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Abstract

Using firm level panel data from the U.S., I explore the relationship between firm size and R&D productivity for two important and R&D-intensive industries: Semiconductors and Pharmaceuticals. I employ two measures of a firm's R&D performance: the number of citations received per patented innovation, and the number of citations received per dollar of R&D expenditures. The former is a measure of the average quality of a firm's patents, and the latter is a measure of total R&D output obtained per dollar of investments. I find that the average quality of patents (citations received per patent) falls with firm size in Pharmaceuticals, but there is no relationship between patent quality and firm size in Semiconductors. Citations received per R&D dollar decrease with size in both industries, which is due to the well-documented negative relationship between patents per R&D and firm size.

Keywords: R&D Productivity, Firm size, Patents, Citations, Semiconductors, Pharmaceuticals, Panel data.

1 INTRODUCTION

The Schumpeterian hypothesis has been a source of much heated debate among economists. While some economists, starting with Schumpeter (1942), claimed that large enterprises are the primary engines of innovation and economic growth, others found evidence for both small-firm and large-firm advantages in innovation. The presence of large fixed costs in innovation (Galbraith, 1952), economies of scale and scope in R&D (Galbraith, 1952; Comanor, 1967), benefits of diversified product lines (Nelson, 1959), ability to spread the risks (Nelson, 1959) and costs (Cohen & Klepper, 1996) of R&D projects, easier access to external financing (Galbraith, 1952; Rothwell, 1989), and possible advantages in the scientific labor market (Idson & Oi, 1999; Kim, Lee & Marschke, 2009a) are commonly stated factors favoring large firm productivity. On the other hand, small firms may have advantages in performing R&D due to a (comparative) lack of bureaucracy (Scherer, 1980; Cooper, 1964; Blair, 1972), flexible decision making processes (Freeman & Soete, 1997; Rothwell, 1989) and a lack of the agency problems that may occur due to the incontractibility of the output of a single scientist in large firms (Lewis & Yao, 2001). Small firms are also argued to have better R&D performances since they tend to be more efficient receivers of spillovers (Acs, Audretsch & Feldman, 1994; Audretsch & Vivarelli, 1994; Shimshoni, 1970). Since it is possible to state reasons for higher productivity in both small and large firms, the final verdict on the Schumpeterian hypothesis needs to come from empirical research (Scherer, 1980).

In this article I perform an empirical test of the Schumpeterian hypothesis on two important R&D-intensive industries in the U.S: Pharmaceuticals and semiconductors. For this purpose I use two different (but related) measures of a firm's R&D output: the number of citations received per patented innovation, and the number of citations received per dollar of R&D expenditures. The former is meant as a proxy for the average quality of firm's patents, while the latter is a proxy for total output achieved per dollar of R&D investments.

Focusing on individual industries has the advantage that economic units are technologically similar, thus citation counts belonging to different firms are comparable with one another. This, of course, comes at the cost of losing generality since we have to make inferences about relatively narrow industry classifications. An empirical analysis of larger magnitude that spans a large number of industry classifications needs to take additional caution to ensure that cross-industry differences in citation (and patenting) rates are not driving the main results. Such an effort is undertaken by Dindaroglu (2010), who addresses the same research question using a large panel of U.S. manufacturing firms, and discusses some of these issues in further detail.

2 BACKGROUND

The relationship between firm size and R&D performance is among the most intensely debated questions in the economics of innovation. R&D performance is traditionally measured by patents (or patents per R&D dollar), or innovation counts. While there are conflicting results, the literature at large does not support the Schumpeterian hypothesis, and often finds evidence on the contrary. In an influential paper, Scherer (1965) studied the relationship between patenting and firm size for the 1955 cross section of the largest firms in U.S. 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. Bound et al (1984) found that smaller firms obtained a larger number of patents per dollar of R&D expenditures in a 1976 cross section of U.S. manufacturing firms. Similar results have been found by Johannisson and Lindstrom (1971) in Swedish, and by Schwalbach and Zimmerman (1991) in German manufacturing. Therefore, such results are not confined to the U.S.

Some authors have utilized databases of significant innovations to study the relationship between firm size and innovation counts[1] . Pavitt, Robson & Townsend (1987) used the database of significant innovations compiled by the Science Policy Research Unit (SPRU) of the University of Sussex to show that there is a U-shaped relationship between size and innovation intensity. Acs & Audretsch (1991a) concluded that the data supported the hypothesis of a negative innovation-firm size relationship as a general rule, while Audretsch and Acs (1991) found a negative relationship between firm size and the number of innovations per employee[2].

The problems with using patents as indicators of innovative performance are well-documented (see, for instance, Griliches 1990). Most importantly, patent counts (or stocks) treat all patents as identical, which can be greatly misleading (Cohen & Levin, 1989; Acs & Audretsch, 1991b). Studies that use patents as indicators of inventive activity are also problematic due to the observed heterogeneity in propensities to patent across industries (Scherer, 1983). Thus, it is usually not clear whether results are due to differences in R&D productivity or differences in propensities to patent across economic units. The use of R&D expenditures is additionally problematic due to the

[1] For a detailed discussion on these databases, see Acs & Audretsch (1990).

