check the robustness of this matching procedure by experimenting with different ways of assigning publications to firms.

\textbf{Accounting.} Accounting information (such as sales, assets, and employment) is taken primarily from Amadeus. The source of the accounting information is typically the Company Register House in each of the countries in our sample. The key advantage of these data is the comprehensive coverage of firms, especially the unique accounting information on private firms. One potential weakness in the Amadeus data is that firms which are missing accounting information for four consecutive years are dropped from the database, resulting in about 5\% of the firms being dropped every year. In order to capture these firms we use historical data in archived Amadeus publications.

4. Descriptive Statistics

Tables 1 and 2 report summary statistics for firms in our sample. 14,899 firms have at least one patent or scientific publication in the period 1978–2006. The average patenting firm holds an annual stock of 7.5 patents, while the average publishing firm holds an annual stock of 2.3 articles. Our sample covers a wide distribution of firm size, especially in the lower tail. The median firm generates about $20 million in annual sales and has 87 employees. 10\% of our firms have 8 employees or less, and generate less than $1.6 million in annual sales. As a comparison, Compustat patenting firms have on average $3 billion in annual sales with a median of $500 million (Bloom et al., 2005). The average inventing firm in our sample generates sales of $326 thousand per employee and enjoys annual employment growth of 4\%, and annual sales growth of 8\%. In total, firms in our sample hold 253,573 patents and publish 58,025 scientific articles in “hard” science journals.\textsuperscript{4}

Table 2 splits the sample of inventing firms into three groups: firms that only patent, firms that only publish, and firms that both patent and publish. The vast majority of firms fall into the first category, with nearly 11,000 firms only patenting. About 3,200 firms only publish, and 939 firms both patent and publish.\textsuperscript{5} Thus, there is a large number of firm publications (about a half) that are not associated with any patent. In terms of size, there is no substantial difference between firms that only patent and firms

\textsuperscript{3}Another way to consider this issue is that to the extent that publications measure intellectual human capital, it might not be essential to know exactly where this knowledge was generated.

\textsuperscript{4}We also match our sample of European firms to patents from the USPTO. We identify 109,170 USPTO patents that are assigned to these firms. The main results of this paper are robust to using USPTO instead of EPO patents.

\textsuperscript{5}An example of a small, only-publishing firm is IDL Biotech AB (Sweden, BioMed). This firm published only one article, “Tissue Polypeptide Specific antigen (TPS), a marker for differentiation between pancreatic carcinoma and chronic pancreatitis” in Cancer, 2000, and it holds no patents. Another example is the German engineering company Brandenburg GmbH. This firm holds 10 publications and no patents. Its research focuses mainly on Cardiac and Cardiovascular Systems and Metallurgical Engineering. A representative publication is “Rail defects: an overview,” in Fatigue & Fracture of Engineering Materials & Structures, 2003.
that only publish (647 and 632 employees, on average, respectively); however, firms that perform both inventive activities are substantially larger, averaging more than 5,000 employees. Publishing firms are about 15% more productive than non-publishing firms. Firms that only publish and those that both publish and patent appear to be similar in terms of productivity.6

We present the unconditional distribution of the gains from invention by firm size in Figures 1 and 2. Figure 1 plots the relationship between labor productivity (sales over employment) and patenting by employment quintiles. Firms are split to high and low patenting based on the sample median value. The bars reflect the percentage difference in labor productivity between high- and low-patenting firms. Within small firms, labor productivity is substantially larger for high-patenting firms than for low-patenting firms. Thus, conditional on being small, patenting appears to be associated with large productivity gains. By contrast, for large firms the difference in labor productivity between high- and low-patenting firms appears to be much smaller. Figure 2 plots the same relationship, but with scientific publications instead of patents, and shows the opposite pattern. The productivity gains associated with publishing are much larger when firms are big than when they are small. Thus, substantial gains from publishing appear to exist primarily for large firms.

5. Econometric Specifications

Our econometric analysis focuses on identifying a robust set of relationships between firm size and returns to patenting and publishing, as measured by productivity gains and employment growth. Our analysis differs from previous “classical” productivity estimations (e.g., Griliches, 1986) in that we do not directly observe R&D expenditures. This implies that we cannot compute net returns to innovation, as the costs associated with the innovative output are not observed. Thus, we focus on differences in the private gains or gross returns associated with invention (both basic and applied) by small and large firms. In all specifications we use counts of the number of patents and scientific publications.7

We estimate the following specification for firm productivity – annual sales conditional on employment and capital:

\[
\ln Sales_{it} = \beta^s_0 + \beta^s_1 \ln Employment_{i,t-1} + \beta^s_2 \ln Assets_{i,t-1} + \beta^s_3 \ln (1 + Patents_{i,t-1}) \\
+ \beta^s_4 \ln (1 + Publications_{i,t-1}) + \beta^s_5 \ln (1 + Patents_{i,t-1}) \times \ln Employment_{i,t-1} \\
+ \beta^s_6 \ln (1 + Publications_{i,t-1}) \times \ln Employment_{i,t-1} + \mu_j + \nu_{it}
\]

6We explore whether publishing firms generate higher quality patents than non-publishing firms. Our analysis confirms such quality differences. The average patent held by a publishing firm receives 1.02 citations over its life-cycle, as compared to 0.91 citations for a patent by a non-publishing firm (the difference is significant at the 1% level). Moreover, we follow Trajtenberg et al. (1997) and construct measures of patent generality and originality. Patents by publishing firms tend to score higher on both measures. Average patent generality for publishing firms is 0.196, as compared to 0.152 for non-publishing firms. For originality, the respective values are 0.087 and 0.067 (differences are significant at the 1% level).

7To mitigate concerns usually tied to count measures of innovation, we test the robustness of our findings by controlling for patent and publication quality, using the number of citations they receive. We also experiment by excluding publications from journals which are ranked relatively low in terms of quality (Journal Impact Factor). The results reported in this paper are robust to the use of citations and to removing publications in low-impact journals.
Employment is number of employees, Assets is fixed-assets, Patents is patent stock computed using the perpetual method with a 15% depreciation rate for past patents, Publications is publication stock also computed using the perpetual method with a 15% depreciation rate for past firm publications, $\mu_j$ is industry dummies, and $v_{it}$ is an iid error term. We include a dummy variable for observations where patent stock is zero, and another dummy variable for observations where publication stock is zero. Dummy variables are also included for publicly listed firms, and for firms that report only consolidated accounts. Because firms in our sample are incorporated in several West-European countries, we include a complete set of country dummies to capture any country-level variation that may be systematically related to the innovation indicators, and the reported financial information. Lagged rather than contemporaneous realizations of the explanatory variables are used to control for transitory shocks that may affect both the incentive to innovate and sales, and to mitigate reverse causality concerns.

