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Propensity to Patent and Firm Size for Small R&D-Intensive Firms

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ABSTRACT: The Schumpeterian hypothesis about the effect of firm size on research and development (R&D) output is studied for a sample of R&D projects for R&D-intensive firms that are small but have substantial variance in their sizes. Across the distribution of firm sizes, the elasticity of patenting with respect to R&D ranged from 0.41 to 0.55, with the elasticities being largest for intermediate levels of firm size and also varying directly with the extent to which the projects are Schumpeterian in the cost or value senses. The paper's findings at the R&D project level are compared with the literature's findings at the line of business, firm, and industry levels, and the findings are consistent with the literature's findings for small firms.

KEYWORDS: Patents, Research and Development (R&D), Firm Size, Schumpeterian hypothesis, Technological Progress, Innovation

JEL CLASSIFICATIONS: L10, L20, L25, O30

1. Introduction

Scherer (1965, 1967a, 1967b, 1970, pp. 346-399) provided the foundational papers that set the research agenda for scholarly investigations of the Schumpeterian hypotheses about seller concentration and rivalry in research and development (R&D) investments and about the advantages of firm size for R&D investments. His subsequent research and reviews of the literature about the Schumpeterian hypotheses (Scherer, 1980, pp. 407-458, 1983a, 1983b, 1984a, 1984b; Ravenscraft and Scherer, 1987; Scherer and Ross, 1990, pp. 613-660) have furthered our understanding of these issues and extended the breadth and scope of related research agendas. In the context of Scherer's foundational work, this paper not only complements the existing literature but also provides a new perspective on the Schumpeterian hypothesis about firm size.[1]

The remainder of the paper is outlined as follows: In Section 2, we discuss the Schumpeterian firm-size hypothesis with regard to the advantages of firm size for the performance of R&D investments, and we explain the theory that underlies our new test of that hypothesis. Section 3 describes the sample of research projects in small R&D-intensive firms that we use to test our hypothesis. Section 4 presents the associated econometric model; also in Section 4 are definitions of the variables in our estimation, relevant descriptive statistics, and a discussion of the estimates. Section 5 compares our findings to the findings in the literature about the Schumpeterian firm-size hypothesis. Finally, Section 6 concludes the paper and emphasizes the ways in which our analysis both complements the extant literature about the Schumpeterian firm-size hypothesis as well as extends it.

[1] Scott and Scott (2014) examine the Schumpeterian hypothesis about innovation rivalry in the context of Scherer's foundational work.

2. The Schumpeterian Firm-Size Hypothesis

Simply stated, the Schumpeterian hypothesis about firm size (Scherer, 1970, pp. 352-362) is that large firms will be more effective than small firms in generating technological progress. Scherer's seminal 1970 treatise also provides an assessment of the evidence at that time—an assessment that was updated in Scherer (1980), Baldwin and Scott (1987), Scherer and Ross (1990), and Cohen (2010).

In addition to Scherer's foundational studies cited in Section 1, there have been many other contributions to the literature about the Schumpeterian firm-size hypothesis. Some of these have compared the R&D activity and performance of small as contrasted with large firms.[2] Others have focused on differences across the range of sizes for large firms.[3]

Within the context of this literature, we focus on small firms and measure the research output from R&D investments in terms of the patents that result, controlling for the differences in the use and quality of patents across technologies with dummy variables, as suggested by Griliches (1990).[4] For our sample of small firms, we ask if the

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[2] Prominent examples include Link (1980), Bound et al. (1984), Pakes and Griliches (1984), and Acs and Audretsch (1988).

[3] Here some prominent examples are Comanor (1967), Scherer (1983a, 1984b), Lunn and Martin (1986), Cohen and Klepper (1992, 1996a, 1996b), and Cohen et al. (1987).