[2] For extensive surveys of the literature between size and innovation, see Symenoidis (1996), Cohen (1995), and Cohen & Levin (1989), as well as the volumes by Acs & Audretsch (1990, 1991b) and Kamien & Schwartz (1982). Scherer (1980, Ch.15) provides an early but excellent discussion on the topic.

bias in reported R&D. This problem is especially pronounced for small firms (Kleinknecht, 1989). Returns to R&D, or R&D-weighted output indicators can therefore be biased, and spurious results may emerge due to the underreporting of R&D by small firms.

The use of innovation counts, on the other hand, fails to account for the variation in the quality of innovations in a systematic way. Hence, this approach mirrors the traditional treatment of patents and R&D dollars as homogenous units, thus inherits the problems therein. It is possible that there are important quality-quantity trade-offs in innovation. That is, even though large firms obtain patented innovations less frequently, it is possible that their patents are of higher quality. In other words, large-firm advantages in innovation may be favorable to the quality of innovations rather than their quantity. This possibility sheds additional doubt on previous results that are obtained using patent and innovation counts as output indicators. Hence, it needs to be properly examined.

This chapter addresses this very issue by employing two measures of a firm's R&D output that have not been previously employed in this line of research. These are the average number of citations received by a company's patents, i.e., *citations per patent* (Citations/Patents; henceforth CP), and *citations received per R&D dollar spent* (Citations/R&D Expenditures; henceforth CR). CP is meant as a proxy for the average quality of a firm's patented innovations, while CR is a measure of the total value generated per dollar of R&D inputs. It is well established that the number of citations made to a given patent is a proxy for its quality (see Trajtenberg, 1990, and the literature that follows). Another important advantage of using CP as an output measure is that it avoids the previously mentioned problems with reported R&D expenditures. Also, studying the variation in CP offers a means to look at innovative output net of the propensity to patent. On the other hand, an important weakness of using CP and CR in the current context is that we do not observe citations for innovations that do not lead to patenting for various reasons. Thus, these measures also inherit some weaknesses of patent data. It should also be noted that CP is a direct indicator of patent *quality*, while CR is not. This is because CR is highly correlated with patents obtained per R&D dollar, which is not necessarily the case for CP. Most granted patents receive at least one citation (while very few receive many), which implies that the total number of citations is highly influenced by the total number of patents at the firm level.

The use of patent citations is now common practice in the economics of innovation. In addition, a small number of authors have used citation data in order to study the relationship between firm size and innovative output. Plehn-Dujowich (2009) finds that patents and citations received per

R&D stock falls with firm size in a cross section of 1976 patents. Huang & Chen (2010), while studying the relationship between R&D performance and technological diversification, control for firm size in their regressions and find that the number of citations received by a firm's patents increase with firm size at a decreasing rate. This finding implies that citations received per R&D dollar falls with firm size. These papers are similar to the current one in their use of citations as proxies for R&D output. However, neither paper attempts to use a quality indicator that is independent of the sizes of patent cohorts. As a result, their analyses that use citations do not provide qualitatively different results than their analyses using patent counts. A similar caution also emerges from Lanjuow & Schankerman (2004), who construct an index of patent quality by taking the common factor of five patent characteristics, including the number of citations received and made. In their analyses, their patent quality index does not behave much differently than simple patent counts unless average patent quality is taken into account rather than total quality. To repeat, total citation counts are not very good indicators of the quality of a firm's innovations since citation counts are highly correlated with patent counts at the firm level. I study the determinants of citations received per patent, which is a more direct indicator of quality, and is more useful to capture possible quality-quantity trade-offs in innovation. Also note that CP is used as a measure of patent quality in different contexts by Ernst (1998) and Narin (2006).

2.1 Pharmaceutical and Semiconductor Industries

Pharmaceutical and semiconductor industries have been fertile ground to test various hypotheses in the economics of innovation due to their dependence on innovation, and their importance for the U.S. economy. Large firms have dominant roles in both industries, mergers have been increasingly common, but the number of small firms has also been increasing during the period under study in the current paper (Graves & Langowitz, 1993; Hall & Ziedonis, 2007; Demirel & Mazzucato, forthcoming). Thus, whether these industries exhibit economies or diseconomies of scale in innovation has been extremely relevant. The pharmaceutical industry has been studied relatively more extensively due to data availability. Comanor (1965) found evidence for scale economies for the lower end of the size distribution of pharmaceutical firms, but scale diseconomies for the higher end. On the other hand, Vernon & Gusen (1974) and Schwartzman (1976) reported significant economies of scale. Graves & Langowitz (1992, 1993) found evidence for decreasing returns to scale in pharmaceutical R&D in the production of new chemical entities and the number of innovations. Jensen (1987) found that firm size did not affect the marginal productivity of R&D efforts beyond a certain size threshold. Henderson & Cockburn (1996) find large firms to be more productive in R&D due to economies of scale and scope. In subsequent work, the same authors report size advantages to be primarily due to scope, rather than scale economies (Cockburn & Henderson, 1996). Dimasi, Grabowski & Vernon (1995) use project-level data obtained from 12 U.S. pharmaceutical companies to claim that the cost of new drug development decreases with firm size, while sales per marketed drug falls with size. In a recent article, Plotnikova (2010) adds to this by showing that scale economies are present in pharmaceuticals during the initial stages of drug development (i.e., the development of new ideas), but large scale is detrimental to project success during later stages (i.e., actual product development).

