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Abstract

I study the size and scope determinants of innovation rate and quality for a large panel of U.S. manufacturing firms. I employ known indicators of patent quality to show that quality-adjusted patents per dollar of R&D fall with firm size. This finding is in line with previous research, and is driven by the variation in patent counts rather than the variation in patent quality. In contrast, firm size has no effect on the average quality of innovation at the firm level. Technological diversity increases the quality-adjusted patent count on most of the diversity scale, but its relationship with average quality is an inverted-U. The paper's results are consistent with the presence of a quality-quantity trade-off in innovation: As R&D intensity increases, the rate of corporate innovation falls, but its average quality increases. Finally, I find that appropriability conditions have a similar, non-linear effect on both the rate and quality of innovation.

Keywords: Innovation quality; Firm size; Technological diversity; Patents; Citations; Apropriability.

JEL Classification: O30, O31, O32, O33, L6, C23.

1 Introduction

The relationship between firm size and R&D productivity has been among the most intensely debated questions in the economics of innovation. The discussion goes back to the writings of Schumpeter (1942) and Galbraith (1952), who claimed that large firms with market power were the primary engines of technological change. Schumpeter challenged the established views behind anti-trust policy and static notions of allocative efficiency, claiming instead that the large firm with market power was the primary engine of technological progress[1].

In this article I investigate the effect of firm size and technological diversity on innovation for a large panel of U.S. manufacturing firms. In contrast to many previous studies that looked at the effect of size on the *rate* (*quantity)* of innovation at the firm level, I focus primarily on the determinants of innovation *quality*. Previous authors found a negative relationship between firm size and innovation productivity, as proxied by quantity indicators such as patents and innovation counts (Bound et al, 1984; Acs and Audretsch, 1991a; among others). A key empirical finding is that small firms obtain more patents (or significant innovations) per dollar of R&D expenditures for most industries and on nearly the entire support of the firm size distribution[2].

However, the rate at which innovations accrue says little about the actual value of a firm's innovative output. It is possible, for instance, for large firms to produce "better" and more important innovations, while also producing them less frequently. In other words, large scale may create advantages that improve the quality of innovation, if not its quantity. This article explores this possibility, by jointly examining quantity and quality indicators for a firm's patented innovations in relation to firm size. The reason for studying technological diversity along with firm size is that it is a key confounder in the size-innovation relationship, i.e., size advantages may be primarily due to increased *scope*, and not increased *scale* (Cockburn and Henderson, 2001). The two issues are intimately related in that while companies grow, the size and diversity of their activities increase concurrently. Then, it is important to test whether scale and scope effects have productivity effects above and beyond that of the other. The strategy is also more useful to capture interesting

[1] This assertion became known as the Schumpeterian hypothesis, even though claims regarding size effects alone do not appropriately capture Schumpeter's claim on the conditions favorable to innovation in industrial R&D (Fisher and Temin, 1973), while arguments related to the importance of firm size are more evident in Galbraith's (1952) writings. For responses from contemporaries of these authors, and an introduction to the discussion they initiated, see Mason (1951) and Mueller (1957).

[2] Some authors found a positive relationship between size and productivity at the very top of the size distribution, often due to a small number of very innovative and very large firms, indicating a U-shaped relationship between firm size and innovativeness (Scherer, 1965; Pavitt, Robson and Townsend, 1987; Audretsch and Acs, 1991).

quantity-quality trade-offs that may be at work.

To study the determinants of innovation quality, I utilize a variety of indicators that can be used as proxies for the quality of a firm's patented innovations. These are (*i*) citations made to a given patent, (*ii*) the index of "importance" developed by Trajtenberg et al (1997), which adds discounted second generation citations (citations received by patents citing the patent in question) to a patent's citation total, and (*iii*) the patent quality index developed by Lanjuow and Schankerman (2004), which extracts the common factor of a number of quality-related attributes. I take ample care to ensure comparability of citations across time and across technology fields by normalizing citation counts against meaningful benchmarks. Then, I study the determinants of *quality-weighted patent count obtained per dollar of R&D expenditures* (i.e., total quality/R&D), which can be considered as a proxy for total output achieved per R&D dollar invested, and the determinants of the *average quality of patented innovations* at the firm level.

It should be noted that this study looks at the effect of size and technological diversity on innovation for the sample of firms that are already innovative (have at least one patent during the year in question). It is established by a number of authors that the probability to innovate increases with size. The same is true for the current sample of firms as well. Also, the study focuses on a large panel of manufacturing firms that spans a large number of industries and technologies, hence seeks results that are to a large extent generalizable. While heterogeneity across industries are expected to exist, any structural relationship between variables of interest should be visible in aggregate data, as long as one is careful while making comparisons across industries and technologies.

The rest of the paper is organized as follows. Section 2 presents a brief summary of the paper's main results. Section 3 outlines main theoretical arguments for scale and scope effects on innovation and Section 4 presents a detailed review of the literature. Section 5 presents indicators of the rate and quality of innovation used in the paper and discusses their merits and basic properties. Section 6 presents empirical specification and estimation strategy. Section 7 describes the data, Section 8 presents main results and Section 9 concludes the paper.

2 Summary of Results

It is useful to summarize the main findings of the paper before delving into details.

- Quality-weighted patent counts obtained per R&D dollar *decrease* with firm size. This finding mirrors the previous literature on the firm size-innovation relationship that used simple patent or innovation counts as output measures. I argue that this finding is driven by the variation in *patent counts*, rather than the variation in *patent quality*. This is due to a problem with merely counting citations: the problems with patent counts are simply transferred to the level of *total* citations, hence the latter falls short of being an adequate quality indicator at the firm level (Atallah and Rodriguez, 2006; Lanjuow and Schankerman, 2004).

- The relationship between quality-adjusted patents per R&D and technological diversity is non-linear and it is best approximated by a cubic polynomial. The shape of the polynomial indicates that total quality per R&D increases for most of the support of the diversity variable as diversity increases.

- Firm size has no effect on average patent quality at the firm level. While large firms have higher propensity to obtain highest quality patents, this is due to the size of their patent cohorts, and not due to size differences per se. Innovation quality is randomly distributed across firms of different sizes.

- Innovation quality has a large stochastic component, but it is not entirely random. It is primarily affected by R&D intensity, technological diversity and appropriability conditions. R&D intensity affects innovation quality positively, and the relationship between technological diversity and innovation quality is an inverted-U.

- Results are consistent with a quality-quantity trade-off in innovation: Increased R&D intensity results in fewer patented innovations per R&D dollar, but an increase in the average quality of innovation.

- Appropriability conditions have similar effects on both the rate and quality of innovation, which are consistent with an inverted-U pattern.

3 Theoretical Arguments

3.1 Innovation and size

Both the small and the large firm have their respective advantages in innovation. Large firm advantage in innovation stems mostly from the control of, and access to material resources, while small firms draw advantages from institutional and behavioral characteristics (Rothwell, 1989). Most important large firm advantage is due to the presence of fixed costs and scale economies.

Galbraith (1952) writes "Because development is costly, it follows that it can be carried on only by a firm that has the resources which are associated with considerable size." Comanor (1967), Mansfield (1964) and Jewkes et al (1971) advance similar arguments. Cohen and Klepper (1996) claim that large firms enjoy advantages in R&D due to a cost spreading effect, i.e., they command a larger output over which they can apply the output of their R&D programs. Furthermore, large firms tend to have diversified product lines and technological capabilities, which allow them to better exploit unforeseen innovation opportunities and spread the risks of R&D into simultaneous projects (Nelson, 1959; Henderson and Cockburn, 1996). Large firms also obtain easier access to outside financing since it is difficult for a small firm to signal favorable future prospects (Galbraith, 1952; Hall, 2002). Finally, large firms are argued to enjoy advantages in the labor market, and hire higher quality technical personnel (Idson and Oi, 1999; Kim, Lee and Marschke, 2009a).

On the other hand, large firms' incentives and ability for innovation is hindered by an excess of bureaucracy and unwieldy mechanisms of decision making. Scherer (1980) notes that bureaucracy in large firms is not conducive to taking the necessary risks required for R&D, where projects need to penetrate layers of risk-averse and conservative resistance. There is abundant anecdotal evidence suggesting that large firms resist radical and disruptive change, and major innovations are disproportionately produced by innovative small companies. Empirical evidence supports such claims. Cooper (1964), interviewing 25 experienced development managers, finds that a given product would cost three to ten times as much to develop in a larger firm than in a small one due to excessive bureaucracy and red tape. Blair (1972) presents evidence that large firms underestimate the demand for new items, neglect inputs from inventors, tend to be satisfied with the status quo and prefer protecting investments in current technologies rather than innovate. A similar argument is known in industrial organization as the *replacement effect*: Innovation entails replacing one's own technologies and cannibalizing its own profits, giving large firms poorer incentives to innovate (Arrow, 1962; Reinganum, 1983). There is some evidence that small firms use external sources of knowledge more effectively (Link and Rees, 1991) and benefit from spillovers from the university to a greater degree than large firms (Acs, Audretsch and Feldman, 1994). In short, both the incentive and the ability to produce high-quality innovation often require the flexible entrepreneurship of the small firm. Also, it is often noted that small firms overcome size disadvantages and sustain high quality innovation by concentration in strategic niches, which allow them to produce specialized but sophisticated innovation (Agarwal and Audretsch, 1999; Pavitt et al, 1987).

3.2 Innovation and technological diversity

Technological diversity in innovating firms is often dictated by the nature, diversity and technological requirements of their production activities. Production of a single commodity increasingly necessitates competence in a variety of related technologies, and so does expanding into new product markets. Firms also diversify in order to exploit scope economies in R&D. Increased diversification may internalize potential externalities between different but related fields and lead to a cross-fertilization of ideas (Henderson and Cockburn, 1996). Previous research has shown that firms do not diversify in a random fashion, but diversify into technologically related areas (Breschi, Lissoni and Malerba, 2003). This suggests that firms' diversification opportunities may be highly constrained, but also that firms use diversification to capture complementarities between related research fields. On the other hand, diversification may induce firms to forgo the benefits of increased focus and specialization, i.e. the long term benefits of building higher comparative advantages in specific fields. Diversification dilutes the firm's financial and intellectual resources in each field of activity, reducing potential benefits from scale economies within each technology. Hence, it is natural to say that a firm faces a trade-off between increased scale of each R&D unit, and increased scope of the company at large. Finally, diversification imposes higher coordination costs (Henderson and Cockburn, 1996; Hueng and Chen, 2010), but (to repeat) allow firms to spread the risks of R&D into simultaneous projects (Nelson, 1959; Henderson and Cockburn, 1996).

4 Literature

4.1 Firm size and innovation

A number of distinct hypotheses were taken to data and were interpreted as tests of the Schumpeterian hypothesis. An early line of literature focused on the relationship between firm size and R&D expenditures at the firm level. These studies were primarily interested in whether R&D expenditures, or R&D intensity grew at a more than proportionate rate along with firm size (usually measured by total sales or employment). An elasticity of R&D with respect to size that is larger (*resp.* smaller) than one, or a positive (*resp.* negative) relationship between R&D intensity and firm size were interpreted as evidence supporting (*resp.* refuting) the Schumpeterian hypothesis. With the increased availability of patent data, it became possible to use patent counts as indicators of the output of R&D. A number of authors studied the relationship between R&D expenditures and the number of patents granted to the firm. In a similar vein, the finding that the R&D elasticity of patents was larger than one (*resp.* smaller than one) was interpreted as confirmation (*resp.* repudiation) of Schumpeter[3].

These earlier strands of the literature are best viewed as testing for the presence economies of scale in R&D, either at the level of R&D investment decisions, or in the mechanisms by which R&D inputs breed innovations. However, finding mere scale effects in either relationship falls short of proving a direct link between firm size and the productivity of the R&D enterprise. A more precise test of the Schumpeterian claim on firm size would ask the following question: Does the rate and/or quality of innovations per R&D dollar (or R&D employment) increase or decrease with firm size? Here I review studies test this assertion directly, and also some others that can be interpreted to provide equivalent findings. By and large, the literature does not support Schumpeter's thesis, and often provides evidence that R&D productivity, as measured by counts of patents or innovations per R&D dollar, falls with firm size.