[4] Schmookler (1966) advocates the use of patent statistics as a measure of research output. Griliches (1990) reviews patents as a measure of R&D output and observes (1990, pp. 1701-1702): "Among the major findings was the discovery of a strong relationship between patent numbers and R&D expenditures in the cross-sectional dimension, implying that patents are a good indicator of differences in inventive activity across different firms." He also observes (1990, p. 1669): "The dream of getting hold of an output indicator of inventive activity is one of the strong motivating forces for economic research in this area. . . . One recognizes, of course, the presence of a whole host of problems: Not all inventions are patentable, not all inventions are patented, and the inventions that are patented differ greatly in "quality," in the magnitude of inventive output associated with them. The first two problems, one thinks, can be taken care of by industry dummy variables, or by limiting the analysis to a particular sector or industry.

size of a firm affects the relationship between research output—as measured by patents—and the firm's R&D investment.[5] The effect of firm size indicates how Schumpeterian the R&D activity is in the cost sense and/or the value sense (Kohn and Scott, 1982).

Although we consider patents to be a measure, albeit an imperfect one, of research output, the Kohn and Scott theory of the way that firm size affects—via a cost sense and/or a value sense—R&D activity applies equally well whether the activity is measured with R&D outputs or instead with R&D inputs.[6]

For the third, one tries to invoke the help of the "law of large numbers": "The economic . . . significance of any sampled patent can also be interpreted as a random variable with some probability distribution" (Scherer 1965, p. 1098)." See also Comanor and Scherer (1969, p. 393) who observe that a patent's ". . . underlying economic or technological significance can be interpreted as a random variable with some probability distribution" and use an examination of pharmaceutical manufacturing firms' invention patents, R&D personnel, and the value of new product sales to ask "whether a simple count of the number of patents reflects only statistical noise or whether there is a meaningful message in the results". They find support for a meaningful message in statistically significant correlations between patent counts and the employment of research personnel and the sales of new products.

[5] In this paper, we study patents as a random count variable. Of importance for the issue of the quality of the counted patents is the distribution of the value of patents, where that value is a random variable. On the distribution of that value, see Harhoff et al. (1999), Scherer et al. (2000), and Harhoff et al. (2003); the ideas in these papers suggest that an interesting extension of the present paper would be to replace our patent counts for each R&D project with the use of quality-weighted patent counts, where quality is determined by the citations to the patents. We could then examine the effect of firm size on the elasticity of the quality of R&D output with respect to the R&D inputs.

[6] That is fortunate, because, as William Comanor has emphasized to us in personal correspondence, what patent statistics actually measure is not at all clear, and rather than measuring research output, patenting may be an important intermediate step between R&D and innovation, and indeed may be a better measure of research input than of research output. In this paper we study the effect of firm size on R&D activity where the activity is measured by patenting. We think of patenting as an imperfect measure of research output, but the theory of how firm size affects R&D activity is valid whether or not patenting is thought of as a measure of innovative output or as an intermediate input in the innovation process.

In Figure 1, we depict the marginal value (MV) of R&D output and also the marginal cost (MC) of R&D output, when R&D output is measured by patents.[7] For a firm of size S_0, the R&D output is P_0 where the marginal value ($MV|S_0$) and marginal cost (MC) of effort are equal. For a larger firm of size S_1, the R&D output, P_1, is greater along MC because the marginal value ($MV|S_1$) of R&D output has increased (shifted to the right).[8]

Kohn and Scott (1982) offer the following statement of the Schumpeterian firm-size hypothesis: In more Schumpeterian industries (in our context, with more Schumpeterian R&D projects), the elasticity of R&D output with respect to firm size will be greater when the industry (or the R&D project) is more Schumpeterian in the value sense or the cost sense. For the value sense, a more Schumpeterian project will have its MV curve shift up further as firm size increases. So, for the firm depicted in Figure 1, if the R&D project is more Schumpeterian in the value sense, MV shifts to $MV|S_1^*$ and R&D output increases to P_1^*. If the R&D activity is more Schumpeterian in the cost sense, then the MC curve shifts down more steeply, as with MC^∇. Thus, if the R&D activity is more Schumpeterian in the value sense only, output is P_1^*; if the activity is

[7] Figure 1 in Kohn and Scott (1982, p. 247) shows R&D output on the horizontal axis, and thus depicts the marginal value and the marginal cost of the R&D output; in our empirical model, we measure that output with patents. However, as Kohn and Scott (1982, p. 246) explain, because the R&D output is an increasing function of the R&D input, the discussion can also be stated in terms of the R&D input, with R&D effort measured on the horizontal axis of Figure 1. Thus, the Kohn and Scott theory that relates firm size to R&D activity applies equally well to R&D input as to R&D output. That is especially important because Comanor and Scherer (1969, p. 397) conclude that "it may be that patents are a better measure of research input than output." Thus, although we interpret patents as a measure of R&D outputs, the theory by which we relate firm size to R&D activity holds equally well for explaining the relation of firm size to R&D inputs or to R&D outputs, and so our hypothesized relations hold if patents measure inputs rather than outputs.