Our second measure of firm performance is employment growth:

$$\Delta \ln Employment_{it} = \beta_5^g + \beta_1^g \ln Employment_{it-1} + \beta_2^g \ln(1 + Patents_{i,t-1})$$
$$+ \beta_3^g \ln(1 + Publications_{i,t-1}) + \beta_4^g \ln(1 + Patents_{i,t-1}) \times \ln Employment_{i,t-1}$$
$$+ \beta_5^g \ln(1 + Publications_{i,t-1}) \times \ln Employment_{i,t-1} + \mu_j + v_{it}$$

$\Delta \ln Employment_{it}$ is $\ln Employment_{it}$ minus $\ln Employment_{it-1}$.

In all specifications we report standard errors that are robust to arbitrary heteroscedasticity, and allow for serial correlation through clustering by firms.

Our coefficients of interest are $\beta_5^g$, and $\beta_6^g$ for the sales specification, and $\beta_4^g$, and $\beta_5^g$ for the growth specification.

It is important to emphasize that we do not include firm-fixed effects in our analysis. Very few firms in our sample experience a substantial change in size that would allow for within-firm identification of a systematic and significant size effect.\footnote{We quantify the within-firm variation in employment as follows. For each firm in the sample we compute the number of employees at the beginning and at the end of the sample. We then classify firms into size categories based on employment distribution quartiles in each period. We compare the two distributions to measure the extent to which firms move across these quartiles over the sample period. We find no mobility for 80 percent of firms, and that even for those that move, this almost always results in at most a move to the adjacent quartile. We complement this investigation with a variance decomposition analysis, which strongly concurs with the small within-firm variation in our data, as 98 percent of the variation in employment is attributed to between-firms.} Firms that experience drastic size changes also arguably differ from other firms on multiple dimensions that are related to innovation and sales. Thus, restricting our sample to these firms in order to estimate a within-firm specification would considerably reduce the degrees-of-freedom for our analysis, and more importantly, also reduce the generalizability of the results.

In addition, we focus on the interaction effects of firm size. These interactions are less likely to be sensitive to time-invariant effects relative to estimates of the linear patent and publication coefficients. For example, while it is reasonable to suppose that the unobserved quality of a firm would upwardly bias the effect of both invention indicators, it is not clear why the same unobserved quality would bias the coefficient estimates on the interaction terms between invention and size. The opposite patterns we
observe on the interaction effects of size with patents and publications make also less plausible that our results are driven by unobserved heterogeneity.

6. Estimation results

Columns 1-7 in Table 3 present the estimation results for the sales specification. Column 1 includes the linear stocks of patents and publications. Both estimates are positive and significant. The estimated elasticity of sales with respect to patents is 0.088 (a standard error of 0.008), and with respect to publications is 0.024 (a standard error of 0.014).

We proceed to investigate how the relationship between patents, publications and sales vary by firm size. Columns 2 to 6 report the elasticity estimates for different subsamples of employment size. A clear pattern emerges: patent elasticity is very large for small firms, and substantially drops in relation to size (from 0.463 for firms with fewer than 10 employees to 0.019 for firms in the upper employment quartile). In contrast, publication elasticity is negative for most firms, and becomes positive only for the largest firms in the sample (upper employment quartile). Interestingly, we find that for large firms the coefficient estimate on publication stock is more than three times larger than the coefficient estimate on patent stock (column 6). This is consistent with a basic research premium for large firms - first documented by Griliches (1986). For small firms, the negative coefficient on publication stock is puzzling (Columns 2-4). It is not clear why small firms should publish at all if they have so little to gain. One possible explanation is that publications have other, less tangible benefits, which are not fully reflected by sales. Section 8 discusses this issue in greater length.

Column 7 includes interaction terms between measures for lagged employment and patent and publication stocks. The same size patterns continue to hold. The interaction between patents and employment is negative and significant (-0.012), while the interaction between publications and employment is positive and significant (0.030).

Based on the estimates from Column 1, we calculate the value of a patent (publication) as the increase in sales in response to a unitary increase in patent (publication) stock. Evaluated at the sample median, a unitary increase in patent stock is associated with a $1.4 million increase in sales (conditional on employment and assets). Repeating the same calculation for publications yields a lower value of $0.6 million. The estimates from Column 7 allow us to quantify how the value of patents and publications vary by firm size. Moving from the first employment quartile (29 employees) to the fourth quartile (381 employees) lowers average patent value by $1.2 million - close to the patent median value. The same movement, on the other hand, raises the median value of a publication by $4.6 million.

Columns 8-14 in Table 3 present the estimation results for the employment growth specification. The pattern of results is similar to the one discussed above. Having a large patent stock appears to be especially important for the growth of small firms, while publication stock has a positive and significant effect only on the growth of large firms. Columns 9–13 explore how the growth-innovation relationship varies by
firm size, by separately estimating the growth equation for each quartile of firm size. As for sales, we
find patents to matter more for the growth of small firms, and publications to matter more to the growth
of large firms. For instance, the coefficient on patent stock drops from 0.164 for firms in the lowest size
quartile, to 0.010 for firms in the highest size quartile. By contrast, the coefficient on publication stock
jumps from 0.006 for firms in the first size quartile, to 0.016 for firms in the highest size quartile. Column
14 further confirms these patterns by adding interaction terms between patents and publications with
lagged employment.

In unreported robustness checks (complete set of results is available upon request) we check the
sensitivity of the results to removing outliers, mitigating the concern that our estimates may be driven
by the difference between very large and very small firms in our sample. We experiment with removing
the lowest and highest 1, 5 and 10 percentile of the employment distribution. In all cases the results are
robust. We also examine the sensitivity of our results to the timing of publication. A concern is that
for very young firms, publications can originate outside the firm and brought in by skilled new hires. To
mitigate this concern, we remove from the sample firms for which publications concentrate very early in
their life-cycle. Our results are not sensitive to the timing of publication. Section 7.2 reports additional
robustness checks to further mitigate concerns about potential biases and sensitivities of our findings.

6.1. Exploring causal mechanisms: industry variation

Using sales and firm growth as measures of performance, we found that, on average, small firms benefit
more from patents than large firms. Large firms, on the other hand, benefit more from publications
than small firms. In this section we take a first step in underscoring potential causal mechanisms behind
these results. Our empirical strategy is to exploit structural industry variation. Specifically, we test
a number of theoretical predictions that depend on industry features. A key identification assumption
underlying our approach is that by splitting the sample along specific industry characteristics, all other
characteristics that are likely to influence the relationship between innovation and size remain unchanged.
While it is likely that this assumption may not hold in all cases, we nonetheless argue that by providing
a comprehensive set of industry breakdown tests, we highlight mechanisms that are likely to drive our
results, as well as mechanisms that are not likely to drive them.

Information on industry characteristics is from the Carnegie Mellon Survey (CMU). We use individual
firm responses to construct aggregate industry measures. Table 4 presents the estimation results of
splitting the sample by industry characteristics.

Rate of technical change. If small firms have an advantage over larger firms because they are more
agile and suffer less from inertia, then we would expect a more negative relationship between firm size
and innovation in fast-moving industries, relative to slow-moving industries.