Many authors studied the relationship between firm size and R&D productivity by using counts of patents as proxy for the output of R&D. Scherer (1965) studied the relationship between patenting and firm size for the 1955 cross section of 448 firms in the Fortune 500 survey. He found that the number of patents increased less than proportionally with firm size for most of the sample, with the exception of a small number of very large firms. He also found that the number of patents per sales revenue decreased with firm sales. Johannisson and Lindstrom (1971) studied a sample of 181 relatively large (500 employees or more) industrial firms in Sweden. They showed that large firms' share of patent applications was less than their share of employment for most of the sample. Bound et al (1984) examined the 1976 cross section of around 2600 U.S. manufacturing firms and found that smaller firms obtained a larger number of patents per dollar of R&D expenditures. For a sample of large U.S. firms with sizeable R&D activities, Chakrabarti and Halperin (1990) reported that patents and scientific papers per R&D dollar fell with firm size. Moreover, smaller firms in their sample had a significantly larger patent-R&D ratio, but a lower paper-R&D ratio than larger firms. Schwalbach and Zimmerman (1991) reported similar results for patent counts for a sample of 143 German manufacturing firms. Kim and Marschke (2009) used panels of firms in the U.S. semiconductor and pharmaceutical industries to show that patents per dollar of R&D expenditures declined with firm size in both industries.

To obtain a more direct measure of the rate of innovation, a number of specialized databases of innovations were compiled. The U.S. Small Business Administration Innovation Data Base (SBIDB)

[3] For a detailed review of these early lines of work, see Kamien and Schwartz (1975).

consisted of 8,074 innovations introduced to the U.S. market in 1982 and deemed significant by industry experts. Another was constructed by the Science Policy Research Unit (SPRU) of the University of Sussex, which included 4,378 significant innovations in the U.K. between 1945 and 1971. Two datasets were compiled by the Gellman Research Associates, one including 500 major innovations introduced in six countries, and another containing 635 U.S. innovations.

Pavitt, Robson and Townsend (1987) used the SPRU database to show that both small (less than 1000 employees) and large (more than 10.000 employees) firms produce a larger number of innovations per employee than medium sized firms, leading to a U-shaped relationship between size and innovation intensity. Freeman (1971) noted that small firms accounted for a larger proportion of important innovations than their share of official R&D expenditures. A Gellman Research Associates study revealed that small firms produced 2.5 times as many innovations per employee than their larger counterparts (Bomberger, 1982). The SBIDB database produced remarkably similar numbers for this same statistic, with small firms having 2.4 times as many innovations as large firms (Edwards and Gordon, 1982). Audretsch and Acs (1991) found a U-shaped relationship between the average number of innovations and firm size among firms grouped into size classes, and a negative relationship between the number of innovations per *employee* and size throughout the entire size spectrum. Acs and Audretsch (1991a) concluded that the data supported the hypothesis of a negative innovation-firm size relationship as a general rule, except for a few very large firms.

While the rate of innovative activity received abundant attention, the literature is not completely silent on innovation quality, either. Innovation databases introduce a quality dimension by identifying *significant* innovations as judged by industry experts. Hamberg (1966) and Jewkes et al (1971) argue that large research labs are not responsible for the bulk of significant inventions. Shimshoni (1970) documents that small firms in the scientific instruments industry played critical roles in innovating several key instruments. A notable study on the food industry is undertaken by Culbertson and Mueller (1980), who find that about half of all Putman Awards (which provides a comprehensive compilation of the most significant innovations in food manufacturing) were granted to small firms. These firms also received 44% of all awards designated as "top honors". Stock, Greis and Fisher (2002) study the determinants of a direct quality attribute (the data transmission rate) in the modem industry, finding that small firms market products that have faster transmission rates in a given year compared to the products of large firms[4].

[4]Note that this finding can be due to higher quality or higher speed-to-market, or merely a result of marketing technologies prematurely.

A small number of studies have incorporated citations into empirical analysis of the size-innovation relationship. Plehn-Dujowich (2009) finds that both patents and citations received per R&D stock falls with firm size in a cross section of 1976 patents. Huang & Chen (2010) report results which imply that citations received per R&D dollar falls with firm size. These papers are similar to the current one in their attempts to account for the variation in innovation quality. These studies, however, suffer from the drawbacks of using quality-adjusted patent counts, and do not look into alternative quality measures. The current paper will argue that quality-adjusted patent counts contain very little quality-related variation. They primarily reflect the variation in patent counts, indicating that problems with patent counts are imposed in data to the level of citations (Atallah and Rodriguez, 2006).

4.2 Technological diversity

There is a sizeable and rapidly growing literature on the determinants and consequences of corporate technological diversity. For a panel of European firms covering the time interval between 1995 and 2000, Garcia-Vega (2006) shows that technological diversity affects R&D intensity and the number of patents positively[5]. Granstrand and Oskarsson (1994) show that greater diversification is associated with greater sales and R&D growth. Miller (2006) finds that technological diversity is positively associated with a number of performance measures. Quintana-García and Benavides-Velasco (2008) report that technological diversification is positively associated with both "exploratory" and "exploitative" innovation, with a more pronounced effect on the former. Gambardella and Torrisi (1998) finds that greater sales and profits are associated with higher technological diversity (but greater business focus). Nesta and Saviotti (2005) show that technological diversification and coherence are positively associated with the number of patents granted to the firm.

A number of papers have incorporated both scale and scope effects in studies of R&D productivity. Henderson and Cockburn (1996) use data on the research program level to show that large firms in pharmaceuticals are more innovative than small firms, owing to economies of scope as well as economies of scale. Similar to the current paper, they explore nonlinearity with respect to scope and find that both highly focused and highly diversified firms are less productive in re-

[5] Authors have used a number of diversity measures, which commonly are inverted concentration indexes, and less often simpler ones such as the number of technological fields a firm is active in. These measures will be discussed in Section 6.

search, implying an inverted-U. In a later study, Cockburn and Henderson (2001) use detailed data on clinical research projects of 10 pharmaceutical companies. They find that the scale of R&D positively affects the probability of success, but this effect is completely explained by the variation in scope, i.e., the fact that larger development efforts are more diversified. I look at whether such a mechanism can be discerned from the current sample with the innovation measures I am using.

Huang and Chen (2010) also discover an inverted-U shaped relationship between technological diversity and the number of patents and citations. This article is closely related to the current one both in their examination of possible nonlinearity between diversification and innovation, and their use of citations to proxy innovation output. They use the total number of citations received by the firm's patents as a dependent variable in some specifications[6].

5 Indicators of innovation rate and quality

The problems with using patent counts as indicators a firm's innovative performance are well known (see, for instance, Griliches, 1990). The number of patents per dollar of R&D is a combination of two distinct effects: a productivity effect, indicating the rate at which R&D inputs produce subsequent innovations, and a propensity effect, indicating the rate at which innovations generate patent applications. It has been noted that industries differ greatly in their propensity to patent (Scherer, 1983). Thus, it is not clear whether results are due to differences in R&D productivity or differences in propensities to patent across economic units[7]. Finally, patent counts or stocks treat all patents as homogenous (Cohen and Levin, 1989; Acs and Audretsch, 1991b), hence fail to account for the value and significance of the underlying contribution. Using innovation counts avoids the bias due to the heterogeneity in the propensity to patent across economic units, but inherits the problem that all observed innovations are treated as homogenous, hence overlooks the variation in the quality, significance, and impact of innovations, as patent counts.

This article aims to contribute to this discussion by employing measures of patent quality that were not previously utilized in this line of inquiry. I use three different indicators to measure patent quality; a normalized count of citations, the importance index of Trajtenberg et al (1997), and the

[6] There is a growing line of literature that is interested in *how* firm diversify, which emphasizes the role of technological relatedness in firms' diversification strategies. For an introduction, see MacDonald (1985), Teece et al (1994) and Breschi, Lissoni and Malerba (2003). I also avoid a detailed discussion on the extant literature on the diversity of product lines, which is indirectly related to the current topic in that product market and technological diversification occur in conjunction with one another. On this topic, also see Pavitt et al (1987), Pavitt (1998) and Scott (1993).

[7] For attempts to identify these two effects separately, see de Rassenfosse (2010) and de Rassenfosse and van Pottelsberghe de la Potterie (2009).

quality index of Lanjuow and Schankerman (2004).

5.1 Citations

The number of citations made to a given patent is known to be good indicator of patent value (Trajtenberg, 1990; Albert et al, 1991; Harhoff et al 1999, 2003). An important difficulty in using citations in large panels is that raw citations do not immediately lend themselves to comparisons across time or across technology fields. Citation counts exhibit variation across technology classes and across time due to reasons not related to patent quality. In order to make meaningful comparisons across time and across technologies, it is necessary to standardize citation counts against meaningful benchmarks. For this purpose, I normalize citations by dividing the citation count of each patent by the third quartile (75th percentile) citation count of all patents *in the same technology class and with the same application year.* Accounting for the variation across technology classes ensures that idiosyncratic citation practices within technology fields are not guiding the paper's main results. It is also expected that patenting frequencies are different across technologies, which may lead patents to make too many citations simply because there is more prior art to cite. Accounting for the variation over time is necessary since citations have been increasing over time due to "mechanical" reasons (such as the variation over time in the number of patents to cite, and the strictness of patent examination procedures), leading to a non-quality related inflation in citations (Hall, Jaffe and Trajtenberg, 2001).

Normalized citation counts measure the quality of a patent *relative* to all others in a technology class-year pair. I prefer the 75th percentile to the median (which could perhaps appear as the more natural choice) since citation counts have a skew distribution, and there are a large number of technology class-year pairs with very low medians[8]. Normalization with respect to percentiles is preferred to normalizing with respect to means since the latter are sensitive to the presence of large outliers, while the former are not. Citation percentiles in comparison groups are calculated using the entire sample of available (more than three million) USPTO patents, not just those that are matched to corporations. Similar normalization procedures have been used in different contexts by Goodall (2009) and Lettl et al (2009), even though careless application of raw citations is common.

Note that it isn't a priori clear whether normalization will "favor" large or small firms. This

[8]Even though groups with zero medians are very few, medians representing one or two raw citations are common. Normalizing using such low numbers can be misleding, hence higher percentiles are prefererred. Nevertheless, I experiment with scores using medians and the 90th percentile, which do not produce different results.

depends on the distribution of innovation activities of small and large firms across technology classes that produce more frequent citations. To the extent that increased firm size implies a restructuring of activity into fields that are more (or less) frequently cited, the more the two sets of results will differ, and normalization will assure higher reliability. Conversely, to the extent the assignment of firms into technological activities is random (independent of firm size and diversity), the two set of analyses are expected to produce more similar results.

Another issue to be resolved is time truncation. Observed citation counts are truncated since citations keep arriving long after the date of patent grant, but only a fraction of overall citations are observed at the time of data collection. Hall, Jaffe and Trajtenberg (2001) correct for truncation by estimating the distribution of citation lags. Once this distribution is estimated, one can approximate the true citation count for an age-a patent by dividing the raw citation count by the fraction of citations an average patent receives during the first a years after the application year. I correct raw citation counts using the implied weights given in tables 6 through 8 in the same study. Note that due this procedure, the number of corrected citations is no longer a count variable. During data construction, citations are first corrected for truncation and the normalization procedure detailed above is applied corrected citation scores.

Citation counts used in constructing quality measures are all are non-self citations, i.e., citations that are made from a company to its prior patents are excluded.