Empirical literature on the semiconductor industry in the current context lags behind that for pharmaceuticals. In an article highly related to the current one, Kim & Marschke (2009) show that patents per dollar of R&D expenditures decline with firm size in U.S. semiconductor and pharmaceutical industries. Rothwell (1984, 1989) emphasizes the role of small firms in this industry and makes a case for the importance complementarities between small and large firms. Saxenian (1994) argues that spin-offs and the mobility of talented personnel have been responsible for the success of the semiconductors industry (and the Silicon Valley at large). Hall & Ziedonis (2001) undertakes a detailed empirical analysis of patenting in semiconductors, with particular attention to the patenting motives and outcomes of small and large firms.

3 EMPIRICAL METHODOLOGY

The main interest of the chapter is the size effects in innovation. To this end, I estimate the following empirical model:

$$y_{it} = \alpha_S \log S_{it} + \mathbf{x}'_{it}\rho + \eta_i + \lambda_t + u_{it} \tag{1}$$

where y_{it} is a measure of the R&D productivity of firm i at year t, S_{it} is deflated sales and $\mathbf{x}_{it}$ is a vector of controls for firm i at year t. These controls will be introduced below. The error term contains an unobservable and time-invariant firm effect (η_i), as well as year effects (λ_t). Equation (1) will be estimated separately for CP and CR, using each as an alternative measure of productivity. Both measures are used after a (natural) logarithmic transformation. The double-log form provides better fit to data according to a Box-Cox test, thus this functional form is adopted for all specifications..

3.1 Independent Variables

I condition the relationship between R&D productivity (the logarithm of CP or CR) and firm size (the logarithm of sales) on a number of independent variables. These include firm characteristics, the characteristics of the firm's R&D organization and those of its patented innovations, as well as some aspects of the firm's industrial and technological environment. All specifications include the logarithm of *R&D intensity*. This is defined as the ratio of R&D stock to sales, where the former is calculated using the perpetual inventory method using a 15% depreciation rate. R&D intensity is an indicator of a firm's dedication to innovation, hence a potentially important determinant of the rate and quality of the firm's innovative output. I also control for (the logarithm of) *capital-labor ratio* since this variable may be a confounder in the size-innovation relationship. This ratio is found by dividing net capital assets by the number of employees (in thousands). Firms with a more capital-oriented production technology are argued to be more vulnerable against patent infringement (Hall & Ziedonis, 2001; Kim, Lee & Marschke, 2009b) therefore may have different incentives for innovation and patenting. When the dependent variable is log (CP), I also control the firm's *patent-R&D ratio* (henceforth PR), which accounts for the variation in firms' patent yields per dollar of current R&D investments. This allows me to evaluate the determinants of patent quality, holding the firm's patenting practices constant.

3.1.1 Technological Diversification

A number of variables are constructed using aspects of firms' patenting activities. Most important among these is a measure of the *diversification of research activity* at the firm level, which is calculated using the set of technological classes the firm patents in. There is a growing literature on the effects of technological diversification on R&D performance. Granstrand & Oskarsson (1994) show that greater diversification is associated with greater sales and R&D growth. Miller (2006) finds that diversification is positively associated with a number of performance measures. Nesta & Saviotti (2005), Leten, Belderbos & Van Looy (2007) and Garcia-Vega (2006) find that technological diversification is positively associated with the number of patents granted to the firm. Huang & Chen (2010) discover an inverted-U shaped relationship between technological diversity and the number of patents, and citations made to these patents.

In order to contribute to this literature, I include a measure of technological diversification as an independent variable. The measure of research diversification I use is one minus the concentration of the firm's patenting activity across different technological classes, where concentration is calculated using the Herfindahl index. That is,

$$DIV_{it} = 1 - \sum\nolimits_{k=1}^{K} \left(P_{it}^{k} / P_{it} \right)^2$$

where $k \in \{1, ..., K\}$ are United States Patent and Trademark Office (USPTO) technology classes, P_{it}^{k} is the number of patents that firm i applied for in year $t$and was classified in technology class k, and P_{it} is the total number of it patents. A more diverse research activity that spans a large number of technological fields will cause the firm's patents to be spread out among a larger number of technological classifications, which motivates this diversification measure. Note that similar measures of diversification have been employed by previous researchers. Huang & Chen (2010) and Leten Belderbos & Van Looy (2007) use a similarly constructed Herfindahl-based index, while Garcia-Vega (2006) uses an index that is based on the entropy index of concentration. Granstrand & Oskarsson (1994) employ both. Both the Herfindahl and entropy indexes are indexes of concentration, hence serve a similar purpose.

Increased diversification may dilute the resources available to each technological activity. Hence, diversification is costly, and it is possible that a firm can be "too diversified". To account for this possibility, I employ a quadratic polynomial for this variable. This will allow me to see whether too much diversification is indeed detrimental for productivity, even if diversification is productivity enhancing initially.