We classify industries as fast or slow moving based on firms’ responses to CMU questions 27a and
27b. Question 27a states: “In your opinion, at what rate have product innovations been introduced in
your industry over the last ten years?” Question 27b is the equivalent question for process innovation.
We construct a single industry measure of the rate of technical change as the weighted average of the responses to each question. The weights are computed as the response to the following question by each respondent (question 46, CMU): “Approximately what percentage of your R&D effort focuses on a. New or improved processes, b. New or improved products.”

Columns 1 and 2 report estimation results of splitting the sample according to the industry rate of technical change. Consistent with Hypothesis 1(i), we find that the effect of patents on sales is bigger for small than for large firms in fast-moving industries, while there is no significant difference between large and small firms in slow-moving industries. The coefficient estimate on the interaction between size and patent stock is in fact negative and significant in the former case, and not significant in the latter case. For publications, we find a strong positive effect of firm size both within fast moving industries and slow moving industries. Thus, the speed of technical progress does not seem to be an important predictor of whether large or small firms benefit from basic research.

**Process innovation.** The cost-spreading argument suggests that large firms should benefit more from innovation than small firms, especially in industries where process innovations are common. Consistent with cost-spreading, we expect the negative patent-size interaction to be larger in absolute value in industries where product innovation is more common, because in these industries the cost-spreading advantage of large firms is lower, if not completely muted.

We classify industries as product or process innovation industries based on firms’ responses to CMU question 36a: “Over the last three years, for approximately what percent of your R&D unit’s product and process innovations did your firm apply for patents?” An industry is classified as a product innovation industry if its average share of product innovations is above the industry median. Conversely, an industry is classified as a process innovation industry if its average share of product innovations is below the industry median.

Columns 3 and 4 report how the innovation-size relationship varies by process and product innovation industries. Consistent with Hypothesis 1(ii), large size appears to confer additional advantages in industries where process innovations are common. For product innovation industries, the coefficient estimate on the interaction between size and patents is negative and large. By contrast, the same coefficient is effectively zero for process innovation industries, suggesting the presence of additional (cost-spreading) advantages of large size. For publications, we find a positive and significant size interaction effect for both product and process innovation industries. Thus, the share of process versus product innovations in an industry does not seem to be an important predictor of whether large or small firms benefit from basic research.

**Complementary assets.** Large firms are more likely than small firms to rely on complementary assets (Teece, 1986). Hence large size can be expected to confer greater advantages in industries where complementary assets are deemed to be important. Consistent with complementary assets, we expect the negative patent-size interaction to be larger in absolute value in industries where complementary assets are less important.
We classify industries as high or low in terms of the importance that R&D managers attach to complementary assets based on the response to question 32f: “During the last three years, for what percent of product innovations were each of the following effective in protecting your firm’s competitive advantage from those innovations? - Complementary manufacturing facilities and know how.” We scale the responses to these questions to the response item midpoints to create percentage measures (0%, 25%, 50%, 75%, and 95%). Based on the response to the questions 46a and 46b on percentage of R&D spent on process and product innovation, we create two variables that reflect the percentage of product and process innovations. The final industry measure is computed as the weighted average of the response to question 32f on product innovation and question 33f which is the equivalent question on process innovation.

Columns 5 and 6 report the estimation results of splitting the sample by the importance of complementary assets at the industry level. The results are consistent with Hypothesis 1(iii). The coefficient estimate on the interaction between size and patents is negative and highly significant in industries where complementary assets are less important, and not significant (essentially zero) in industries where complementary assets are more important. Thus, large firms appear to enjoy additional appropriability advantages in the latter case. Surprisingly, for publications there is a positive and significant size effect in both types of industries. We had expected large firms to enjoy additional appropriability advantages in industries where complementary assets are more important also for basic research.

Product complexity. The Carnegie Mellon Survey also allows us to investigate the effect of product complexity on appropriability. Complex product industries are those characterized by products that require the integration of a large number of patentable elements. Discrete product industries, by contrast, are characterized by products that require the integration of relatively few patentable elements (Cohen et al., 2000). We conjecture that, because in complex product industries cross-licensing agreements are common (Cohen et al., 2002), product market competition in these industries will revolve more around the possession of complementary assets (often associated with large size) than the ability to enforce exclusivity through patents. Thus, for patents, (provided that performance is measured by sales or employment growth), we expect the appropriability advantages of large size to be especially important in complex product industries.9

We classify industries as either complex or discrete based on firms’ response to CMU question 32g: “During the last three years, for what percent of your product innovations were each of the following effective in protecting your firm’s competitive advantage from those innovations?” Complexity is then based on the number of times product complexity is selected by the respondent. We combine this answer with the answer to the equivalent question about process innovation (question 33g). Complexity is computed as the weighted average of the answers to the two questions, where weights are computed based on the response to question 36, which gives us the proportion of R&D that is directed to product or

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9Note that we make no claim about interfirm differences in profitability. Small firms can benefit greatly from their patents in complex product industries by licensing to other firms. Thus it is not clear whether large size confers appropriability advantages in complex product industries when performance is measured as profits.
process innovation (as explained above).

Columns 7 and 8 report the estimation results of the sales equation separately for complex and discrete industries. We find a negative and significant size interaction effect for patents in discrete industries, but a statistically insignificant size effect in complex industries. Thus, size seems to confer appropriability advantages in complex industries, as the argument above suggests. For publications, we find a positive and significant coefficient estimate on size interaction for both complex and discrete industries.

**Reputation.** Patents and publications may also raise the reputation of the sponsoring firm and its products, thus facilitating sales and firm growth. To the extent that these reputational effects mainly benefit firms with substantial (ex ante) market share, patents and publications might benefit chiefly those firms.

We examine the reputational effects of patents and publications by classifying industries based on the response to CMU question 38g: “For your R&D unit’s application for a product or process patent, which of the following reason motivated the decision to apply for a patent?” – b. To enhance the reputation of the firm or its R&D employees – Yes or No. We use the industry share of respondents who answer “yes” as our industry measure of the importance of reputation.

Columns 9 and 10 present the estimation results of splitting the sample according to the importance of reputation by industry. The results show that, for patents and especially for publications, interaction coefficients are substantially bigger in high reputation industries than in low reputation industries. Thus, large size appears to be more beneficial (or at least less detrimental) in industries where reputation is important. This supports the idea that patents and publications might complement large firms’ marketing efforts.

### 6.2. Robustness tests

We perform several tests to check the robustness of our results. In this section we report detailed estimation results for selection into invention, which we view as the main source of potential concern. For the remaining tests, we summarize the key findings, but for brevity we do not include them in separate tables.

#### 6.2.1. Selection into invention

The decision to patent and/or publish may be driven by unobserved characteristics correlated with firm size. For instance, it could be that small firms produce on average better inventions than large firms because they face more severe constraints. Small firms could face higher unit costs than large firms when filing a patent, or the cost of external finance could be higher for them. Such constraints would lead to small-firm selection bias: only the best small firms that were able to overcome the constraints and come up with an invention would enter our sample. We investigate this concern by comparing quality measures of patents and publications for small and large firms. The presence of small-firm selection bias would
imply that patents and publications by small firms would be of higher average quality than those of large firms.