5.2 Importance

In addition to normalized counts of citations, I also construct and use the measure of importance developed by Trajtenberg, Henderson and Jaffe (1997). This measure counts citations received by the patent, and adds to this a fraction of the sum of second generation citations, i.e., the number citations received by patent's citing antecedents. For patent p,

$$Import_p = Citations_p + \lambda \cdot \sum_{j=1}^{nciting(p)} Citations_j \tag{1}$$

where $j = 1, ..., nciting(p)$ indexes patents that cite p, and λ is a discount factor that captures the relative significance of second generation cites. Following Trajtenberg, Henderson and Jaffe (1997), I choose $\lambda = 0.5$, but also experiment with different λ values. These analyses produce similar results. All citation counts in the above formula are corrected for truncation *before* summation, and the normalization procedure is applied to the importance measure itself. That is, importance index for each patent is divided by the 75th percentile of the measure in its technology class and application year.

5.3 Lanjuow and Schankerman quality index

Finally, I use a slight variant of the patent quality index proposed by Lanjuow and Schankerman (2004) (henceforth *LS*). The original index extracts the common factor of five indicators of patent quality and scope: citations received within five years of patent application, citations received within five to ten years of patent application, backward citations (citations made by the patent), the number of claims made by patent application, and family size (the number of countries the innovation is patented in). Since I do not have access to large-scale data on family size for USPTO patents, I extract the common factor of the remaining four indicators described above[9]. The index was separately estimated for six aggregate technology classifications (Chemicals, Computers and Communication, Drugs and Medical, Electric and Electronics, Mechanical, and Others) and was subjected to the same normalization procedure described above. Truncation is not an issue here, as the index uses citations received in fixed time windows.

5.4 On observable innovation indicators

I use all quality indicators to construct two different types of proxies for a firm's innovative output. The first is a quality-weighted patent count obtained per dollar of R&D expenditures, which can be considered as a proxy for total output achieved per R&D dollar invested. The second is the average quality of patented innovations at the firm level. Hence, a total of six quality-related measures will be examined: average quality per patent ($\sum$Q/patents), where Q $\in$ {citations, importance, LS} which will be called CP, IP and LSP, respectively. Quality-adjusted patents per R&D ($\sum$Q/R&D) will be named analogously as CR, IR and LSR. For completeness and comparison, I will examine the determinants of the patent-R&D ratio (PR) as well. For brevity, quality-adjusted patents per R&D will be referred to as QR, while average patent quality will be termed QP.

To put various output measures utilized here and elsewhere in perspective, it is a good idea to keep in mind the timeline of innovative activity, and observable indicators of innovation from its different stages. It is instructive to look at the following natural decomposition of a quality-adjusted

[9] Lanjuow and Schankerman (2004) obtain family size for a random sample of a little over 100,000 patents, which makes up a mere 20% of their entire sample of patents. Hence, including family size is impractical unless one wishes to omit a large fraction of the patent database from the sample.

patent count and the innovation indicators it "hides" within:

$$\frac{\sum \mathrm{Q}}{\mathrm{R\&D}} = \frac{\sum \mathrm{Q}}{\mathrm{PAT}} \cdot \underbrace{\frac{\mathrm{PAT}}{\mathrm{INN}} \cdot \frac{\mathrm{INN}}{\mathrm{R\&D}}}_{\mathrm{PAT/R\&D}} \tag{2}$$

At the first stage of innovation, R&D investments are made. These investments lead to a number of innovations (INN). If these innovations are observed, the number of innovations that results per R&D dollar of expenditures (the third term in (2)) is a direct measure of output from this stage, even though differences in the social or private values of these innovations aren't observed. Some innovations are patented, and patents per innovation (second term in (2)) is a measure of the firm's pure "propensity to patent". The second and the third term together produce the patent-R&D ratio. Finally, the average quality of these patents ($\sum$Q/Patents) is an indicator of the average value and impact of these patents. These three measures together produce total quality per R&D dollar ($\sum$Q/R&D)[10].

An important advantage of using average quality is that it avoids the well documented problems with reported R&D expenditures, especially with those of small firms (Kleinknecht, 1989). Also, studying the variation in average quality offers a means to look at innovative output *net* of the propensity to patent. That said, we directly inherit some of the problems with using patents as output measures. Most importantly, one doesn't observe quality indicators for unpatented (and unpatentable) innovations.

6 Empirical specification

The main interest of the study lies on the effects of size and scope differences on innovation. The baseline empirical model to be estimated is

$$\log(y_{it}) = \gamma + \alpha_S \log S_{it} + f\left(TD_{it}; \boldsymbol{\theta}\right) + \mathbf{x}_{it}'\boldsymbol{\beta} + \eta_i + \delta_t + u_{it} \tag{3}$$

[10] This decomposition also highlights a difference between an "ideal" output indicator and the indicators we actually observe. Ideally, we would like to observe innovations at the firm level, along with a direct measure of the value of these innovations. Since this is elusive, this study uses quality indicators of the value of *patented* innovations, rather than that of the entire cohort of a firm's inventive output. Patent quality can deviate from innovation quality to the extent that a firm's decision to patent an innovation is correlated with the expected value of the innovation.

where y_{it} is a measure of the R&D productivity of firm i at year t, S_{it} is deflated sales[11], TD_{it} is a measure of technological diversity, and $\mathbf{x}_{it}$ is a vector of controls for the it (firm i, year t) observation, including firm and industry characteristics, as well as characteristics of the firm's R&D organization and those of its patented innovations. I allow for nonlinearity with respect to TD_{it} by approximating f with a polynomial expansion, where $\boldsymbol{\theta}$ is the vector of parameters in the expansion. The error term $\eta_i + \delta_t + u_{it}$ is the usual two-way error components specification that includes an unobservable and time-invariant firm effect, as well as year effects. Year effects control for the overall variation in productivity over time, which can occur due to aggregate economic conditions, changes in the legal environment and innovation policy[12]. It could be more desirable to use lags of firm size and the spillover pool instead of their current values. Regressions with lags of these variables produce estimates that are very similar to those with current values. Hence, I report results using current sales and spillovers to avoid the cost of losing an additional year of observations.

Equation (3) is estimated by using measures of innovation performance described in the previous section. A general-to-specific specification search is performed in order to account for possible nonlinearity with respect sales, technological diversity and other key independent variables. For all dependent variables used, as well as for sales, a Box-Cox test indicates that a logarithmic transformation gives the best fit, which is natural for both skew and size-related variables. For all specifications, a Hausman tests rejects the null hypothesis that permanent effects are random, hence a fixed effects (within) specification is adopted. To account for a serially correlated component in u_{it}, all equations are estimated after performing a correction for first order serial correlation (Bhargava, Franzini and Narendranathan, 1982; Baltagi and Wu, 1999). Year effects are controlled for using year dummies.

6.1 Independent variables

All specifications include a measure of R&D intensity (in logs), firm age, and the firm's capital-labor ratio (in logs). R&D intensity is calculated by dividing contemporaneous R&D to net capital. The use of contemporaneous R&D (rather than stocks) follows extensive evidence on the R&D-patents relationship that current patents mostly result from current R&D. The capital-labor ratio

[11] Using alternative measures of firm size, such as employment and net capital gives results that are qualitatively identical to current ones.

[12] A few important policy changes regarding patent law occur during the sample period. For a review, see Jaffe (2000).

is simply net capital assets divided by the number of employees. Capital-intensity may affect both the incentives to innovate and the incentives to patent, hence it may be an important confounder (Kim, Lee and Marschke, 2009b). When the dependent variable is average quality, I also include the firm's patent-R&D ratio as a regressor, which controls for the firm's patent yield per dollar of current R&D investments. In all specifications, I include the logarithm of industry size (total value of shipments) in the firm's 3-digit SIC industry classification, as well as the annual compounded growth in industry size. The former is intended to control for size effects and demand conditions at the industry level. The latter captures effects of industrial economic conditions, such as industrial expansion and decline.

Remaining controls are introduced below.

6.1.1 Technological diversity

Technological diversity of the firm is measured as one minus the concentration of the firm's patenting activity across different technological classes, based on the Herfindahl index. That is,

$$TD_{it} = 1 - \sum_{k=1}^{K} \left(\frac{P_{it}^k}{P_{it}} \right)^2$$

where $k \in \{1, ..., K\}$ are USPTO technology classes, P_{it}^k is the number of it patents in technology class k, and P_{it} is the total number of it patents. The idea is that a more diverse research activity that spans a large number of technological fields will be observed in the firm's patents being spread out among a larger number of technological classifications. Similar measures of diversity have been previously employed by researchers. Gambardella and Torrisi (1998) and Leten et al (2007), among others, use a similarly constructed Herfindahl-based index, while Garcia-Vega (2006) (and few others) employ an entropy-based index of diversity. Granstrand and Oskarsson (1994) use both to measure spread of a company's engineering employment across fields of specialization. Both the Herfindahl and entropy indexes are indexes of concentration, hence serve similar purposes.

Since the diversity measure uses knowledge of a firm's patents, low patent counts are naturally associated with low diversity. This can be considered as a "natural" case of non-diversification rather than a bias in the measurement of diversity, and it is normal to attribute zero diversity to a firm with one or zero patents in a given year. However, it is not desirable for all results to be driven by a large number of low-patent, hence, low-diversity observations, especially while investigating average patent quality. For this purpose, I include separate dummies for having one and two patents in a given year in each regression.

6.1.2 Spillovers

Explanations for the differences in small and large firm productivity include differences in ways small and large firms benefit from spillovers. Thus, it is also useful to directly control for such spillover effects. To this end, I include a weighted sum of external R&D expenditures in some specifications, which is calculated as

$$SP_{it} = \log \sum\nolimits_{i \neq j} w_{ij} RS_{jt}$$

where RS_{jt} denotes the R&D stock of firm j during year t, and w_{ij} is a measure of the technological proximity between firms i and j. I follow Jaffe (1986), and calculate w_{ij} as

$$w_{ij} = \frac{T_i' T_j}{\|T_i\| \, \|T_j\|}$$

where T_i is a $\kappa \times 1$ vector that contains the number of patents of firm i in USPTO technology class $k \in \{1, \ldots, \kappa\}$ in its k^{th} element. T_i can be called the "technological position vector" of firm i, and w_{ij} is the uncentered correlation between vectors T_i and T_j. Thus, w_{ij} is a metric in the technology space and captures the coincidence of patenting activities of firms i and j across USPTO technology classifications[13].

6.1.3 Appropriability

As an imperfect indicator of appropriability conditions, I use the fraction of self-citations received by the firm's patents (Trajtenberg et al, 2002). This ratio gauges the extent the original innovator, and not others, capture future benefits from innovation. I calculate the ratio at the firm level, i.e., by dividing total self-citations to total citations received for each firm-year. This is not a direct measure of the fraction of total economic rents appropriated by the original innovator. However, it does quantify the difficulty of imitation and backward engineering.

[13] See Jaffe (1986) for additional properties of this proximity metric.

6.1.4 Technological opportunity

To capture and control for changes in technological opportunity, I include the annual growth of patenting in the firm's technological neighborhood. This variable is calculated as the annual compounded growth of the sum $\sum_{i \neq j} w_{ij} P_{jt}$ for firm i, where P_{jt} is the number of patents of firm $j \neq i$, and $\{w_{ij}\}$ are the proximity measures that were introduced above. Effects of technological opportunity aren't straightforward to study in isolation. Previous work attempted to control for them using group effects, such as dummies for industries or technology classes, or dummies for group-time pairs (Jaffe, 1986, and others). The growth of innovation activity in a firm's technological neighborhood has a straightforward interpretation in terms of technological opportunity, as it captures the increased (collective) incentives to innovate and the abundance of innovations during periods of high opportunity (Breschi, Malerba and Orsenigo, 2000). Note that we are interested more in *netting out* the effects of technological opportunity from remaining coefficients rather than estimating its precise effect.

6.1.5 Visibility

It is possible that a large firm receives more citations simply because its patent portfolio is more visible to potential citing firms[14]. This could bias results toward a more favorable outcome for large firms, as increased visibility would be mistakenly interpreted as higher patent quality. To fend off this possibility, I control for a measure of a firm's visibility to others. For the firm i and year t observation, my visibility measure is the number of firms (excluding firm i) that have cited firm i's patents until year t (excluding year t)[15].