3.1.2 Basicness (Generality) of Patents

In addition, I control for a measure of the average *basicness* of the firm's patented innovations. This variable is included to control for the variation in the types of innovations patented by different firms, which may have implications for citation patterns. The basicness of patented innovations is measured by the index of generality constructed by Trajtenberg, Henderson & Jaffe (2002), which is based on citations made to the original patent and their decomposition into different technological classes. Suppose that patent p receives a total of N_p citations, N_{pk} of which come from patents in technological class $k \in \{1, ..., K\}$. Generality index for patent p is defined as

$$GEN_p = 1 - \sum\nolimits_{k=1}^{K} \left(N_{pk} / N_p \right)^2 \tag{2}$$

I take the average generality for all it patents to get the generality score for firm i's year t patents. Trajtenberg et al (2002) validate this measure by comparing a matched sample of university and corporate patents, and noting that patents granted to universities score higher than corporate patents on this scale. Thus, the average generality of it patents measures to what extent the research undertaken within the firm is science-oriented, as opposed to applied product development.

3.1.3 Spillovers

Spillovers may play different roles in small and large firm innovation (Audretsch & Feldman, 1994; Audretsch & Vivarelli, 1994). Therefore, it is also useful to directly control for *spillover effects.* To accomplish this I include a weighted sum of external R&D expenditures in all regressions, which is calculated as

$$SP_{it} = \log \sum_{i \neq j} w_{ij} R_{jt}$$

where R_{jt} denotes the R&D expenditures of firm j during year , and w_{ij} is a measure of the technological proximity between firms i and j. I follow Jaffe (1986) and construct w_{ij} as follows. Let T_i be a K-dimensional vector that contains the number of patents of firm i that are classified in USPTO technology class $k \in \{1, ..., K\}$ in its k^{th} element. This can be called the *technological position vector* of firm i. The technological proximity between firms i and j (w_{ij}) is defined as the uncentered correlation between vectors T_i and T_j. Additional properties of this distance metric are discussed in Jaffe (1986). The spillover measure is lagged one year.

3.1.4 Technological Opportunity

Finally, to capture the effects of *technological opportunity*, I include the annual growth of the total R&D expenditures in the firm's technological neighborhood as an independent variable. This variable is calculated as the annual growth of the total weighted R&D annual expenditures of all external firms where weights are the technological distance metrics constructed above.

3.2 Data and the Sample

All data on patents and citations are taken from the NBER patents and citations data file (Hall, Jaffe and Trajtenberg, 2001). 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. The stock of R&D expenditures is calculated as a perpetual inventory using an annual depreciation rate of 15%. The procedure outlined in Hall, Jaffe and Trajtenberg (2001) is used to correct for the effect of time truncation in the arrival of citations. This method is based on an estimate of the citation lag distribution. When an estimate of the lag distribution of citations is available, one can estimate the true citation count for an age-a patent by dividing the raw (observed) citation count by the fraction of citations an average patent receives during the first a years after application year. All raw citation counts are corrected using the estimated weights given in tables 6 through 8 of the same study. Note that this procedure is valid only for patents that have received citations for a significant number of years, since estimation of lifetime citations become unreliable as one approaches the final year citation data is available. For instance, a patent classified under "Drugs & Medical" receives 2.6% of its lifetime citations during the first year, and 6.7% of its lifetime citations during the first two years after patent application. The corresponding percentages are 4.8% and 11.5% for a patent classified under "Electrical & Electronic". Predicting total citations from such small percentages of observed citation counts can be misleading. I leave a nine year window between the final year used in this study (application year 1993) and the final year there is citation data available (2002). On average, patents receive about half of their lifetime citations during the first nine years after application.

Tables 1 and 2 should be placed about here

All variables in current dollar values are deflated using the GNP deflator. After deleting large outliers and firms with only a single year in the data, I am left with unbalanced panel of 362 observations for pharmaceuticals and an unbalanced panel of 310 observations for semiconductors, both covering a period of 24 years between 1969 and 1992. Sample statistics are provided in Table 1 (pharmaceuticals) and Table 2 (semiconductors).

4 RESULTS

4.1 Citations per Patent

I begin by reporting estimates of equation (1) that take log (CP) as the dependent variable. Tables 3 and 4 report regression estimates for the baseline regression for pharmaceuticals and semiconductors, respectively. Recall that CP is a proxy for the average quality of a firm's patents, while CR is a proxy for the total R&D output per R&D dollar invested. In other words, CP can be taken as an indicator of *quality*, while CR can be considered as an indicator of *quantity*. Therefore, we also get the opportunity to study the possibility of quality-quantity trade-offs in innovation.

Table 3 provides estimates from fixed effects OLS regressions for the sample of pharmaceuticals. Column 1 in this table provides coefficient estimates for equation (1) controlling for permanent firm effects, while column 2 introduces year effects in addition to firm effects. While it is important to control for year effects, this may also hinder the estimation of coefficients for which the independent variable is relatively stable over time. Therefore, initial estimates (columns 1 in all tables) ignore year effects, which are introduced in later regressions (columns 2 and 3 in all tables). Column 3 estimates the same specification in column 2, but uses the number of non-self citations instead of total citations while constructing CP. While both self citations and non-self citations can be considered important indicators of patent value, using non-self cites has the additional property that it measures the external "impact" of a firm's patents. Results in this column should be treated as complementary to those in columns 1 and 2. Table 4 contains estimates from regressions identical to those in Table 3, but for the sample of firms in the semiconductors industry.