[8] If MC is constant, then R&D activity is not Schumpeterian in the cost sense.

more Schumpeterian in the cost sense only, output is P_1^{∇}; and if output is more Schumpeterian in both the value and the cost senses, the firm's R&D output (measured by patenting in the empirical work of this paper) increases even more as the firm's size increases and equals $P_1^{*\nabla}$.

In all, the test of the Schumpeterian firm-size hypothesis that Kohn and Scott (1982) propose is whether the elasticity of R&D activity with respect to firm size is greater when the R&D activity is more Schumpeterian in the cost or the value senses. Building from Kohn and Scott (1982), we construct such a test, and it is that test that provides our new perspective on the Schumpeterian hypothesis about firm size.

FIGURE 1 ABOUT HERE

3. Sample of Small R&D Firms

The data that are analyzed in this paper come from a representative sample of the U.S. Department of Energy's (DOE's) Phase II Small Business Innovation Research (SBIR) projects.[9] The sample was assembled by the National Research Council (NRC) of the National Academies for the NRC's 2005 evaluation of the SBIR programs.[10] The NRC's sample of DOE projects has 436 randomly surveyed SBIR Phase II projects from

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[9] Phase I awards are small and are intended to assist firms assess the feasibility of an idea's scientific and commercial potential in response to the funding agency's objectives and they generally last for six-months. Phase II awards are focused on the initial steps toward commercialization, and they generally last for two years. Link and Scott (2012, pp. 19-32) provide a detailed description of the SBIR program and its Phase I and Phase II awards.

[10] The scope of the NRC 2005 database was limited to Phase II SBIR awards by the largest five agencies that participated in the SBIR program. The other agencies are the Department of Defense (DoD), the National Institutes of Health (NIH), the National Aeronautics and Space Administration (NASA), and the National Science Foundation (NSF). Collectively, these five agencies funded 11,214 SBIR Phase II projects during the scope of the NRC study (1992 through 2001). Among those projects, DOE had 808 or 7.21 percent of the total number.

DOE's SBIR Phase II projects over the period from 1992 through 2001. There were 154 responses from the random sample.[11] Our analysis focuses on the 154 responses for which we have all of the data. Table 1 describes the process that reduced the population of DOE SBIR Phase II projects to the random sample of 436 projects and then ultimately to the 154 responses comprising our sample.[12]

Of the five agencies for which the NRC gathered data about SBIR Phase II projects, DOE's projects seemed the most appropriate for the study of the Schumpeterian firm-size hypothesis. The projects of the other agencies are influenced by institutional characteristics that could make results for our firm-size hypothesis test less general. For the SBIR projects of the DoD and NASA, there is a military/defense focus; for NIH projects, there is an academic research focus; and the NSF projects have a special noncommercial research focus. The commercial energy-related focus for the DOE SBIR projects seems broadly attuned to private sector R&D efforts.[13]

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[11] Link and Scott (2012, pp. 33-43, 128-130) provide detailed discussion and description of the NRC's 2005 SBIR sampling strategy and the resulting samples and explain the data reduction process that resulted in the samples of projects from DoD, NIH, NASA, DOE, and NSF. Also Link and Scott (2012) estimate a Probit model of response to the NRC's survey. The response model estimates well, with variables such as the project's age and the number of Phase II awards that the firm had over the period from 1992 to 2001 being important for response. However, for variables that describe the commercialization of the Phase II project's results and for the patent variable that we use in the present paper, the correlation of the error in the model of response and in the model of substantive interest is low; consequently, response bias is not an issue. For an explanation of the absence of selection bias when the error in the equation that determines the sample selection is uncorrelated with the error in the equation of primary interest, see Greene (2012, pp. 872-876); for an example, see Link and Scott (2009, pp. 271, 274).