7 Data sources and description

Information on patents and citations come from the latest edition of the NBER patent and citations data file (Hall, Jaffe and Trajtenberg, 2001). This edition contains all USPTO patent applications and all citations made to these patents until 2006. All data on annual R&D expenditures, sales, and other firm level variables are taken from the historical Compustat panel compiled by the same authors. I use the latest edition of the match between USPTO assignee names and Compustat

[14] I thank Pelin Demirel for reminding me of this possibility.

[15] Note that if we were interested in the "impact" of innovations alone, it wouldn't be desirable to net out visibility effects from coefficients, since increased visibility would be a natural part of a firm's external impact. This argument does not necessarily hold when one is interested in *quality*.

(Bessen, 2009). I follow the convention in the literature and calculate R&D stocks as a perpetual inventory with 15% annual depreciation. Since Compustat does not provide the birth year of firms, firm age is calculated from the first year a firm appears on Compustat tapes. While this is a noisy measure of age, it is very close to the actual foundation year for most firms, and errors will be sizeable only for very old ones. Firm age is used as a natural logarithm which should render such errors minimal[16].

Recall that raw citations are corrected for truncation using the estimated correction weights in Hall et al (2001). This procedure makes it necessary to leave a sufficient time gap between the last year studied in the sample (here: 1995) and the final year we have access to citation data (2006), since predicting total citations using only a few years of observed citations can be very misleading[17]. This time window is 11 years in the current study. On average, a patent receives 48.6% (Drugs and medical) to 68.3% (Computers and communications) of its lifetime citations during the first 11 years after application depending on its technological category.

An interesting observation about quality indicators is that they are not persistent over time, reflecting that eventual success of patented innovations are inherently unpredictable and contain a fair amount of noise. In simple OLS regressions of (log) average quality on its first lag produces lag coefficients ranging from 0.30 (for LSP) to 0.35 (for IP), and explains between 9.5% to 12.6% of the variation in current quality. In contrast, the lag coefficient is 0.82 for patents per R&D (PR), 0.91 for patents and 0.99 for R&D expenditures (respective R^2 values are 0.67, 0.82 and 0.98). For quality-adjusted patents per R&D, coefficients range from 0.60 to 0.71 (R^2 is between 0.38 and 0.51). As expected, innovation quality is less persistent and hence, less predictable than innovation quantity and innovation inputs. It is also noteworthy that the persistence of the series falls as one moves from input to output indicators, and from crude output indicators to finer ones.

Data on industry level variables are taken from the NBER-CES Manufacturing Industry Database (Bartelsman and Gray, 1996). The dataset contains annual data on output, employment, various indicators of costs, investments, capital stocks, and other variables for each 4-digit SIC classification in U.S. manufacturing between 1958 and 2005. I use the annual value of shipments for each industry as a measure of industry size. Annual industry growth for each SIC classification is computed as the (log-compounded) growth rate of the industry's value of shipments. Note that I

[16] I thank Bronwyn Hall for pointing this out.

[17] Also note that for many patents of great significance (and with high lifetime citations as a result), one may expect fewer citations after the initial few years after grant, as these innovations could take longer time to be understood, adopted, and then cited.

use the 3-digit SIC as the industry classification, and aggregate the value of shipments in relevant 4-digit SIC classes to the 3-digit classification to get industry size.

All variables in current dollar values are deflated using the GNP deflator. After deleting large outliers ($|\log x_{it} - \log x_{it-1}| > 2$), firms with only a single year in the data and removing observations with missing variables, the remaining sample consists of nearly 11000 observations covering the 20 years between 1976 and 1995 (sample sizes differ slightly across specifications). One year of observations are lost due to the AR(1) correction, and sample sizes for different specifications differ slightly depending on the quality indicator used. All aggregations regarding "external" firms have been undertaken using the largest possible sample at hand. Throughout the paper , the mathematical operation "log" is used to denote natural logarithms. Sample statistics for all variables are provided in Table 1. Table 2 reports correlations between independent variables and Table 3 provides correlations between innovation indicators.

8 Results

8.1 Quality-adjusted patents

Table 4 reports results on the determinants of quality-adjusted patents per R&D. I also study patents per R&D (unadjusted for quality) for comparison. The dependent variable in columns one through four are the logarithms of PR (patents per R&D), CR (citations per R&D), IR (importance per R&D) and LSR (LS index per R&D), respectively. In all specifications, the coefficient of sales is negative and significant, indicating that both quality-adjusted patents (QR) and patents per R&D (PR) fall with firm size. Thus, using quality adjustments on patents does not lead to a different conclusion than what was previously known on relationship between size and patents per R&D. Interestingly, the coefficient of the size term does not significantly differ across specifications. The coefficient is not greatly affected when patents are interchanged with quality-adjusted patents, as well as when we use (arguably more accurate) patent quality indicators, citations, importance, and the LS quality index. Possible implications of this finding will be discussed below.

The coefficients of the polynomial expansion for technological diversity indicate a highly non-linear diversity-QR relationship, with significant coefficients up to the cubic term. Higher order polynomial terms tend to be insignificant for all specifications, and do not alter the shape of the polynomial significantly. The cubic term has a positive coefficient, while the coefficients of the remaining terms are negative. The coefficients of the polynomial terms are consistent with an *nearly* U-shaped relationship between technological diversity and QR: The S-shape consists of a slight increase in the dependent variable as diversity increases from zero to about 0.1, then a fall until around 0.5, and then an increase between diversity values in 0.5 and 1. This contradicts previous studies that also investigated possible nonlinearity between diversity and innovation (Henderson and Cockburn, 1996; Huang and Chen, 2010). It is important to note that this difference isn't simply due to the inclusion of the cubic term. Excluding this term (while keeping the rest of the specification intact) also yields a U-shaped relationship that increases in the larger part of the support of diversity variable (coefficients are 0.258 for the second, and -0.054 for the first order terms). Hence, we find that higher technological diversity is associated with higher QR for most of the variable's support, with a slight S-shape for the lower end of the diversity scale.

All independent variables except visibility, technological opportunity, industry size and industry growth have significant coefficients in all regressions. Most notably, I find that the coefficient of R&D intensity is negative and significant; firms with higher dedication to R&D obtain fewer patents and attain lower total quality per R&D dollar. Firm age and capital intensity are negatively associated with patents and quality-adjusted patents per R&D, while the spillover pool and technological opportunity have positive impacts on these variables. Industry size has a positive coefficient in column 1 (PR), but the coefficient is insignificant in the remaining columns, where the dependent variable uses quality-adjusted patents. In all columns, the coefficients on the quadratic specification for appropriability indicate a statistically significant inverted-U shaped relationship with all dependent variables. The visibility of the firm has a significant coefficient only in column 4 (LSP) and only at the 10% significance. The negative coefficient of this variable is unexpected, and it is most likely due to the high within-firm persistence of this variable.

8.2 Quality vs. quantity

The most striking aspect of the regressions in Table 4 is that the determinants of patents per R&D, and those of quality-adjusted patents per R&D are very similar. As long as one is *counting* patents, it appears that almost nothing new is learned by counting them after a quality adjustment. Coefficients are also insensitive to the use of different quality indicators: CR, IR and LSR all give coefficients for key variables that are very similar to their counterparts for PR, both in sign and in magnitude. Recall that QR $\in$ {CR, IR, LSR} is simply the product of QP $\in$ {CP, IP, LSP} and PR. Our results may indicate that most of the variation in quality-weighted patents is due to the variation in patent counts themselves, and has little to do with patent quality. The high correlation coefficients between these two sets of indicators (Table 3) also support this claim. Correlations between patents per R&D and its quality-weighed counterparts range from 0.79 to 0.91. The correlations between *average* quality indicators and PR, on the other hand, are small and negative, ranging from -0.03 to -0.07.

By and large, it seems that citation-weighted patent counts reflect the behavior of the patent-R&D ratio to a much greater extent than they reflect patent quality. Hence, these measures fall short of representing true quality effects, and seem to directly inherit problems with simple patent counts. As a result, Table 4 may be highlighting the determinants of innovation *quantity* by looking at quality-adjusted patents, and not telling us much about patent quality. It is therefore more meaningful to interpret results in Table 4 as evidence regarding the *rate* of a firm's patenting activity, rather than overall innovation quality. Note that a similar point, in a different context, was also raised by Lanjuow and Schankerman (2004). While their primary focus was on using their quality index to explain trends in research productivity, they also report that R&D expenditures failed to explain the variation in innovation quality among innovating firms in the U.S. These authors test whether including innovation quality improves the explanatory power of standard regressions of firm performance, but do not provide a detailed account of the determinants of innovation quality at the firm level. Atallah and Rodriguez (1996) raises the same concern with such counting procedures as well. I study average patent quality in detail in the next subsection.

8.3 Average patent quality

I now turn to the determinants of average patent quality at the firm level. Table 5 reports regression results in which indicators of a firm's average patent quality are dependent variables. The specifications are similar to those in Table 4, except that the patent-R&D ratio is included as an additional regressor. The polynomial in diversity is reduced to a quadratic form, as higher order terms are insignificant in these regressions.

In columns 1 through 3, I study the determinants of CP (citations per patent), IP (importance per patent) and LSP (LS index per patent), in the given order. Taking these regression at face value, the most notable result is that the coefficient of firm size is insignificant in all columns at all reasonable levels of significance, indicating that firm size has no bearing on the average quality of a firm's patents. The effect of technological diversity on average innovation quality is consistent with an inverted-U pattern. However, both polynomial terms are statistically significant only in column 3 (LSP). Neither polynomial coefficient appears to be significant in column 1 (CP), while only the first order term is statistically significant in column 2 (IP). Hence, there is evidence for an inverted-U type relationship between technological diversity and innovation quality, but the evidence is somewhat weak unless LSP is considered to be the preferred quality indicator. Both the insignificance of firm size and the inverted-U pattern with respect to technological diversity are robust to alternative specifications and estimation techniques that will be explored below[18].

Notably, R&D intensity has a positive and significant coefficient in all columns. Along with the evidence from Table 4, this can be interpreted as evidence for a quality-quantity trade-off in innovation. As R&D efforts (per capital asset) increase, firms obtain fewer patents (and fewer quality-adjusted patents) per R&D dollar, but the average quality of these patents increases. R&D intensity is conducive to higher quality innovation, while the *rate* of innovation falls with it. The relationship between appropriability and patent quality is an inverted-U (except in column 1 where only the squared term is significant), similar to the results in Table 4. Visibility, again, has the unexpected negative sign.

8.4 Is patent quality unpredictable?

A number of important observations are in order. First, it is easy to observe that innovation quality is less predictable than innovation quantity, which renders it more difficult to explain its determinants. Many variables with statistically significant effects on quality-adjusted patents per R&D (Table 4) fail to account for quality differences, as indicated by the fewer explanatory variables with significant coefficients in Table 5. The explanatory power of these regressions are much lower compared to their counterparts in Table 4 as well. Our regressions can explain only 3.1% of the variation in log(CP), 2.6% of the variation in log(IP) and 3.8% of the variation in log(LSP). It appears that patent quality has a large stochastic component, presumably because much of the variation in average patent quality is due to chance[19].

The low explanatory power of these regressions could indicate that innovation quality is randomly distributed across firms to a large extent, and little can be learned about its determinants. A number of additional possibilities remain, though. First, recall that quality indicators for each patent are normalized with respect to the 75th percentile of the quality distribution in the same

[18] It is worth noting that the insignificance of firm size is not due to the presence of the diversity measure. The coefficient of firm size remains highly insignificant in regressions where average quality is not conditioned on technological diversity.

[19] It is also unlikely that unobserved permanent effects are responsible for quality differences, since these are differenced away in the fixed effects specification.

technology class and with the same application year as the patent in question. This procedure naturally reduces the variation in quality indicators. One possibility to consider is that our normalization procedure may be removing too much information. I examine this possibility by studying the determinants of *non-normalized* quality indicators while controlling for *backward* citations. While being a poor substitute to normalization, this can also be considered as an input-output exercise. If quality indicators (which are all based on forward citations to varying degrees) are measures of the innovator's intellectual output, backward citations would qualify as intellectual inputs for innovation[20]. This strategy greatly improves regression fit (R^2 is 0.19 for log(LSP)) and gives similar regression coefficients for key variables. Firm size remains insignificant, the technological diversity polynomial has similar coefficients, and the positive effect of R&D intensity on average quality is retained, again with a similar coefficient to its counterpart in Table 5. Previous findings on appropriability carry through these regressions as well.