Table 5 summarizes the comparison between measures of patent quality for patents held by small and large firms. The main finding is that both patents and publications held by large firms are of higher quality than patents by small firms. For example, a patent by a large firm (top size quartile) receives on average 1.05 citations, compared to a patent by a small firm (lower size quartile) that receives on average 0.85 citations (the difference in means is significant at the 1% level). This result is not consistent with the idea that only the best small firms are able to finance and patent their projects, and therefore high-quality small firms are over-represented in our sample.\(^{10}\)

To further test for selection, we use data on firms that never patent or publish. Restricting our analysis to a sample of patenting or publishing firms may upward bias the estimated value of patents and publications. For instance, if selection into patenting is such that firms that do not patent are the ones that are better at protecting their knowledge assets in non-proprietary ways, and if these non-patenting firms are as productive as patenting firms, then our patent value estimates would be upward biased (yet, even in this case, it is not clear that the size interactions - the main focus of this paper, would be biased). A similar argument can be made for publications. Non-publishing firms may still perform basic research. If these firms are as productive as publishing firms (especially in the high-end side of the size distribution), our estimated publication value would be upward biased. To check the sensitivity of our results to selection into patenting and publishing, we perform non-parametric estimations using the complete population of firms - pooling together those firms that patent or publish, and those firms that neither patent nor publish.

We include all firms that report financial information, have at least 10 employees, and generate at least $1 million in annual sales. We exclude industries where patenting or publishing is not likely to take place (such as retail, insurance, and legal services). This leaves us with more than 400,000 firms. Of these firms about 2% have at least one patent from the EPO, and 0.4% have at least one scientific publications. Using nearest-neighbor propensity-score matching, we non-parametrically estimate the effect of patenting and publishing on labor productivity. For patenting, the dependent variable in the first-stage estimation is a dummy variable that receives the value of one for firms that have at least one patent from the EPO, while for publishing the dependent variable is a dummy that receives the value of one for firms that have at least one scientific publication. First-stage regression controls include number of employees (level and squared), firm age (years from date of incorporation), complete sets of dummies for three-digit industry SIC codes and countries, and dummies for public firms and firms that report only consolidated accounts.

Table 6 presents the second-stage estimation results for the whole sample, and separately for size quartiles. The non-parametric estimation results are generally consistent with the parametric results in

\(^{10}\)We also find that patents by large firms are more general and original than patents by small firm. Publications by large firms also tend to be of higher quality than small-firm publications, as indicated by the number of citations they receive, and the quality of the journals where they are published.
the restricted innovating-firm sample. The average labor productivity for patenting firms is $298 thousand, while for non-patenting firms it is $253 thousand. Thus, patenting firms are 18% more productive than non-patenting firms. For firms in the first size quartile, the productivity gap between patenting and non-patenting firms is larger (about 20%) and highly significant. As firms grow the productivity gap between patenting and non-patenting firms tends to decrease. For example, for firms in the fourth size quartile, patenting firms are only 12% more productive than non-patenting firms.

Moving to publications, we find that publishing firms are substantially more productive than non-publishing firms, with a labor productivity gap of 25%, significant at the 1% level. As in the parametric estimation results, this difference is driven by the larger firms in the sample. For firms in the fourth size quartile, the productivity gap between publishing and non-publishing firms is 27% (significant at the 1% level), while for firms in the first quartile, the gap is only 6%.

6.2.2. Alternative assignments of publications to firms

We assign a publication to a firm if the firm’s name appears on the list of author affiliations of that article. There are two potential issues concerning this assignment scheme. First, scientific publications usually have more than one author (the average number of authors per publication is 4.2). Second, coauthors often belong to different organizations. To examine the sensitivity of our results to alternative assignment schemes, we take two steps. First, we divide each publication by the number of distinct affiliations that appear on the publication. Thus, publications where a firm appears to have contributed less (because more institutions are involved) are given less weight. Second, we distinguish between fully corporate publications and publications coauthored with scientists working in universities or other research institutions. This is important because coauthorship of scientific papers with academics may measure “connectedness” to the public sector – a potentially valuable form of absorptive capacity (Cockburn and Henderson, 1998). For both the sales and growth specifications, the same pattern of results continues to hold when publications are normalized by the number of different affiliations. We also find no significant differences between fully corporate publications and publications coauthored with university scientists. Thus, at least in the whole sample of innovating firms, connectedness to the public sector does not seem to have a large effect on firm performance.

6.2.3. Additional firm controls and temporal lag

To mitigate concerns of unobserved heterogeneity, we include additional firm controls in the sales and growth equations, including firm age, liquidity (cash flow over assets), and a dummy for whether the firm belongs to a corporate group. Controlling for firm age is important because firm age and firm size are strongly correlated. Thus there is the risk that the firm size effects we document may actually capture a “firm life-cycle” effect. Controlling for liquidity and corporate group affiliation is also important as these factors may affect the propensity to patent and publish, as well as affect firm performance (Belenzon and Berkovitz, 2010). Thus, to control for life-cycle effects we interact firm age with patents and publications.
To control for liquidity and group affiliation, we interact those variables with employment. The size interactions remain robust to including these interaction terms in both sales and growth specifications.\footnote{We also experiment with other potentially important omitted variables. For instance, we include (non-logged) squared term of employment to check whether the innovation-employment interactions are picking up non-linear effect of employment on sales (as higher levels of innovation are correlated with larger size). We also check for non-linear effects of patenting and publishing by including squared terms of each. In both cases there is no evidence that the innovation-employment interactions are picking up non-linear effects of either size or innovation.}

Our analysis assumes a specific structure on how past patenting and publishing affects sales and growth. We check the sensitivity of our results to alternative assumptions by imposing longer lags on patenting and publishing, as well as examining longer periods for employment growth. The same pattern of results continue to hold.

Finally, we examine the sensitivity of our results to the composition of inventive activity. Among our estimation sample of inventing firms, firms that patent may differ from non-patenting firms in ways that are not picked up by our controls. For example, Gittelman and Kogut (2003) suggest that firms that are affiliated with scientists who both patent and publish should perform better than firms that are affiliated with scientists who engage in only one of these inventive activities. To control for variation in the composition of inventive activity, we estimate the baseline sales and employment growth specifications with samples that include only patenting firms (firms with at least one patent), publishing firms (firms with at least one publication), and firms that have at least one patent and one publication. We observe no important differences across these subsamples.

6.3. Comparison to Compustat

A key advantage of our dataset is the wide coverage of firms of different size. To demonstrate this advantage, we estimate productivity-invention specifications for Compustat firms and large European firms – thus focusing only on the high-end side of the size distribution. The sample of Compustat firms includes all patenting firms, where patent data are taken from the NBER archive. We follow the same matching procedure as for the European firms to assign publications to Compustat firms. The average US firm in our sample, which covers the period 1980–2001, has 14,843 employees with a median of 2,625 (in our sample, in contrast, the average firm has 1,111 employees with a median of 87).