Table 3 should be placed about here

In all reported regressions in Table 3, the coefficient of log(Sales) is negative and statistically significant. Therefore, we see that average patent quality falls with firm size in the pharmaceutical industry. This is in contrast to the results we get in Table 4 for semiconductors. According to the estimates in Table 4, the coefficient of log(Sales) is positive in column 1, negative in columns 2 and 3, but it is statistically indistinguishable from zero at all at all reasonable levels of significance. Therefore, we conclude that firm size is not a determinant of average patent quality in semiconductors.

Regarding remaining variables of interest, we find that increased R&D intensity has a negative effect on CP in both industries (in both Table 3 and Table 4). This implies that there are decreasing returns to R&D dollars in both industries in terms of the total value generated by R&D inputs.

Table 4 should be placed about here

Patent/R&D ratio has a negative and significant coefficient in Table 3 (pharmaceuticals), but its coefficient is statistically insignificant in all columns of Table 4. That is, the marginal patent seems to be of lower quality than the average patent in pharmaceuticals, but there is no such relationship between average and marginal patent quality in semiconductors. The capital-labor ratio has negative coefficients in all columns in Table 3, has positive coefficients in all columns in Table 4, while *all* of these coefficients are statistically indistinguishable from zero. Thus, I find no effect of a firm's capital intensity on patent quality.

While generality has a positive effect on CP (and CP, non-self) for both industries, the impact of technological diversification is different for pharmaceuticals and semiconductors. In Table 3, the coefficients of the quadratic specification of diversification are statistically insignificant at the 5% level of significance. Hence, diversification is found to have no significant impact on patent quality in the pharmaceutical industry. For semiconductors (Table 4), the estimated coefficients of the quadratic specification of the diversification measure are consisted with an inverted-U type relationship between CP and diversification. That is, increased diversification causes patent quality to increase up to a certain level, after which diversification impedes patent quality. On the other hand, this result is lost when self-citations are excluded from the citation measure (Table 4, column 3). When self-citations are excluded, we still observe the inverted-U pattern, but the polynomial terms are significant only at the 10% level of significance.

Regarding remaining variables of interest, technological opportunity and spillovers have positive impacts on CP in the pharmaceutical industry (Table 3, column 1). However, the significance of these coefficients is lost when year effects are included (Table 3, columns 2 and 3). Neither variable has a significant impact in the semiconductor industry in any specification. It is natural that estimating the effect of technological opportunity while controlling for both firm and year effects proves difficult, as little variation is left in this variable after these effects are accounted for. For this variable, it may be more desirable to put faith in the estimates in column 1 for both industries (Tables 3 and 4), which implies a positive effect for both variables in pharmaceuticals, but no significant effect in semiconductors.

4.2 Citations per R&D Dollar

In Tables 5 and 6 I explore the determinants of citations received per R&D dollar. The dependent variable in these regressions is the logarithm of CR. Table 5 reports results for the pharmaceutical industry, while Table 6 contains estimates for the semiconductor industry. Recall that CR has the interpretation of the total R&D output achieved per dollar of investments. The progression of estimates in Tables 5 and 6 is similar to that in Tables 3 and 4; I first estimate equation (1) using fixed effects OLS (column 1), then introduce year effects to the same specification (column 2). Column 3 includes estimates for the same regression equation in column 2 except that self-citations are excluded when CR is calculated (we called this variable CR, non-self).

Table 5 should be placed about here

The most important result here is that log(Sales) has a negative and significant coefficient in all specifications. Therefore, CR falls with firm size in both industries considered. This parallels previous results on the dependence of patent per R&D on firm size (Acs & Audretsch, 1991a; Kim, Lee & Marschke, 2009a; Bound et al, 1984). R&D intensity has a negative coefficient in all columns as well, mirroring the results presented in Tables 3 and 4.

Capital-labor ratio has an insignificant coefficient in most columns, though it does have a negative and statistically significant effect on “non-self CR” for semiconductors (Table 6, column3). This coefficient is significant only at the 10% level of significance in column 2 of the same table, where the dependent variable is log (CR). These observations are in line with the arguments of Hall & Ziedonis (2001) that large, capital intensive semiconductor firms began patenting their "latent", previously unpatented innovations, and strategically patented around already existing designs since the beginning of 1980s. These patents are expected to have lower quality and impact. Similar to previous estimates, generality has a positive coefficient in all specifications.

Technological diversification affects CR positively according to all estimates. Interestingly, the relationship between diversification and CR is linear for pharmaceuticals (where the squared term has an insignificant coefficient), but it is quadratic for semiconductors (where only the squared term has an significant coefficient). I find a positive effect of technological opportunity for pharmaceuticals (column 2 of Table 5), but no such effect for semiconductors (Table 6). Spillovers, on the other hand, affect CR positively for both industries (with the exception of column 3 of Table 5), but has no significant impact on CP. This suggests that spillovers are helpful mostly during the development of new ideas, but do not necessarily improve the success of existing projects. In other words, quantity seems to benefit from externally produced knowledge, but quality is determined mostly by in-house research efforts.