Second, the variation in quality may be absent only in the within dimension of the data. To explore this possibility, I estimate the main regression equation using a between firm specification. A larger variation exists between firms in normalized quality indicators (R^2 is at the order of 0.13). The coefficient of firm size remains insignificant, and the polynomial in technological diversity is again consistent with an inverted-U pattern. R&D intensity has a positive and significant coefficient, which is comparable in magnitude to its counterpart in within regressions. Firm age has a negative effect on average quality, and we retain similar results to Table 5 for appropriability. The coefficient of visibility is positive, confirming the argument that the within-firm persistence of this variable is responsible for the unexpected coefficients previously obtained.

Third, taking averages of our quality indicators for each firm may be destroying valuable information about the entire spectrum of quality within firms. To highlight this, Figures 1 and 2 show scatterplots of patent quality (the logarithm of normalized LS index) against firm size at two different levels of aggregation. Figure 1 is generated using firm level data, with each dot representing a firm-year observation. Here, the vertical axis represents the logarithm of *average* patent quality at the firm level. Figure 2 plots patent quality (again, the logarithm of the normalized LS index) against firm size at the patent level, each dot representing a single patent. Comparing these figures, it is easy to see the consequence of taking averages. Figure 1 indicates that innovation quality in small firms is more dispersed around the mean, and dispersion of *average* quality *falls* as firms grow larger. In fact, average patent quality converges roughly to unity for the largest firms in our sample,

[20] I thank Adam Jaffe for pointing this out.

which indicates convergence close to the 75th percentile in the respective group[21]. Figure 2, on the other hand, reveals a different picture. As firms grow larger, the variety of patented innovations grows toward both ends of the quality spectrum. The scatterplot indicates that the ability to obtain higher quality patents increases with firm size on nearly the entire firm size spectrum. The figure also indicates that large firms also obtain a larger number of "worthless" patents compared to small firms, which dilute the firm's quality average. The tendency for patent variety to increase with size is reversed for the very largest firms in the sample, whose patents exhibit lower dispersion around mean quality[22].

From these observations, one may be inclined to draw the conclusion that large firms are more successful in innovation due to a higher propensity to produce "top quality" patents. However, such an interpretation would be unwarranted. A careful examination of Figures 1 and 2 suggests that they are not at odds with the hypothesis that patent quality is distributed randomly across firms of different sizes, and they do not contradict our previous conclusions on the determinants of average quality. Consider the extreme scenario that innovation quality is entirely random, and that each patent draws its quality from a common probability distribution. Then, a large firm will get more draws at the upper tail of this distribution owing to its larger number of patents (not necessarily larger per R&D, per employment or per sales). As a result, the average quality of its best patents will be higher as well. An interesting figure is given in Figure 3, which plots the quality index for each patent against the logarithm of the patent portfolio size of the firm that patented the innovation. The association between the two variables appears to be almost entirely random. All quality levels are associated with almost all patent counts at the patent level, except for firms with the largest patent portfolios (who obtain a slightly more selective set of patents). The figure supports the idea that the shape of the scatterplot in Figure 2 is due to the increased patent counts of large firms, and not due to size differences.

This claim can easily be put to test using arguments that do not appeal to mean quality of the firm's entire patent portfolio. From Figure 2, it is clear that a regression of the average quality of a firm's "top" patents (say, the average quality of its 5, 10 or 20 patents with highest quality) on

[21] One may consider the possibility that this is a statistical fluke due to the potential "dominance" of some technology classes by a small number of very large firms. This isn't the case, as indicated by the scatterplots of quality normalized with respect to different percentiles, which do not converge to unity for the largest firms. Also recall that percentiles of quality distributions are calculated for *all* patents in the USPTO sample in a given year, not just those that are matched to corporations.

[22] To provide a more precise statistic, a regression of the coefficient of variation of patent quality, calculated for each firm, on a polynomial in sales reveals that the variation increases and then falls with size, with the highest variation around 166 million in sales.

firm size will produce a positive coefficient. However, if the distribution of quality across small and large firms is random, this effect should be completely explained by the variation in the number of patents, if we control for the latter. The data clearly supports this claim. Without conditioning on the number of patents, regressions of the average quality of the top 5, 10 and 20 patents of each firm (using the same specification and methods in Table 5) produce the expected positive coefficient for firm size. Controlling for the number of patents, however, the effect of firm size is completely picked up by the coefficient of patents, and firm size is driven into insignificance. Hence, higher patent quality at the higher end of the quality distribution in large firms is simply due to their larger patent portfolios, and not due to size effects per se[23].

Fourth, it is possible that important aspects of innovation quality may be lost in *annual* data, and it may be preferable to aggregate a firm's innovative output over longer time periods. Note that this is a noise reduction exercise; if annual stochastic shocks that are part of patent quality have low covariance across periods, their average over T years will have lower variance than each individual shock if they also have common variance[24]. For this purpose, I construct a three-period panel consisting of the five-year periods between 1976-1980, 1981-1985 and 1986-1990. Flow variables (patents and quality-weighted patents, R&D, sales, industry size) are summed, and stock variables (capital, employment, spillover pools) are averaged for each five year period. Firm age and visibility are taken as the age and visibility at the beginning of the period, while technological diversity is re-calculated using all patents of the firm in the five year interval[25]. These regressions increase explanatory power of the baseline specification, with regressions explaining 6.6% to 8.2% of the within variation in normalized patent quality (compared to 2.6% to 3.8% in Table 5), which still remain quite low. It could be that annual shocks to patent quality have non-negligible positive covariance over time, in which case the variance of averaged shocks need not be much smaller that the average variance of the shocks. Recall that I control for serial correlation in errors, which allows consistent estimation of parameters under correlated shocks, but this need not increase the explanatory power of regressions. These regressions produce qualitatively identical results to those

[23]This is also a useful exercise in order to see which factors lead firms to increase the quality of their "best" patents, *holding firm size and the number of patents constant.* R&D intensity has a large, positive coefficient in these regressions. They give mixed results on the effect of technological diversity, depending on whether the sample is restricted to firms with at least n patents for regressions that use the average quality of the firm's top n patents. Previous results regarding appropriability conditions carry though these analyses as well.

[24]Similarly, under different variances of shocks, the average shock will have lower variance than the average variance of annual shocks.

[25]I also undertook regressions in which all regression variables are directly averaged across the relevant five year window. These regressions do not produce different results.

in Table 5.

These analyses reveal that quality is to a large extent randomly distributed across firms, but the distribution is not completely stochastic: technological diversity and R&D intensity affect innovation quality, holding firm size and remaining controls constant. However, there seems to be less in the hands of firms to affect the quality of their innovative output. Quality is distributed randomly across innovating firms of different sizes, a result that appears to be robust across many specifications. The Lanjuow and Schankerman (2004) suggestion that innovation quality is most useful after taking averages seems to have mixed appeal: too much information is lost by taking averages at the firm level, but taking averages over time somewhat reduces the noise in the quality measure. Even then, a substantial stochastic component remains. Appropriability conditions also affect innovation quality, which will be highlighted further in the next subsection.

8.5 On appropriability

The paper's results on appropriability conditions merit some emphasis. First, appropriability has statistically significant effects on both the rate (Table 4) and quality (Table 5) of innovation. Also, and uniquely among our explanatory variables, its effects on the rate and quality of innovation are remarkably similar. This is among the most robust results of the current paper: it is observed in all main and exploratory regressions detailed above. The estimated relationship is consistent with an inverted-U type relationship between appropriability and both the rate and quality of innovation. According to the point estimates, the "peak" innovation rate occurs at the self-citation rate of 0.39, and peak innovation quality is observed at the self-citation rate of 0.40. When all alternative estimation strategies discussed in the above subsection are considered, this "optimum" self-citation rate varies between 0.32 and 0.40. Therefore, peak rate and quality for innovation occur at very similar self-citation rates. Hence, these results may indicate a genuine and strong productivity effect.

The finding that increased appropriability is initially conducive to both higher innovation rate and higher innovation quality is intuitive, as better appropriability conditions will provide better incentives to innovate and to patent high quality innovations. However, too much appropriability is detrimental to innovation. The obvious interpretation of this finding is that while an initial increase in patent protection (which will inadvertently vary across sectors and technologies even if the overall legal environment were identical) is conducive to innovation, too strong a patent protection can be detrimental. This finding echoes a concern that has been stated by many previous researchers, both in empirical and theoretical work (Lerner, 2002; Gallini, 1992, 2002).

However, it is also possible that the appropriability indicator (which is the rate of self-citations at the firm level) is acting as a proxy for a more fundamental attribute of the firm's technological environment. Keep in mind that different meanings can be attributed to, or will be correlated with, the rate of self-citations at the firm level. One such property is the *cumulativeness* of innovation; the extent innovations build on existing capabilities rather than being independently conceived. On the other hand, subscribing to a somewhat unusual interpretation of patent citations, it is easy to imagine that the rate of self-cites partly represents a firm's relative position with respect to its technological rivals. Increased self-citation rate (which also means lower rate of citations from other firms) could indicate that the firm in question is among the few that can capitalize on existing opportunities in the relevant technology field, and there aren't many other firms (competing or collaborating) that can dip into the same opportunity well. This interpretation would lend itself to an argument on the relationship between competition and innovation, between which many authors have found an inverted-U type relationship (Aghion et al, 2005; among others). In short, the effect of the self-citation rate on the rate and quality of innovation opens up interesting possibilities and questions for detailed future investigation.

9 Conclusion

Results of the paper are at odds with the Schumpeterian claim that large firms are the primary engine of innovation. I find evidence that innovation quality is randomly distributed among firms of different sizes. Neither small, nor large firms have inherent advantages in producing higher innovation quality. The paper emphasizes that patent quality has a large stochastic component, rendering its analyses difficult, as few variables are successful in explaining quality differences within and between firms. Indeed, investigating the determinants of innovation quality is a bit like looking for a needle in a haystack. However, I also find that the distribution of quality across innovating firms is not entirely random: It is affected by R&D intensity, technological diversity and appropriability conditions. It is observed that large firms have higher propensities to obtain "top quality" patents compared to small ones, but this is merely a result of the size of their patent cohorts, which supports the random distribution hypothesis.

The paper also highlighted problems with treating quality-adjusted patent counts as indicators of pure quality, as there is ample evidence that they are primarily driven by patent counts. It is best to treat quality-adjusted patent counts as alternative indicators of the *rate* of innovation, and not innovation *quality*. As found elsewhere, patents per R&D fall with firm size, and so do quality-adjusted patents per R&D. The relationship between quality-adjusted patents per R&D and technological diversity is highly non-linear, with polynomial expansion terms significant up to the cubic term. The shape of the polynomial is such that it increases for most of the support of the diversity variable, mostly indicating a U-shaped relationship, with a small S-shape at the lower end of the diversity scale.

Alternative explanations for the stochastic nature of innovation quality need to be highlighted. One intriguing possibility is that innovation quality is inherently unpredictable to a great extent, and differences across firms are mostly due to stochastic events that are outside the firm's control. Another possibility is that determinants of innovation success lie elsewhere: the firm's organizational choices, technological capabilities that are not visible in aggregate patent or accounting data, or communication channels through its management hierarchy. Examining such properties require a level of detail that immediately faces severe data constraints, but much can be accomplished by focusing on a carefully selected sample of industries or technologies, which will allow data collection for a small sample of innovating firms. However, we can comfortably rule out explanations that are due to unobserved permanent characteristics, and characteristics that are directly related to the size of the innovating firm. Finally, it is possible, however unlikely, that results of the paper are driven simply by patenting choices of innovating firms. If firms' patenting decisions with respect to the expected quality of innovation (and other characteristics) are uniform across innovating firms, this would lead to similar relationships between firm characteristics and innovation quality that we have observed. This is an unlikely explanation as highlighted by numerous studies that point to differences in the patenting practices and motives of small and large firms (Arundel and Kabla, 1998; Arundel, 2001; Leiponen and Bima, 2009; among others).