Table 7 presents the estimation results. In column 1, we regress sales against patent and publication stocks for Compustat firms. The coefficient estimate on patent stock is negative and statistically insignificant, and the coefficient estimate on publication stock is positive and significant. Column 2 adds interactions between patent and publication stocks with lagged employment. None of the interactions are significant. In columns 3-6 we perform similar estimations for large European firms. We are unable to replicate our key results in any of these specifications.
7. Discussion and Conclusion

Using a novel and comprehensive dataset, this paper examines how firm size mediates firms’ ability to benefit from invention. We distinguish between output indicators of applied research and output indicators of basic research, respectively using patents and scientific publications in “hard science” journals. By focusing on different types of firms (large and small) and different types of inventions (basic and applied), this paper makes three important contributions.

First, we demonstrate that the ability of large and small firms to appropriate the benefits from invention depends crucially on the “basicness” of their research activities. We find that large firms benefit the most from the outputs of basic research, while small firms benefit the most from the outputs of applied research. With some notable exceptions (e.g., Mitchell, 1991; Tripsas, 1997; Reitzig and Puranam, 2009), relatively little research has focused on interfirm differences in appropriability (“value capture”). More commonly, scholars have examined how firms differ in research productivity (“value creation”), usually measured using patent data. Previous work on firm size and innovation has also often neglected the distinction between applied and basic research, and has generally produced inconclusive or contradictory results (Cohen, 2010). This paper suggests that these studies may have inappropriately aggregated the effects of different types of investments. A final issue with prior work has been the focus on very large firms – typically the 500 or 1000 largest firms in the manufacturing sector – which may not be representative of the whole firm size distribution (Cohen, 2010). We address this in our sample, where about 10 percent of the innovating firms have fewer than 8 employees and less than $1.5 million in annual sales. We demonstrate the importance of wide coverage by showing that none of our key results can be replicated by restricting attention to the largest European firms or by using Compustat data.

There are very few studies that compare the appropriability of applied and basic research. Our findings broadly support the conjecture that large firms are the ones best positioned to exploit the outcomes of basic research, and confirm Griliches’s (1986) classic result of a “basic research premium” for very large firms. From a broader perspective, our results underscore the dangers of drawing strong conclusions based solely on patent-based indicators of inventive activity. As our evidence indicates, large and small firms may in fact have a comparative advantage at different types of inventive activities.

The second contribution of the paper is to investigate the mechanisms through which firm size matters. It has long been recognized that size might be correlated with a number of more fundamental appropriability mechanisms such as first-mover advantage and complementary assets. Previous research on appropriability mechanisms has demonstrated that the traditional emphasis on patents as a way to appropriate the returns from invention is often misplaced (Levin et al., 1987; Cohen et al., 2000). Firms rely on a number of appropriability mechanisms, most notably first-mover advantages, secrecy, and complementary assets, to appropriate the returns from their inventions. While our findings support the view that appropriability is driven by several coexisting mechanisms, it also suggests that the importance of these mechanisms may vary depending on the “basicness” of research. The appropriability of applied
research (captured by patents) appears to be affected by mechanisms such as large firms’ inertia, cost-spreading advantages, and complementary assets. Conversely, these mechanisms do not seem to play a very important role for basic research. Instead, the main effect of publishing in scientific journals (our measure of basic research) appears to be that of enhancing the sponsoring firm’s reputation, as stressed by some scholars (Hicks, 1995; Azoulay, 2002). Moreover, because on average small firms benefit from patents more than large firms, especially in dynamic environments, our evidence suggests that the most important appropriability mechanism for applied research is the ability to overcome organizational inertia. This last finding lends some support to a key tenet of competitive dynamics research, namely that speed and “aggressiveness” are key sources of competitive advantage in high-velocity environments (Eisenhardt, 1989; D’Aveni, 1994).

Finally, this paper shows that the incentives for firms to publish (and by proxy to engage basic research) are quite complex. Firm publications are often regarded as a measure of the “basicness” of patented knowledge (Murray, 2002; Murray and Stern, 2006). We do find evidence in support of that view. For instance, we show that patents by publishing firms tend to be more general and original than patents by non-publishing firms. However, firm publications cannot simply be regarded as a by-product of the patenting process. More than half of the articles we identify belong to firms that never patent. The idea that the knowledge in a patent may often be inscribed in a publication (Murray and Stern’s ‘patent-paper hypothesis’) is also difficult to reconcile with our finding that patents and publications have markedly different effects on performance depending on firm size, although it is possible that different firms may value different types of benefits, such as patent protection or reputation, differently.

If publications cannot simply be regarded as a by-product of the patenting process, we must continue to search for alternative explanations for the prevalence of this activity. Because valuable information may leak out to competitors, in fact, publishing in academic journals is inherently risky. As already mentioned, our evidence points to enhanced reputation as an important benefit of publishing. We find that large firms especially gain from publications, relative to small firms, in industries where reputation is important. This indicates that publications may complement large firms’ marketing and sale efforts (Hicks, 1995; Azoulay, 2002).

We acknowledge that small and large firms may publish for very different reasons. A puzzling finding of our analysis is that small firms hold a substantial fraction of firm publications (9%, compared to only 2.5% for patents) despite apparently getting very little out of them, and often even appearing to sacrifice sales and growth prospects in order to publish. It is possible that many small firms publish because of their owners’ preferences. They might be run by scientists/entrepreneurs who have internalized the norms of science, or care about their personal academic reputations (Dasgupta and David, 1994; Stern, 2004). Small firms may also publish to signal scientific or technical competence and become more attractive targets for acquisitions or partnerships (Arora and Gambardella, 1990; Higgins et al., 2011). These benefits could partially explain small firms’ high propensity to publish. Investigating these issues is clearly an important direction for future research.
There are of course limitations to our work. Although we provide robust correlations between performance, size, and multiple indicators of inventive activity, we fall well short of proving causality. For instance, it could be that because patenting is costly, small firms only patent their best ideas. This would suggest that patents by small firms are on average of higher quality, thus potentially biasing our results. Basic research could also be a “luxury” that only the best large firms can afford. We attempt to address these concerns using propensity-score matching techniques and by analyzing growth rates rather than levels. We also tease out some of the causal mechanisms that may generate the firm size effects we observe. However, more work is certainly needed to address the issue of causality.

Another limitation is that we have no information on R&D expenditures. This means that we cannot control for tacit dimensions of knowledge that are not well captured by patents or firm publications. Moreover, patents can be correlated with firm value not just because they embody knowledge, but also because they provide legal protection (the “patent premium”). While a few papers have attempted to measure the size of the patent premium (e.g., Pakes, 1986; Schankerman and Pakes, 1986), and have shown that it varies with firm size (Arora et al., 2008), our data does not allow us to distinguish between the intrinsic value of the idea and the value of proprietary rights created by the patent laws.