Table 6 should be placed about here

4.3 Discussion

Coming back to the main research question of the paper, my results indicate that small firms produce higher quality patents in pharmaceuticals (higher CP), while also producing higher patent value per dollar invested in R&D (higher CR). For the semiconductor industry, I find no significant difference in the average patent quality of small and large firms. These results are true holding constant key firm characteristics (capital-labor ratio, R&D intensity), characteristics of firm technology (diversification, generality) and aspects of the firm’s technological and industrial environment (spillovers, technological opportunity).

Considering these findings in conjunction with those of the previous literature on the size-innovation relationship, my results add valuable insights into these two industries. The finding that patent quality is higher for small firms in pharmaceuticals are in line with previous research on the different stages of drug development in this industry. Drug development occurs through several stages, with the average drug being developed over a period of 10 to 15 years, including FDA review (Plotnikova, 2010). Patenting occurs at a very early phase during these stages, but failure in later stages is common. Lower patent quality in large firms may be due to the fact that large firms take on a large number of simultaneous development projects and have higher failure rates at later stages, as stressed by Plotnikova (2010). This is possible if the firm needs to diversify into more risky research areas as the number of development projects increase. Hence, many patents that large firms obtain during earlier stages of development belong to projects that fail during later stages, leaving the firm with low-quality patents for its dead-end efforts. These observations are supported by the findings of Dimasi, Grabowski & Vernon (1995), i.e., that the cost of new drug development decreases, but sales per marketed drug falls with firm size. Their former finding implies that there are incentives for large firms to take on riskier projects as they diversify, while the latter is in line with lower success and lower patent quality, even if the project leads to the marketing of a drug.

The result that small semiconductor firms obtain patents that are not inferior in quality than those of large firms is meaningful when the organization of this industry is taken into account. The technological base of this industry is highly complex and the development of a product often requires the use interdependent, complementary technologies. While large firms hold dominant positions in the manufacturing and distribution of new technologies, small, specialized firms are known to be able to sustain high quality innovation by occupying strategic niches (Hall & Ziedonis, 2001; Agarwal and Audretsch, 1999). My results indicate that small firms are indeed as successful as large firms in this industry, in terms of the average quality of their patents. Other factors aid the success of small firms, such as the abundant availability of venture capital in Silicon Valley, which helped technology-based small firms to enter the market with new designs and technologies, often through entrepreneurial spin-offs from larger firms (Saxenian, 1994). The geographic location of this industry also facilitates spillovers and entrepreneurial capital emanating from nearby universities. The finding that small firms are not better innovators than large firms may be an indication that small and large firm success is highly interdependent in this industry. For instance, Rothwell (1983, 1989) argues that semiconductor innovation thrives on synergies (which he calls "dynamic complementarities") between small and large firms. Similar arguments have also been raised by Pavitt & Wald (1971) and Acs & Audretsch (1988) in different contexts.

5 FUTURE RESEARCH DIRECTIONS

In the current chapter it has been observed that the response of R&D productivity to firm size is not homogenous among two of the most R&D-intensive industries. A natural next step to take is to study the causes of this discrepancy. A promising point of departure for future work is to exploit the "technology regimes" concept of Winter (1984). In Winter (1984), industrial conditions that favor small firm and large firm innovation are characterized by the so-called *entrepreneurial regime* and *routinized regime*, respectively. Acs & Audretsch (1990) find some evidence for the existence of these regimes using data on innovation counts. These observations are also in line with the often cited innovation patterns that large firms are likely to be the sources of minor, incremental innovations, while the majority of major, radical innovations come from small firms (Hamberg, 1966).

On a related note, further research will also need to take additional characteristics of these two industries, and characteristics of the particular technologies into account. Research in these directions is somewhat disadvantaged due to data constraints and a lack of empirical measures for detailed technological characteristics. For instance, it is difficult (but necessary) to have empirical measures that describe to what extent innovations are "radical", or "cumulative" in a given industry. The effects of the major episodes these two industries went though during the period in question needs to be examined as well. While results of the current paper add important insights, the analyses are admittedly "aggregate" in the sense that they include a large number of years spanning three decades. Hence, more detailed studies of the two industries are called for, with particular attention to various sub-periods, including a re-examination of both industries for more recent years.

6 CONCLUSION

This chapter performed empirical tests of the Schumpeterian hypothesis using U.S. data on pharmaceutical and semiconductor industries. Two innovation indicators have been used as measures of R&D outputs. These were citations received per patent, which is an indicator of the average quality of a firm's patents, and citations received per R&D dollar invested, which is an indicator of total output achieved per R&D dollar. It has been shown that citations received per patent

(CP) falls with firm size in pharmaceuticals. There is no significant relationship between average patent quality and firm size in semiconductors. On the other hand, citations received per R&D dollar invested (CR) falls with firm size in both industries. This latter result is in line with the previous literature on the size determinants of patent yields (patents per R&D dollar invested) and innovation counts. An important contribution of the chapter, therefore, is that quality and quantity of invention may have different determinants.