On the other hand, it is perhaps more likely that quality differences, and the quality distribution within firms are driven by more fundamental characteristics of the technological environment firms operate in. Future work needs to examine how the links between R&D investments, innovation rate and innovation quality is determined and conditioned by fundamental characteristics of the technologies involved, such as their current stages during the technology (and not just industry) life cycle, and the cumulativeness, radicality and sequentiality of innovation in the related technology field. There is some previous work on industry characteristics that are most conducive to innovation and how these characteristics condition the size-R&D-innovation relationship, but research on these issues is hampered by the lack of empirical measures for important theoretical constructs (Trajtenberg et al, 1997). Future research should also focus on uncovering and measuring the exact technological properties that determine, and condition the relative contribution of small and large firms.

It is surprising that innovation quality has been studied so scarcely compared to other aspects of innovation. Results of the current paper have several implications for innovation quality at the firm level, and suggests future work in several additional directions. An important recommendation of the current paper is that further studies of innovation quality need to pay focused attention to the entire *distribution* of innovation quality within firms, not just its average. Furthermore, by studying all USPTO patents that are assigned to manufacturing companies, this paper focused on large-scale and generalizable properties of innovation quality. While ample effort has been expanded to ensure comparability of quality indicators across different technologies, this general view certainly hides the finer details of the innovation process in each industry and the technologies behind its products. The trade-offs between generalizability and specificity should be evident. Examining innovation quality at smaller levels of aggregation, such as within specific and narrow technology fields, is a promising avenue and would supplement current analyses.

The article's results regarding appropriability conditions open up interesting questions as well. While it is possible to interpret these findings as pure productivity effects of the strength of IP protection, alternative explanations are possible, and future research needs to disentangle the separate roles of characteristics that may be correlated with the appropriability measure used in the current paper, the rate of self-citations.

10 References

1. Acs, Zoltan J., and David B. Audretsch., "R&D, firm size and innovative activity" in Zoltan J. Acs and David B. Audretsch (Eds.), *Innovation and Technological Change: An International Comparison*, (Ann Arbor: University of Michigan Press, 1991a).

2. Acs, Zoltan J., and Audretsch, David B., "Innovation and technological change: An overview", in Zoltan J. Acs and David B. Audretsch (Eds.), *Innovation and Technological Change: An International Comparison*, (Ann Arbor: University of Michigan Press, 1991b).

3. Acs, Zoltan J., David B. Audretsch. and Maryann P. Feldman (1994) "R&D Spillovers and Recipient Firm Size," *The Review of Economics and Statistics* 76(2): 336-340.

4. Agarwal, Rajshree, and David B. Audretsch (1999) "The two views of small firms in industry dynamics: a reconciliation," *Economics Letters* 62: 245-251.

5. Aghion, Philippe, Nick Bloom, Richard Blundell, Rachel Griffith and Peter Howitt (2005) "Competition and Innovation: An Inverted-U Relationship," *The Quarterly Journal of Economics* 120(2): 701-728.

6. Albert, M.B., D. Avery, F. Narin and P. McAllister (1991) "Direct validation of citation counts as indicators of industrially important patents," Research Policy 20(3): 251-259.

7. Arrow, Kenneth J., "Economic welfare and the allocation of resources for invention," in Richard R. Nelson (Ed.), *The rate and direction of inventive activity: Economic and social factors*, (Princeton, NJ: Princeton University Press, 1962).

8. Arundel, Anthony (2001) "The relative effectiveness of patents and secrecy for appropriation," *Research Policy* 30: 611-624.

9. Arundel, Anthony and Isabelle Kabla (1998) "What percentage of innovations are patented? Empirical estimates for European firms," *Research Policy* 27: 127-141.

10. Atallah, Gamal and Gabriel Rodríguez (2006) "Indirect patent citations," *Scientometrics* 67(3): 437-465.

11. Audretsch, David B. and Zoltan J. Acs (1991) "Innovation and Size at the Firm Level," *Southern Economic Journal* 57(3): 739-744.

12. Bartelsman, Eric J. and Wayne Gray (1996) "The NBER Manufacturing Productivity Database," NBER technical working paper no. 205.

13. Baltagi, Badi H. and Ping X. Wu (1999) "Unequally spaced panel data regressions with AR(1) disturbances," *Econometric Theory* 15(6): 814-823.

14. Bessen, James (2009) "NBER PDP Project User Documentation: Matching Patent Data to Compustat Firms," unpublished manuscript.

15. Bhargava, Alok, Luisa Franzini and Wiji Narendranathan (1982) "Serial correlation and fixed effects model," *Review of Economic Studies* 49(4): 533-549.

16. Bomberger, Earl E. (1982) “The relationship between industrial concentration, firm size, and technological innovation,” report prepared for the Office of Advocacy, U.S. Small Business Administration under award no. SBA-2633-OA-79, May 1982.

17. Bound, John, Clint Cummins, Zvi Grilliches, Bronwyn H. Hall, and Adam Jaffe, "Who Does R&D and Who Patents?," in Zvi Griliches (Ed.), *R&D, Patents and Productivity* (Chicago, IL: University of Chicago Press, 1984).

18. Breschi, Stefano, Franco Malerba and Luigi Orsenigo (2000) "Technological Regimes and Schumpeterian Patterns of Innovation," *The Economic Journal* 110: 388-410.

19. Breschi, Stefano, Francesco Lissoni, and Franco Malerba (2003) "Knowledge-relatedness in firm technological diversification," *Research Policy* 32: 69–87.

20. Chakrabarti, Alok K. and Michael R. Halperin (1991) "Technical performance and Firm Size: Analysis of Patents and Publications of U.S. Firms," *Small Business Economics* 2: 183-190.

21. Cockburn, Iain M. and Rebecca M. Henderson (2001) "Scale and scope in drug development: unpacking the advantages of size in pharmaceutical research," *Journal of Health Economics* 20: 1033-1057.

22. Cohen, Wesley M. and Steven Klepper (1996) "A Reprise of Size and R&D," *The Economic Journal* 106: 925-951.

23. Comanor, William S. (1967) "Market Structure, Product Differentiation, and Industrial Research," *The Quarterly Journal of Economics* 81(4): 639-657.

24. Cooper, Arnold C. (1964) "R&D is More Efficient in Small Companies," *Harvard Business Review* 42(3): 75-83.

25. Culbertson, John D. and Willard F. Mueller (1980) “The Influence of Market Structure on Technological Performance in the Food Manufacturing Industries,” University of Wisconsin-Madison, Department of Agricultural & Applied Economics, Food Systems Research Group working paper no. 47.

26. de Rassenfosse, Gaetan and Bruno van Pottelsberghe de la Potterie (2009) "A policy insight into the R&D-patent relationship," *Research Policy* 38: 779-792.

27. de Rassenfosse, Gaetan (2010) "Productivity and Propensity: The Two Faces of the R&D-Patent Relationship," ECARES working paper no. 2010-23, Univérsite Libre de Bruxelles.

28. Edwards, Keith L., and Theodore Gordon (1982) "Characterization of Innovations Introduced on the U.S. Market in 1982," report prepared for the U.S. Small Business Administration under contract no. SBA-6050-0A-82 (March 1982).

29. Fisher, Franklin M. and Peter Temin (1973) "Returns to Scale in Research and Development: What does the Schumpeterian Hypothesis Imply?" *The Journal of Political Economy* 81(1): 56-70.

30. Freeman, Chris (1971) "The Role of Small Firms in Innovation in the United Kingdom since 1945," Research Report No. 6. Committee of Inquiry on Small Firms. London: Her Majesty's Stationery Office.

31. Galbraith, John Kenneth, *American Capitalism: The Concept of Countervailing Power*, (Boston, MA: Houghton Mills, 1956).

32. Gallini, Nancy T. (1992) "Patent Policy and Costly Imitation," *RAND Journal of Economics* 23(1): 52-63.

33. Gallini, Nancy T. (2002) "The Economics of Patents: Lessons from Recent U.S. Reform," *Journal of Economic Perspectives* 16(2): 131–154.

34. Gambardella, Alfonso and Salvatore Torrisi (1998) "Does technological convergence imply convergence in markets? Evidence from the electronics industry," *Research Policy* 27, 445-463.

35. Garcia-Vega, Maria (2006) "Does technological diversification promote innovation? An empirical analysis for European firms," *Research Policy* 35: 230-246.

36. Goodall, Amanda H. (2009) "Highly cited leaders and the performance of research universities," *Research Policy* 38: 1079-1092.

37. Granstrand, Ove and Christer Oskarsson (1994) "Technology Diversification in "MUL-TECH" Corporations," *IEEE Transactions on Engineering Management* 41(4): 355-364.

38. Griliches, Zvi (1990) "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature* 28(4): 1661-1707.

39. Hall, Bronwyn H. (2002) "The financing of research and development," *Oxford Review of Economic Policy* 18: 35-51.

40. Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg (2001) "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools," NBER working paper no. 8498.

41. Hamberg, Daniel, *R&D: Essays on the Economics of Research and Development*, (New York, NY: Random House, 1966).

42. Harhoff, Dietmar, Francis Narin, Frederic M. Scherer and Katrin Vopel (1999) "Citation Frequency and the Value of Patented Inventions," *Review of Economics and Statistics* 81(3): 511-515.

43. Harhoff, Dietmar, Frederic M. Scherer and Katrin Vopel (2003) "Citations, family size, opposition and the value of patent rights," *Research Policy* 32: 1343-1363.

44. Henderson, Rebecca M. and Iain M. Cockburn (1996) "Scale, Scope and Spillovers: The Determinants of Research Productivity in Drug Discovery," *The RAND Journal of Economics* 27(1): 32-59.

45. Huang, Yi-Fen, and Chung-Jen Chen (2010) "The impact of technological diversity and organizational slack on innovation," *Technovation* 30: 420-428.

46. Idson, Todd L., and Walter Y. Oi (1999) "Workers are More Productive in Large Firms", *The American Economic Review* 89:2, Papers and Proceedings of the One Hundred Eleventh Annual Meeting of the American Economic Association, 104-108.

47. Jaffe, Adam B. (1986) "Technological Opportunity and Spillovers of R&D: Evidence From Firms' Patents, Profits, and Market Value," *The American Economic Review* 76(5): 984-1001.

48. Jaffe, Adam B. (2000) "The U.S. patent system in transition: policy innovation and the innovation process", *Research Policy* 29: 531–557.

49. Jewkes, John, David Sawers and Richard Stillerman, *The Sources of Invention* (2nd edition), (New York, NY: Norton, 1971).

50. Johannisson, Bengt and Christian Lindström (1971) “Firm Size and Inventive Activity,” *The Swedish Journal of Economics*, 73(4): 427-442.

51. Kamien, Morton I. and Nancy L. Schwartz (1975) "Market Structure and Innovation: A Survey," *The Journal of Economic Literature* 13(1): 1-37.

52. Kim, Jinyoung, Sangjoon John Lee, and Gerald Marschke (2009a) "Inventor Productivity and Firm Size: Evidence From Panel Data on Inventors", *Pacific Economic Review* 14(4): 513-531.

53. Kim, Jinyoung, Sangjoon John Lee, and Gerald Marschke (2009b) "Relation of Firm Size to R&D Productivity", *International Journal of Business and Economics* 8(1): 7-19.

54. Kleinknecht, A. (1987), "Measuring R & D in Small Firms: How Much are we Missing?", *The Journal of Industrial Economics* 36(2): 253-256.

55. Lanjuow, Jean O., and Mark Schankerman (2004) "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators," *The Economic Journal* 114: 441-465.