Some important determinants of appropriability could also not be empirically examined. Nelson’s (1959) conjecture is based on the presumption that large firms’ broad technological base helps them find valuable commercial applications for the unpredictable outcomes of basic research. Henderson and Cockburn (1996) and Cockburn and Henderson (2001) also emphasize the importance of scope economies in drug discovery and commercialization. However, our accounting data from Amadeus does not provide information on firm diversification. Future research, building on the seminal work of Henderson and Cockburn, should investigate the role of scope economies in appropriating the benefits of basic and applied research.

We conclude by briefly summarizing the main managerial implications of the paper. These implications differ depending on firm type (large or small) and invention type (applied or basic). Especially in fast-moving industries, many large (European) firms appear to do a poor job at exploiting the competitive potential of their patent portfolios. They would arguably benefit from improving how they manage their intellectual capital (Rivette and Kline, 2000; Reitzig, 2004) and by redesigning their internal structures to promote speedy actions. While in fact large size may lead to inertia or complacency, the connection is neither simple nor deterministic. The experience of many successful firms such as Apple and Oracle demonstrates that it is possible to be both entrepreneurial and big.

Small firms benefit substantially from their patents, but some of them seem to forgo opportunities for sales and further growth in order to publish. When evaluating the opportunity to engage with the broader scientific community, small firms should carefully weigh these costs against the potential benefits of publishing, such as the ability to attract better scientists, or the ability to broadcast firm capabilities to prospective business partners. They should also be well aware of the risks and the long lags associated with the exploitation of basic research results. Scholars have suggested that the comparative advantage
of small firms may be their willingness to explore technological paths and markets that large firms are unwilling to explore (Klepper and Thompson, 2006; Giarratana, 2004). This high-risk strategy may backfire. By contrast, large firms appear to follow a safer, more remunerative strategy of using basic research as a way to link with the outside world and generate interest in their products.

References


25


transferring knowledge: 366–382.


### TABLE A. Three streams of research on the relative advantages and disadvantages of large size for the appropriability of inventions

<table>
<thead>
<tr>
<th>Theoretical focus</th>
<th>Determinants</th>
<th>Consequences</th>
<th>Key empirical findings</th>
<th>Indicative literature</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Organizational inertia</td>
<td>A. Bureaucracy, entrenched routines and information filters</td>
<td>Large firms may delay the commercialization of some types of inventions, thereby foregoing first-mover advantages</td>
<td>Small firms benefit more from applied inventions (patents) than large firms, especially in industries where technological progress is fast</td>
<td>A. Schumpeter (1942), Leonard-Barton (1992), Tripsas and Gavetti (2000)</td>
</tr>
<tr>
<td></td>
<td>C. Past commitments</td>
<td></td>
<td></td>
<td>C. Christensen and Bower (1996), Christensen (1997), Sull et al. (1997)</td>
</tr>
<tr>
<td>2 Scale, scope, and capabilities</td>
<td>A. Cost spreading</td>
<td>Large firms typically enjoy scale, scope, and capabilities advantages in the commercialization of inventions</td>
<td>However, this small firm advantage disappear in industries where product innovations are common and complementary assets are important</td>
<td>A. Cohen and Klepper (1996a,b)</td>
</tr>
<tr>
<td></td>
<td>B. Scope economies in product development and commercialization</td>
<td></td>
<td></td>
<td>B. Henderson and Cockburn (1996), Hargadon (2003), Leiponen and Helfat (2010)</td>
</tr>
<tr>
<td>3 Nature of inventive activities: basic versus applied</td>
<td>A. Differences in the objectives of research and the temporal lags for exploitation</td>
<td>Large firms are more likely than small firms to benefit from the outputs of basic research</td>
<td>Large firms benefit relatively more from basic inventions (publications), especially in industries where reputation is important</td>
<td>A. Rosenberg (1990), Cohen and Levinthal (1990), Fleming and Sorenson (2004), Hicks (1995), Stern (2004), Roach and Sauermann (2010), Azoulay (2002), Stephan et al. (2007)</td>
</tr>
</tbody>
</table>
Note: This figure plots percentage differences in labor productivity (sales per employee) between high- and low-patenting firms across quintiles of number of employees. A firm is assumed to be a high- (low-) patenting firm if its number of patents is higher (lower) than the sample median number of patents.

Note: This figure plots percentage differences in labor productivity (sales per employee) between publishing and non-publishing firms across quintiles of number of employees.
<table>
<thead>
<tr>
<th>Variable</th>
<th>Number of Firms</th>
<th>Observations</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>10(^{th})</th>
<th>50(^{th})</th>
<th>90(^{th})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patent Stock</td>
<td>11,664</td>
<td>84,553</td>
<td>7.5</td>
<td>114.0</td>
<td>0</td>
<td>0.6</td>
<td>6.3</td>
</tr>
<tr>
<td>Publication Stock</td>
<td>4,174</td>
<td>30,861</td>
<td>2.3</td>
<td>17.6</td>
<td>0</td>
<td>0.4</td>
<td>3.5</td>
</tr>
<tr>
<td>Sales ($, '000)</td>
<td>13,956</td>
<td>87,964</td>
<td>376,436</td>
<td>3,765,901</td>
<td>1,575</td>
<td>20,023</td>
<td>331,758</td>
</tr>
<tr>
<td>Number of Employees</td>
<td>14,176</td>
<td>83,578</td>
<td>1,111</td>
<td>10,923</td>
<td>8</td>
<td>87</td>
<td>1,055</td>
</tr>
<tr>
<td>Assets ($, '000)</td>
<td>10,603</td>
<td>73,728</td>
<td>308,068</td>
<td>3,677,702</td>
<td>98</td>
<td>3,822</td>
<td>145,348</td>
</tr>
<tr>
<td>Employment Growth</td>
<td>13,254</td>
<td>67,275</td>
<td>0.04</td>
<td>0.41</td>
<td>-0.13</td>
<td>0</td>
<td>0.22</td>
</tr>
<tr>
<td>Sales Growth</td>
<td>13,405</td>
<td>74,065</td>
<td>0.08</td>
<td>0.46</td>
<td>-0.17</td>
<td>0.04</td>
<td>0.33</td>
</tr>
<tr>
<td>Sales/Employees ($, '000)</td>
<td>13,369</td>
<td>76,391</td>
<td>326</td>
<td>277</td>
<td>119</td>
<td>239</td>
<td>623</td>
</tr>
<tr>
<td>Firm Age</td>
<td>14,771</td>
<td>106,860</td>
<td>27</td>
<td>29</td>
<td>3</td>
<td>18</td>
<td>64</td>
</tr>
</tbody>
</table>