The chapter also studied the effects of technological diversification, generality of a firm's patents, technological opportunity and spillovers on the two performance measures used in the chapter. Among interesting results related to these set of variables is that there is an inverted-U type relationship between technological diversification and average patent quality for semiconductors. This implies that increased diversification initially increases patent quality, but hinders it if the firm is already highly diversified. In other words, while increased diversification is initially beneficial to a semiconductor firm, the firm can also be "too diversified". On the other hand, total value generated per R&D dollar increases with diversification at an increasing rate in this industry. Hence, too much diversification does not hinder a firm's total R&D output. On the other hand, we observe no significant relationship between patent quality and diversification the pharmaceutical industry, and observe a positive and linear relationship between total output per R&D dollar and diversification in the same industry.

In terms of industrial research policy, my results suggest that subsidies for research and development activities need to support innovative small firms in these two industries, as small firms are found to publish higher quality patents in pharmaceuticals, and do not seem to have a disadvantage in terms of quality in semiconductors. Hence, at the outset, a reallocation of subsidies from larger to smaller firms may be called for. However, further recommendation on whether and how these reallocations should be performed will require more detailed insight into these two industries that will come from more detailed empirical research.

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KEY TERMS AND DEFINITIONS

Schumpeterian hypothesis: The claim that larger firms in more concentrated industries have better innovative performances. While the hypothesis speaks of both the size of the firm and the concentration of the industry it operates in, the economic literature has mostly focused on the former.

Patent citation: A reference made by a patent on its front page to a previously granted patent, indicating that the former (citing patent) builds on the knowledge embodied within the latter (cited patent). Patent applicants have the responsibility to cite all relevant "prior art" that they are aware of. During patent examination, it is the patent examiner's duty to make sure that all relevant prior art is cited by the patent in examination.

R&D intensity: R&D expenditures of the firm divided by a measure of its size. The size measure is usually taken to be sales, but other indicators of scale (such as net capital, employment, or value added) can be used. R&D intensity of a firm quantifies its devotion to research and development activities.

Technological diversification: A measure of the diversity of a firm's technological activities. In the current chapter it is measured by an index that is based on the Herfindahl index of concentration. The index measures the extent that a firm's patents are "spread" across different technology classifications, rather than being concentrated into a few.

Generality: The generality index constructed and proposed by Trajtenberg, Henderson & Jaffe (2002). It measures the extent at which a firm's patented inventions provide the foundations for future patents. Trajtenberg et al (2002) motivate generality as an indicator of the "basicness" of an innovation by demonstrating that patents owned by universities score much higher scores in this measure than patents owned by corporations.

Technological opportunity: A term describing all external factors that favor invention and growth in a given technology.

Table 1
Sample Statistics – Pharmaceuticals

	Mean	Standard Deviation	Minimum	Maximum
log (CP)	2.471	0.747	.136	5.148
log (CR)	1.168	1.222	-3.195	5.094
log (Sales)	7.245	1.730	.948	9.529
log (R&D Intensity)	-1.391	.811	-4.366	2.454
log (Patents/R&D)	-1.245	1.111	-6.142	2.777
log (Capital/Labor)	4.423	.469	3.158	6.551
Generality	.329	.120	0	.764
Diversification	.698	.281	0	.958
R&D Growth in Tech. Neighborhood	.075	.047	-.417	.4101
log (Spillover pool)	9.500	.556	7.217	11.554

Notes: *All dollar values are in millions of 1992 dollars, deflated using the GNP deflator. All logarithms are natural logs. Sample size: 362. Sample period: 1969-1992.*

Table 2
Sample Statistics – Semiconductors

	Mean	Standard Deviation	Minimum	Maximum
log (CP)	2.672	.736	.059	5.022
log (CR)	1.825	1.182	-1.445	5.366
log (Sales)	5.407	1.485	1.841	8.915
log (R&D Intensity)	-1.374	.701	-4.258	.106
log (Patents/R&D)	-.846	1.099	-4.074	2.582
log (Capital/Labor)	3.902	.581	2.269	5.183
Generality	.419	.163	0	.876
Diversification	.573	.338	0	.970
R&D Growth in Tech. Neighborhood	.072	.206	-.119	2.401
log (Spillover pool)	9.813	.768	7.081	11.069

Notes: *All dollar values are in millions of 1992 dollars, deflated using the GNP deflator. All logarithms are natural logs. Sample size: 310. Sample period: 1969-1992.*

Table 3
Pharmaceuticals
Dependent Variables: log (CP) (Columns 1 and 2), and log (CP, non-self) (Column 3)
Fixed Effects OLS

	(1) log (CP)	(2) log (CP)	(3) log (CP, non-self)
log (Sales)	-0.381***	-0.389***	-0.357***
	(-3.88)	(-3.69)	(-3.27)
log (R&D Intensity)	-0.0845	-0.0916	-0.110
	(-0.74)	(-0.74)	(-0.86)
log (Patents/R&D)	-0.239***	-0.200***	-0.205***
	(-3.96)	(-2.95)	(-2.91)
log (Capital/Labor)	-0.0267	-0.0476	-0.0293
	(-0.21)	(-0.35)	(-0.21)
Diversification	0.623	0.584	0.503
	(1.44)	(1.30)	(1.08)
Diversification^2	-0.290	-0.225	0.0646
	(-0.62)	(-0.46)	(0.13)
Generality	1.549***	1.543***	1.559***
	(6.74)	(6.30)	(6.15)
R&D Growth in Tech. Neighborhood	1.632***	1.168	0.850
	(3.35)	(0.81)	(0.57)
Spillovers | t - 1	0.640***	0.682	0.539
	(5.37)	(1.02)	(0.78)
Year Dummies	No	Yes	Yes
Intercept	-2.103***	-2.208	-1.311
	(-2.61)	(-0.32)	(-0.18)
R^2	.394	.434	.420
N	362	362	362