56. Leiponen, Aija and Justin Bima (2009) "If you cannot block, you better run: Small firms, cooperative innovation, and appropriation strategies," *Research Policy* 38: 1478-1488.

57. Lerner, Josh (2002) "Patent Protection and Innovation over 150 Years," NBER working paper no. 8977.

58. Link, Albert N. and John Rees, "Firm size, university-based research and the returns to R&D," in Zoltan J. Acs and David B. Audretsch (Eds.), *Innovation and Technological Change: An International Comparison*, (Ann Arbor: University of Michigan Press, 1991).

59. MacDonald, James M. (1985) "R&D and the directions of diversification," *The Review of Economics and Statistics* 67: 583-590.

60. Mansfield, Edwin (1964) "Industrial Research and Development Expenditures: Determinants, Prospects, and Relation to Size of Firm and Inventive Output," *The Journal of Political Economy* 72(4): 319-340.

61. Mason, Edward S. (1951) "Schumpeter on Monopoly and the Large Firm," *The Review of Economics and Statistics* 33(2): 139-144.

62. Miller, Douglas J. (2006) "Technological Diversity, Related Diversification, and Firm Performance," *Strategic Management Journal* 27: 601-619.

63. Mueller, Willard F. (1957) "A Case Study of Product Discovery and Innovation Costs," *Southern Economic Journal* 24(1): 80-86.

64. Nelson, Richard R. (1959) "The Simple Economics of Basic Scientific Research," *Journal of Political Economy* 67(3): 297-306.

65. Nesta, Lionel and Pier P. Saviotti (2005) "Coherence of the Knowledge Base and the Firm's Innovative Performance: Evidence from the U.S. Pharmaceutical Industry," *The Journal of Industrial Economics* 53(1): 123-142.

66. Pavitt, Keith (1998) "Technologies, products and organization in the innovating firm: what Adam Smith tells us and Joseph Schumpeter does not," *Industrial and Corporate Change* 7(3): 433-452.

67. Pavitt, Keith, Michael Robson, and Joe Townsend (1987) "The Size Distribution of Innovative Firms in the U.K.: 1945-1983", *The Journal of Industrial Economics* 35(3): 297-316.

68. Plehn-Dujowich, Jose M. (2009) "Firm size and types of innovation," Economics of Innovation and New Technology 18(3): 205-223.

69. Quintana-García, Cristina and Carlos A. Benavides-Velasco (2008) "Innovative competence, exploration and exploitation: The influence of technological diversification," *Research Policy* 37: 492-507.

70. Reinganum, Jennifer F. (1983) "Uncertain Innovation and the Persistence of Monopoly," *The American Economic Review* 73: 61-66.

71. Rothwell, Roy (1989) "Small Firms, Innovation and Industrial Change," *Small Business Economics* 1: 51-64.

72. Scherer, Frederic M. (1965) "Firm size, market structure, opportunity and the output of patented innovations," *The American Economic Review* 55(5): 1097-125.

73. Scherer, Frederic M., *Industrial Market Structure and Economic Performance,* 2nd ed. (Chicago, IL: Rand McNall, 1980).

74. Scherer, Frederic M., (1983) "The Propensity to Patent," *International Journal of Industrial Organization* 1(1), 107-128.

75. Schumpeter, Joseph, A., *Capitalism, Socialism and Democracy*, (New York, NY: Harper, 1942)

76. Schwalbach, Joachim and Klaus F. Zimmerman, "A Poisson model of patenting and firm structure in Germany," in Zoltan J. Acs and David B. Audretsch (Eds.), *Innovation and Technological Change: An International Comparison*, (Ann Arbor: University of Michigan Press, 1991).

77. Scott, John T., *Purposive Diversification and Economic Performance*, (Cambridge,MA: Cambridge University Press, 1993).

78. Shimshoni, Daniel (1970) "The Mobile Scientist in the American Instrument Industry," *Minerva* 8(1-4): 59-89.

79. Stock, Gregory N., Noel P. Greis and William A. Fischer (2002) "Firm size and dynamic technological innovation," *Technovation* 22: 537-549.

80. Teece, David J., Richard Rumelt, Giovanni Dosi and Sidney G. Winter (1994) "Understanding corporate coherence: theory and evidence," *Journal of Economic Behaviour and Organization* 23: 1-3.

81. Trajtenberg, Manuel (1990) "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *RAND Journal of Economics* 21(1): 172-189.

82. Trajtenberg, Manuel, Rebecca Henderson, and Adam B. Jaffe (1997) "University versus Corporate Patents: A Window on the Basicness of Invention", *Economics of Innovation and New Technology* 5(1): 19-50.

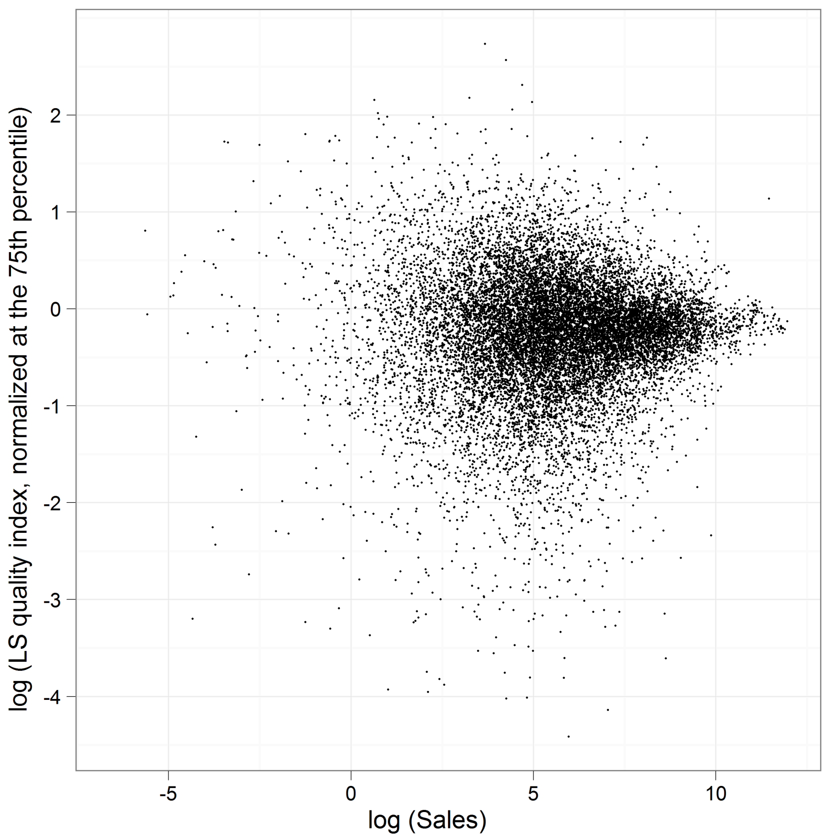

Figure 1: Scatterplot of average patent quality (logarithm of the Lanjuow and Schankermann index, normalized) against firm sales, plotted at the firm level. Each dot represents a firm-year observation.

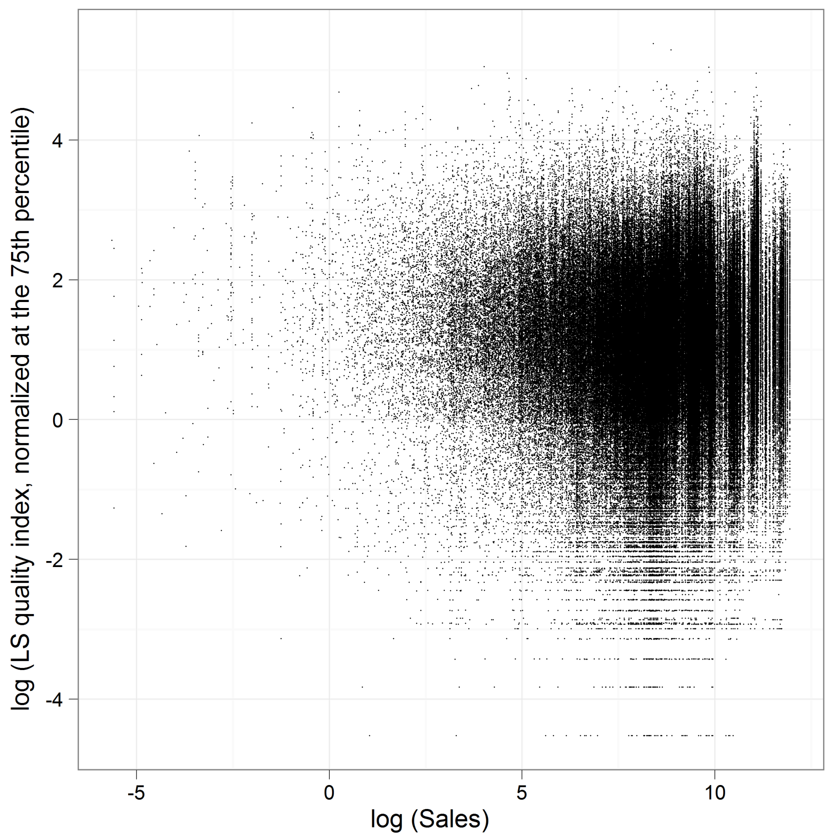

Figure 2: Scatterplot of patent quality (logarithm of the Lanjuow and Schankermann index, normalized) against firm sales, plotted at the patent level. Each dot represents a single patent.

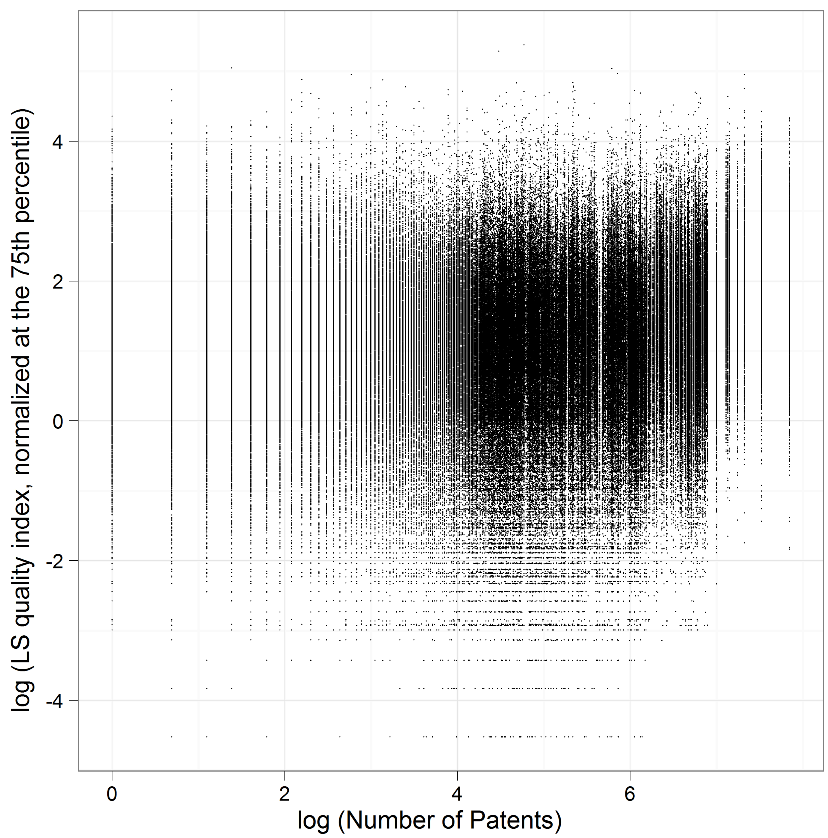

Figure 3: Scatterplot of patent quality (logarithm of the Lanjuow and Schankermann index, normalized) against the (logarithm of) annual patent count of the firm that owns the patent. Each dot represents a single patent.