**Notes:** This table provides summary statistics for firms in our estimation sample over the period 1997–2006. The sample includes all Amadeus firms with at least one patent or one academic publication in "hard" science journals between 1978 and 2006. Patents are constructed by matching the names of all Amadeus firms to EPO patent records. Academic publications are constructed by matching the name of the firm to the address field in the complete ISI Web of Science database. Patents are reported only for firms with at least one patent, and publications are reported for firms with at least one publication. Firm Age is the number of years from year of incorporation.
<table>
<thead>
<tr>
<th></th>
<th>Patenting Only</th>
<th>Publishing Only</th>
<th>Patenting &amp; Publishing</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No. of Firms</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Total number of patents</td>
<td>10,725</td>
<td>9.1</td>
<td>1</td>
</tr>
<tr>
<td>Total number of publications</td>
<td>10,725</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Employees</td>
<td>10,045</td>
<td>647</td>
<td>80</td>
</tr>
<tr>
<td>Sales ($, '000)</td>
<td>9,770</td>
<td>219,798</td>
<td>20,511</td>
</tr>
<tr>
<td>Sales/Employees ($, '000)</td>
<td>9,251</td>
<td>328</td>
<td>269</td>
</tr>
<tr>
<td>Employment Growth</td>
<td>9,331</td>
<td>0.02</td>
<td>0</td>
</tr>
</tbody>
</table>

*Notes:* This table presents summary statistics for different subsamples of innovation composition. The sample includes firms with at least one patent or one publication. The unit of analysis is the firm.
### TABLE 3. Innovation, Sales and Employment Growth, by Firm Size

<table>
<thead>
<tr>
<th>Firms:</th>
<th>Productivity (lnSales)</th>
<th>Employment growth (ΔlnEmployment)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5) (6)</td>
<td>(7) (8) (9) (10) (11) (12) (13)</td>
</tr>
<tr>
<td>Lagged number of employees</td>
<td>All 1st decile (≤9) 1st quartile (&lt;29) 2nd quartile (29 - 99) 3rd quartile (99 - 381) 4th quartile (≥381)</td>
<td>All 1st decile (≤8) 1st quartile (&lt;27) 2nd quartile (27 - 89) 3rd quartile (89 - 311) 4th quartile (≥311)</td>
</tr>
<tr>
<td>ln(Patents stock)_t-1</td>
<td>0.088** (0.008) 0.463** (0.131) 0.350** (0.051) 0.114** (0.030) 0.114** (0.019) 0.019 (0.010)</td>
<td>0.178** (0.024) 0.039** (0.003) 0.390** (0.082) 0.164** (0.030) 0.012 (0.007) 0.014* (0.007) 0.010** (0.004) 0.076** (0.013)</td>
</tr>
<tr>
<td>ln(Publications stock)_t-1</td>
<td>0.024* (0.014) -0.141* (0.071) -0.085* (0.037) -0.124** (0.039) -0.022 (0.033) 0.068** (0.017)</td>
<td>-0.154** (0.034) 0.022** (0.005) -0.039** (0.048) 0.006 (0.019) 0.021 (0.013) 0.012 (0.013) 0.016** (0.005) -0.020 (0.015)</td>
</tr>
<tr>
<td>ln(Patents stock)_t-1 × ln(Employment)_t-1</td>
<td>-0.012** (0.003)</td>
<td>-0.005** (0.002)</td>
</tr>
<tr>
<td>ln(Publications stock)_t-1 × ln(Employment)_t-1</td>
<td>0.030** (0.005)</td>
<td>0.007** (0.002)</td>
</tr>
<tr>
<td>ln(Employment)_t-1</td>
<td>0.740** (0.008) 0.373** (0.033) 0.533** (0.018) 0.734** (0.028) 0.740** (0.027) 0.778** (0.018) 0.742** (0.008)</td>
<td>-0.059** (0.002) -0.406** (0.023) -0.237** (0.010) -0.266** (0.029) -0.024 (0.007) -0.028** (0.004) -0.058** (0.002)</td>
</tr>
<tr>
<td>ln(Assets)_t-1</td>
<td>0.190** (0.006) 0.142** (0.015) 0.148** (0.011) 0.142** (0.010) 0.188** (0.012) 0.202** (0.014) 0.188** (0.006)</td>
<td></td>
</tr>
<tr>
<td>Industry Dummies (237)</td>
<td>Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes Yes</td>
<td></td>
</tr>
<tr>
<td>R²</td>
<td>0.905 0.368 0.479 0.440 0.526 0.871 0.905 0.058 0.213 0.133 0.126 0.067 0.050 0.059</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>51,407 5,223 12,895 12,810 12,858 12,844 51,407 67,275 6,742 17,099 16,730 16,619 16,787 67,275</td>
<td></td>
</tr>
<tr>
<td>Number of Firms</td>
<td>9,305 1,810 3,334 3,023 2,911 2,475 9,305 13,254 2,348 4,611 4,040 4,126 3,461 13,254</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table reports the results of OLS estimations that examine how the innovation–productivity relation varies by firm size. The sample covers the period 1997–2006 and includes firms with at least one patent or one scientific publication. All regressions include complete sets of year and country dummies. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. ** significant at 1%; * significant at 5%
### TABLE 4. Industry Characteristics

<table>
<thead>
<tr>
<th>Industry measure:</th>
<th>Rate of Technical Progress</th>
<th>Process vs. Product innovation</th>
<th>Complementary Assets</th>
<th>Complex/Discrete Product</th>
<th>Importance of Reputation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Fast</td>
<td>Slow</td>
<td>Product</td>
<td>Process</td>
<td>High</td>
</tr>
<tr>
<td>ln(\textit{Patents stock})<em>{t-1} \times ln(\textit{Employment})</em>{t-1}</td>
<td>-0.018** (0.006)</td>
<td>-0.007 (0.004)</td>
<td>-0.024** (0.005)</td>
<td>-0.002 (0.005)</td>
<td>-0.008 (0.005)</td>
</tr>
<tr>
<td>ln(\textit{Publications stock})<em>{t-1} \times ln(\textit{Employment})</em>{t-1}</td>
<td>0.037** (0.011)</td>
<td>0.039** (0.010)</td>
<td>0.042** (0.010)</td>
<td>0.032** (0.014)</td>
<td>0.038** (0.011)</td>
</tr>
<tr>
<td>ln(\textit{Patents stock})_{t-1}</td>
<td>0.204** (0.046)</td>
<td>0.151** (0.038)</td>
<td>0.263** (0.040)</td>
<td>0.081 (0.044)</td>
<td>0.133** (0.043)</td>
</tr>
<tr>
<td>ln(\textit{Publications stock})_{t-1}</td>
<td>-0.247** (0.090)</td>
<td>-0.224** (0.090)</td>
<td>-0.279** (0.079)</td>
<td>-0.166* (0.128)</td>
<td>-0.274** (0.094)</td>
</tr>
<tr>
<td>ln(\textit{Employment})_{t-1}</td>
<td>0.737** (0.018)</td>
<td>0.699** (0.016)</td>
<td>0.739** (0.015)</td>
<td>0.686** (0.015)</td>
<td>0.721** (0.019)</td>
</tr>
<tr>
<td>ln(\textit{Assets})_{t-1}</td>
<td>0.216** (0.014)</td>
<td>0.212** (0.013)</td>
<td>0.198** (0.011)</td>
<td>0.245** (0.018)</td>
<td>0.233** (0.014)</td>
</tr>
</tbody>
</table>