Notes: *All logarithms are natural logs. Standard errors are robust to arbitrary form of heteroscedasticity. t statistics in parentheses.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4
Semiconductors
Dependent Variables: log (CP) (Columns 1 and 2), and log (CP, non-self) (Column 3)
Fixed Effects OLS

	(1) log (CP)	(2) log (CP)	(3) log (CP, non-self)
log (Sales)	0.0710	-0.00598	-0.0197
	(0.70)	(-0.05)	(-0.18)
log (R&D Intensity)	-0.0369	-0.135	-0.124
	(-0.45)	(-1.38)	(-1.28)
log (Patents/R&D)	0.0892^{*}	0.0408	0.0187
	(1.73)	(0.71)	(0.33)
log (Capital/Labor)	0.193	0.242	0.239
	(1.46)	(1.64)	(1.64)
Diversification	0.891^{**}	0.791^{**}	0.746^{*}
	(2.36)	(2.01)	(1.92)
Diversification^2	-1.300^{**}	-1.081^{**}	-0.959^{*}
	(-2.55)	(-2.04)	(-1.83)
Generality	1.848^{***}	1.929^{***}	1.950^{***}
	(9.42)	(9.53)	(9.77)
R&D Growth in Tech. Neighborhood	0.203	-0.786	-0.770
	(1.25)	(-0.85)	(-0.84)
Spillovers | t - 1	0.205^{*}	0.0233	0.0417
	(1.65)	(0.02)	(0.03)
Year Dummies	No	Yes	Yes
Intercept	-1.182	0.786	0.560
	(-1.16)	(0.06)	(0.04)
R^2	.290	.369	.371
N	310	310	310

Notes: *All logarithms are natural logs. Standard errors are robust to arbitrary form of heteroscedasticity. t statistics in parentheses.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5
Pharmaceuticals
Dependent Variables: log (CR) (Columns 1 and 2), and log (CR, non-self) (Column 3)
Fixed Effects OLS

	(1) log (CR)	(2) log (CR)	(3) log (CR, non-self)
log (Sales)	-1.082***	-1.100***	-0.951***
	(-11.00)	(-10.56)	(-8.88)
log (R&D Intensity)	-0.892***	-0.886***	-0.912***
	(-7.68)	(-7.12)	(-7.13)
log (Capital/Labor)	0.148	0.0453	-0.104
	(0.94)	(0.28)	(-0.62)
Diversification	2.202***	2.239***	2.300***
	(4.36)	(4.36)	(4.36)
Diversification^2	-0.773	-0.819	-0.745
	(-1.37)	(-1.40)	(-1.24)
Generality	1.153***	1.032***	1.296***
	(4.16)	(3.55)	(4.34)
R&D Growth in Tech.	0.735	4.843***	1.920
Neighborhood	(1.25)	(2.87)	(1.10)
Spillovers | *t* - 1	0.799***	1.795**	1.245
	(5.55)	(2.25)	(1.52)
Year Dummies	No	Yes	Yes
Intercept	-2.015**	-12.00	-8.078
	(-2.05)	(-1.44)	(-0.94)
R^2	.509	.551	.570
N	362	362	362

Notes: *All logarithms are natural logs. Standard errors are robust to arbitrary form of heteroscedasticity. t statistics in parentheses.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6
Semiconductors
Dependent Variables: log (CR) (Columns 1 and 2), and log (CR, non-self) (Column 3)
Fixed Effects OLS

	(1) log (CR)	(2) log (CR)	(3) log (CR, non-self)
log (Sales)	-0.859***	-0.931***	-0.828***
	(-5.78)	(-6.06)	(-5.85)
log (R&D Intensity)	-0.526***	-0.663***	-0.972***
	(-4.04)	(-4.66)	(-7.41)
log (Capital/Labor)	0.328	0.387*	0.485**
	(1.51)	(1.72)	(2.34)
Diversification	0.871	0.968	0.863
	(1.41)	(1.61)	(1.56)
Diversification^2	2.043**	1.770**	1.775**
	(2.58)	(2.29)	(2.50)
Generality	1.074***	1.329***	1.644***
	(3.40)	(4.37)	(5.86)
R&D Growth in Tech.	0.136	0.712	0.915
Neighborhood	(0.51)	(0.50)	(0.70)
Spillovers | *t* - 1	0.739***	4.750**	5.751***
	(3.71)	(2.38)	(3.12)
Year Dummies	No	Yes	Yes
Intercept	-4.644**	-46.15**	-59.64***
	(-2.83)	(-2.25)	(-3.16)
R^2	.369	.512	.575
N	310	310	310

Notes: *All logarithms are natural logs. Standard errors are robust to arbitrary form of heteroscedasticity. t statistics in parentheses.* * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$