Table 1
Sample Statistics
Sample with non-zero patents, citations and R&D

	Mean	**Median**	**Standard Deviation**	**Minimum**	**Maximum**
Patents	25,16	4,00	80,53	1,00	2559,00
Citations	376,34	59,23	1485,57	1,04	57356,70
Citations, *Normalized*	21,79	3,70	71,26	0,03	2361,13
Importance	2801,70	333,03	11587,20	1,05	350817,13
Importance, *Normalized*	28,16	4,11	96,60	0,00	3247,25
Lanjuow & Schankerman (2004) index	120,23	16,81	516,25	0,05	19246,61
Lanjuow & Schankerman (2004) index, *Normalized*	22,33	3,69	71,51	0,02	2202,09
R&D Expenditures	82,71	10,11	360,89	0,00	8026,67
Patents and Quality-Adjusted patents per R&D					
PR (Patents per R&D)	1,43	0,52	5,95	0,00	307,06
CR (Citations per R&D)	1,67	0,19	9,97	0,00	548,06
CR (Citations per R&D), *Normalized*	1,31	0,41	6,17	0,00	258,36
IR (Importance per R&D)	177,81	33,69	1149,88	0,02	68736,29
IR (Importance per R&D), *Normalized*	1,60	0,44	8,14	0,00	339,44
LSR (LS Quality per R&D)	6,01	1,86	29,12	0,00	2133,53
LSR (LS Quality per R&D), *Normalized*	1,26	0,42	5,22	0,00	232,86
Average Quality					
CP (Citations per Patent)	17,07	11,91	18,60	0,45	243,11
CP (Citations per Patent), *Normalized*	0,97	0,80	0,81	0,03	13,24
IP (Importance per Patent)	128,45	63,98	247,38	0,45	8165,47
IP (Importance per Patent), *Normalized*	1,22	0,85	1,55	0,00	28,49
LSP (LS Quality per Patent)	4,80	3,63	4,61	0,05	97,24
LSP (LS Quality per Patent), *Normalized*	0,94	0,83	0,62	0,02	13,03
Independent Variables					
Sales	2249,04	298,91	8138,40	0,00	155067,43
Technological Diversity	0,49	0,56	0,36	0,00	0,99
Age	16,89	17,00	9,89	1,00	38,00
R&D Intensity	0,18	0,06	0,63	0,00	25,32
Capital/Labor ratio	84,17	61,59	86,48	0,91	1073,97
Appropriability	0,07	0,04	0,10	0,00	0,88
Visibility	38,74	8,00	83,19	0,00	1193,00
External Variables (3-digit SIC and Technological Proximity)					
Spillover Pool (in logs)	9,71	9,84	0,83	4,58	11,43
Technological Opportunity	0,02	0,01	0,08	-0,39	4,50
Industry Sales (Value of Shipments)	39788,48	26042,00	44270,69	557,20	327907,50
Industry Growth (Growth of Value of Shipments)	0,08	0,08	0,09	-0,36	0,56

NOTES: All citations are non-self cites and are corrected for time truncation, except those used in the calculation of the Lanjuow & Schankerman quality index (which uses total citations during fixed time windows following patent application). Normalization is performed on each quality index before taking logarithms. All dollar values are in millions of 1992 dollars, deflated using the GNP deflator. Employment is in thousands of employees. All logarithms are natural logs. Sample size: 11860. Sample period: 1976-1995.

Table 2
Correlation Matrix

Variable Name	Abbrev.	log (S)	Tech. Div.	log (A)	log (R/C)	log (P/R)	log (C/E)	App	SP	Tech. Opp.	Vis	Ind S	Ind Gr
log (Sales)	log (S)	1											
Technological Diversity	Tech. Div.	0,58	1										
log (Age)	log (A)	0,61	0,38	1									
log (R&D Intensity)	log (R/C)	-0,46	-0,09	-0,38	1								
log (Patents/R&D)	log (P/R)	-0,38	0,04	-0,15	-0,26	1							
log (Capital/Employment)	log (C/E)	0,39	0,23	0,19	-0,33	-0,18	1						
Appropriability	App.	0,13	0,17	0,08	0,03	0,04	0,12	1					
Spillovers	SP	0,32	0,44	0,24	0,20	-0,30	0,21	0,06	1				
Technological Opportunity	Tech. Opp.	-0,12	-0,02	-0,11	0,32	-0,08	0,01	-0,01	0,18	1			
Visibility	Vis	0,58	0,55	0,50	0,02	-0,21	0,28	0,17	0,55	0,15	1		
log (Industry Size)	Ind S	0,04	0,05	0,00	0,21	-0,17	0,16	0,01	0,36	0,27	0,28	1	
Industry Growth	Ind Gr	-0,04	-0,01	-0,11	0,06	0,01	-0,12	-0,04	-0,07	-0,01	-0,17	-0,03	1
Dependent Variables													
log (Citations/Patents)	log (CP)	-0,03	0,08	-0,08	0,19	-0,07	-0,01	-0,05	0,10	0,06	0,06	0,04	0,03
log (Importance/Patents)	log (IP)	0,03	0,17	-0,04	0,19	-0,06	0,02	0,09	0,13	0,06	0,13	0,03	0,03
log (LS Quality /Patents)	log (LSP)	0,00	0,10	-0,05	0,17	-0,03	0,01	0,17	0,09	0,08	0,10	0,06	0,00
log (Citations/R&D)	log (CR)	-0,36	0,07	-0,17	-0,14	0,87	-0,17	0,01	-0,22	-0,04	-0,16	-0,14	0,03
log (Importance/R&D)	log (IR)	-0,30	0,13	-0,14	-0,10	0,79	-0,14	0,09	-0,17	-0,03	-0,09	-0,12	0,03
log (LS Quality/R&D)	log (LSR)	-0,35	0,07	-0,15	-0,17	0,91	-0,17	0,11	-0,24	-0,05	-0,15	-0,14	0,01

Table 3
Correlations between innovation indicators

Dependent Variables		log (PR)	log (CR)	log (IR)	log (LSR)	log (CP)	log (IP)	log (LSP)
log (Patents/R&D)	log (PR)	1						
log (Citations/R&D)	log (CR)	**0,87**	1					
log (Importance/R&D)	log (IR)	**0,79**	0,96	1				
log (LS/R&D)	log (LSR)	**0,91**	0,94	0,91	1			
log (Citations/Patents)	log (CP)	-0,07	0,42	0,50	0,24	1		
log (Importance/Patents)	log (IP)	-0,06	0,40	0,57	0,26	0,92	1	
log (LS/Patents)	log (LSP)	-0,03	0,33	0,43	0,39	0,73	0,74	1

Table 4 **Patents and Quality-Adjusted Patents per R&D**
Fixed Effects regressions with AR(1) correction

	Patents		Quality – Adjusted Patents					
	log (PR): Patents per R&D		log (CR): Citations per R&D Normalized at 75th percentile		log (IR): Importance per R&D Normalized at 75th percentile		log (LSR): Lanjuow & Schankermann (2004) Quality Index Normalized at 75th percentile	
	1		2		3		4	
log (Sales)	-0.428**	(-27.86)	-0.471**	(-18.03)	-0.476**	(-14.78)	-0.467**	(-19.09)
Technological Diversity	0.186**	(17.93)	0.190**	(9.33)	0.221**	(8.57)	0.217**	(11.72)
Squared	-0.428**	(-16.14)	-0.481**	(-9.23)	-0.532**	(-8.08)	-0.498**	(-10.45)
Cubed	0.294**	(20.23)	0.331**	(11.71)	0.363**	(10.15)	0.331**	(12.78)
log (Age)	-0.194**	(-4.42)	-0.273**	(-4.22)	-0.302**	(-3.85)	-0.263**	(-4.24)
log (R&D Intensity)	-0.826**	(-60.05)	-0.811**	(-32.72)	-0.798**	(-25.94)	-0.811**	(-35.42)
log (Capital/Employment)	-0.603**	(-25.34)	-0.617**	(-14.69)	-0.594**	(-11.44)	-0.644**	(-16.44)
Appropriability	0.516**	(5.81)	0.784**	(3.77)	1.717**	(7.58)	2.296**	(14.48)
Squared	-0.727**	(-5.06)	-3.826**	(-8.53)	-3.451**	(-8.67)	-2.958**	(-11.47)
Spillovers	0.217**	(4.62)	0.283**	(3.57)	0.301**	(3.06)	0.345**	(4.69)
Technological Opportunity	0.225**	(2.88)	0.295*	(1.86)	0.180	(0.89)	0.312**	(2.17)
Visibility	0.0047	(0.28)	-0.0336	(-1.17)	-0.0585*	(-1.65)	-0.0638**	(-2.37)
log (Industry Size)	0.0832**	(2.01)	0.0478	(0.68)	0.0411	(0.47)	0.0025	(0.04)
Industry Growth	-0.0351	(-0.59)	0.0581	(0.51)	0.0608	(0.42)	0.115	(1.10)
Year Dummies (1977-1995)	YES		YES		YES		YES	
Dummy for Patents in {1,2}	YES		YES		YES		YES	
Intercept	-0.0799**	(-2.27)	0.0564	(0.62)	0.115	(0.94)	0.0445	(0.57)
R-squared	0.650		0.382		0.311		0.425	
Modified Durbin-Watson	1.077		1.444		1.510		1.394	
LBI (Baltagi & Wu 1999)	1.454		1.902		1.970		1.864	
ρ	0.537		0.364		0.332		0.396	
N	10439		10317		10328		10414	

Notes: *t*-statistics are reported in paranthesis. Non-self cites are excluded while constructing CR and IR. All logarithms are natural logs.

Significance indicators: ** $p < 0.05$, * $p < 0.10$.

Table 5 **Average Patent Quality**
Fixed Effects regressions with AR(1) correction

	Dependent Variable: Average Patent Quality					
	log (CP): Citations per Patent, Normalized at 75th percentile		**log (IP): Importance per Patent (Trajtenberg et al, 199x) Normalized at 75th percentile**		**log (LSP): Lanjuow & Schankermann (2004) Quality Index Normalized at 75th percentile**	
	1		**2**		**3**	
log (Sales)	0.0121	(0.55)	0.0332	(1.13)	0.0212	(1.09)
Technological Diversity	0.0193	(1.26)	0.0490**	(2.38)	0.0427**	(3.21)
Squared	-0.0110	(-0.84)	-0.0149	(-0.85)	-0.0270**	(-2.37)
log (Age)	-0.0646	(-1.31)	-0.0842	(-1.27)	-0.0542	(-1.22)
log (R&D Intensity)	0.0445*	(1.87)	0.0886**	(2.77)	0.0526**	(2.51)
log (Patents/R&D)	0.0179	(1.14)	0.0549**	(2.61)	0.0292**	(2.12)
log (Capital/Employment)	-0.0015	(-0.04)	0.0429	(0.92)	-0.0200	(-0.65)
Appropriability	0.0762	(0.44)	1.136**	(5.65)	1.711**	(13.58)
Squared	-2.564**	(-6.89)	-2.647**	(-7.49)	-2.142**	(-10.44)
Spillovers	0.0124	(0.20)	0.00345	(0.04)	0.0638	(1.14)
Technological Opportunity	-0.0800	(-0.60)	-0.225	(-1.25)	0.0081	(0.07)
Visibility	-0.0556**	(-2.46)	-0.0823**	(-2.69)	-0.0767**	(-3.81)
log (Industry Size) (3-digit SIC)	-0.0034	(-0.06)	-0.0016	(-0.02)	-0.0414	(-0.84)
Industry Growth (3-digit SIC)	0.0804	(0.85)	0.0731	(0.58)	0.121	(1.47)
Year Dummies (1977-1995)	YES		YES		YES	
Dummy for Patents in {1,2}	YES		YES		YES	
Intercept	0.0904	(1.02)	0.145	(1.22)	0.103	(1.42)
R-squared	0.0314		0.0256		0.0380	
Modified Durbin-Watson	1.602		1.601		1.566	
LBI (Baltagi & Wu 1999)	2.101		2.087		2.094	
ρ	0.295		0.295		0.321	
N	10317		10328		10414	

Notes: *t*-statistics are reported in paranthesis. Non-self cites are excluded while constructing CP and IP. All logarithms are natural logs.
Significance: ** $p < 0.05$, * $p < 0.10$.