R$^2$ | 0.906 (0.904) | 0.895 | 0.915 | 0.910 | 0.899 | 0.906 | 0.903 | 0.902 | 0.907 |

Observations | 15,435 | 15,010 | 20,792 | 9,653 | 12,958 | 17,487 | 14,074 | 16,371 | 19,022 | 11,423 |

Number of Firms | 2,693 | 2,625 | 3,637 | 1,681 | 2,291 | 3,027 | 2,457 | 2,861 | 3,363 | 1,955 |

Notes: This table examines how the relationship between innovation and productivity varies by industry characteristics. All regressions include complete sets of three-digit industry, year, and country dummies. Standard errors (in brackets) are robust to arbitrary heteroskedasticity and allow for serial correlation through clustering by firms. ** significant at 1%; * significant at 5%.
TABLE 5. Comparison of Means: Patent Characteristics for Large vs. Small Firms

<table>
<thead>
<tr>
<th>Variable</th>
<th>Large - Small</th>
<th>Large firms (Employees&gt;75th)</th>
<th>Small firms (Employees≤25th)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs.</td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>Patents:</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citations Received</td>
<td>0.201**</td>
<td>29,847</td>
<td>1.049</td>
</tr>
<tr>
<td>Citations received: 3-year window</td>
<td>0.076**</td>
<td>29,847</td>
<td>0.421</td>
</tr>
<tr>
<td>Citations received: 5-year window</td>
<td>0.142**</td>
<td>29,847</td>
<td>0.733</td>
</tr>
<tr>
<td>% of citations from the same technology area</td>
<td>-0.082**</td>
<td>6,778</td>
<td>0.536</td>
</tr>
<tr>
<td>Generality</td>
<td>0.058**</td>
<td>6,784</td>
<td>0.170</td>
</tr>
<tr>
<td>Originality</td>
<td>0.019*</td>
<td>5,960</td>
<td>0.075</td>
</tr>
<tr>
<td>Scientific publications</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Citations Received</td>
<td>1.133**</td>
<td>10,851</td>
<td>6.776</td>
</tr>
<tr>
<td>% of publications that receive at least one citation</td>
<td>0.001</td>
<td>10,851</td>
<td>0.572</td>
</tr>
<tr>
<td>Average Journal Impact Factor</td>
<td>0.112**</td>
<td>10,329</td>
<td>2.627</td>
</tr>
</tbody>
</table>

Notes: This table reports mean comparison tests for measures of patents and publications quality between large and small firms. Patents are from the EPO. Patents and publications cover the period 1978–2006. Self-citations are citations where the citing firm cites one of its predecessor patents. Generality is calculated as one minus the Herfindahl-Hirschman Index of the concentration of the citations a patent receives across three-digit technology fields. Originality is defined as one minus the Herfindahl-Hirschman Index of the concentration of the citations a patent makes across three-digit technology fields. Journal Impact Factor is from the ISI Web of Science and measures the journal scientific importance. ** and * indicate that the difference in means is significant at the one- and five-percent level, respectively.
<table>
<thead>
<tr>
<th>Dependent Variable First-stage:</th>
<th>Dummy for Patenting</th>
<th>Conditional difference in means</th>
<th>Dummy for Publishing</th>
<th>Conditional difference in means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patenting firms</td>
<td></td>
<td></td>
<td>Publishing</td>
<td>Non-publishing</td>
</tr>
<tr>
<td>Non-patenting firms</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All firms</td>
<td>298.0</td>
<td>253.3</td>
<td>44.7*</td>
<td>329.1</td>
</tr>
<tr>
<td>Quartiles of employment:</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1st</td>
<td>287.7</td>
<td>239.8</td>
<td>57.5**</td>
<td>263.1</td>
</tr>
<tr>
<td>2nd</td>
<td>281.9</td>
<td>245.6</td>
<td>36.3**</td>
<td>324.7</td>
</tr>
<tr>
<td>3rd</td>
<td>294.7</td>
<td>261.3</td>
<td>33.5**</td>
<td>353.8</td>
</tr>
<tr>
<td>4th</td>
<td>327.8</td>
<td>292.9</td>
<td>34.9**</td>
<td>375.4</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of non-parametric propensity-score matching estimations for the relation between patenting and publishing and labor productivity. The sample covers all firms in Amadeus that report accounting information, have more than 10 employees, and generate at least $1 million in annual sales. The estimation is cross-sectional for the most recent year firms report accounting. For patenting, the dependent variable in the first-stage regression is a dummy variable that receives the value of one for firms that have at least one patent from the EPO. For publishing, the dependent variable is a dummy that receives the value of one for firms that have at least one publication. All first-stage regressions include the following controls: number of employees (level and squared), firm age (years from date of incorporation), complete sets of dummies for three-digit industry SIC codes and countries, and dummies for public firms and firms that report only consolidated accounts. ** significant at 1%; * significant at 10%.
**TABLE 7. Comparison Between Large European and U.S. Compustat**

<table>
<thead>
<tr>
<th>Firms:</th>
<th>US Compustat firms</th>
<th>Large European firms (&gt;1000 Employees)</th>
<th>Large European firms (&gt;1600 Employees)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln(Patents stock)_{t-1}</td>
<td>-0.010</td>
<td>0.012</td>
<td>-0.045</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>ln(Publications stock)_{t-1}</td>
<td>0.022**</td>
<td>-0.043</td>
<td>0.055*</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.049)</td>
<td>(0.026)</td>
</tr>
<tr>
<td>ln(Patents stock)<em>{t-1} × ln(Employment)</em>{t-1}</td>
<td>-0.002</td>
<td>0.006</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>ln(Publications stock)<em>{t-1} × ln(Employment)</em>{t-1}</td>
<td>0.007</td>
<td>-0.002</td>
<td>-0.001</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.009)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>ln(Employment)_{t-1}</td>
<td>0.676**</td>
<td>0.671**</td>
<td>0.711**</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.029)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>ln(Assets)_{t-1}</td>
<td>0.314**</td>
<td>0.315**</td>
<td>0.238**</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.025)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Three-digit SIC Dummies (183)</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.951</td>
<td>0.951</td>
<td>0.870</td>
</tr>
<tr>
<td>Observations</td>
<td>21,416</td>
<td>21,416</td>
<td>6,549</td>
</tr>
<tr>
<td>Number of Dirms</td>
<td>1,502</td>
<td>1,502</td>
<td>1,269</td>
</tr>
</tbody>
</table>

Notes: This table reports the results of OLS regressions that estimate the size effects for U.S. Compustat, and large European firms. The sample covers the period 1997–2006 for European firms, and includes all Amadeus firms with at least one patent or one scientific publication between 1978 and 2006. For the U.S., the sample covers the period 1980–2001 and includes only firms with at least one patent from the USPTO or a publication over the period 1969–2006. The sample included in columns 4–6 matches the average number of employees for the sample of Compustat firms. All regressions include a complete set of year dummies. Columns 3–6 include an additional set of country dummies. Standard errors (in brackets) are robust to arbitrary heteroskedasticity, and allow for serial correlation through clustering by firms. ** significant at 1%; * significant at 5%