[12] See note *a* of Table 1 in particular.

[13] As with all agencies' SBIR programs, DOE states (http://science.energy.gov/sbir/about/ accessed July 23, 2016) that it pursues the four legislated goals for the SBIR program: to stimulate technological innovation; use small business to meet Federal research and R&D needs; foster participation by small businesses that are socially and economically disadvantaged and those that are women-

TABLE 1 ABOUT HERE

In addition to the focus on DOE SBIR projects, our sample of R&D projects has three unique characteristics: First, at the level of the performance of the R&D project—and that is the level of activity that we observe—the firms in our sample are in a sense in the same industry. More specifically, the industry is the set of R&D-intensive firms that allocate science and engineering resources to provide contract commercial research services of R&D projects that are aimed at developing technologies that meet the goals of the DOE—or more generally, the goals of U.S. government agencies that participate in the SBIR programs.[14] Using an internet search, we examined each observation to find descriptions of the projects and the firms that performed them. Many of the firms are solely performing commercial research services for whatever targets of opportunity appear, and the remaining firms are devoting a subset of their science and engineering resources to such activity. Further, the SBIR Phase II award process is competitive.

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owned; and increase the commercialization of innovation that is derived from Federal support for R&D. For details of these legislated goals that all agencies' SBIR programs address, see Link and Scott (2012, pp. 21-24); DOE's particular emphasis is on technologies that address energy-related concerns such as environmental concerns of promoting clean, renewable energy. DOE emphasizes commercialization, which requires an evaluation of commercial potential in Phase I and Phase II applications. The Bayh-Dole Act (P. L. 96-517, Patent and Trademark Act Amendments of 1980) applies, and government grants then lead to privately held patents, although the DOE retains certain rights in those patents that allow it to license the technology. On the history, legislation, and implementation of Bayh-Dole, see Scherer (2009).

[14] The Census assigns the primary category for many of these firms as "commercial physical research" (SIC 8731) or "research and development in the physical, engineering, and life sciences (except biotechnology)" (NAICS 541712). Others have portions of their firms that are devoted to such activity to expand their sales opportunities. The firms all use SBIR funding for their R&D project, but venture capital and other sources of capital are also used in some cases. Additional understanding of small, R&D-intensive, SBIR-supported firms, including their views about venture capital, is provided in case studies (e.g., see Wessner, 2000, pp. 104-140, and the material there from discussions with the principals of the SBIR firms).

This first point is important because we focus on the Schumpeterian firm-size hypothesis, which applies most convincingly to samples of R&D projects where the performing firms of different sizes are competing broadly in the same industry. It is the industry that is characterized by how Schumpeterian R&D activity is in the value sense and in the cost sense; there is then, as is illustrated in Figure 1, variance in R&D activity across the industry's firms of various sizes, with a larger responsiveness of the activity to firm size when the industry is more Schumpeterian in either or both senses.[15]

Another reason to limit attention to a single industry is that the scope of patenting is very different among industries. For example, patenting is very important in pharmaceuticals, but less important in many other industries.[16]

We are asking if and how firm size affects the productivity of R&D efforts, however measured. The theory that we have discussed and illustrated in Figure 1 implies that the Schumpeterian hypothesis would apply in some circumstances but not others—namely, it should apply in industries that are Schumpeterian in either or both the value sense and the cost sense. Where our industry fits with regard to the importance of firm size for R&D activity is a matter that our examination of the elasticity of patenting with respect to firm size will reveal.

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[15] See the discussion in Kohn and Scott (1982, p. 248).

[16] See Cohen (2010, pp. 183-185), and also see Henderson and Cockburn (1996, pp. 48-49) for a discussion and an illustration, in the context of their study of the pharmaceuticals industry, of the importance of controls for differences in technological opportunities when explaining patenting—in their case across different therapeutic classes (such as arthritis and related disorders as compared with anti-infectives). In Link and Scott (2013), we have shown that patents are important for the commercialization success (as measured by the firm's employment growth that resulted because of the research project) of the small, research-intensive firms that participated in the SBIR program.

Second, there is heterogeneity in the sizes of the small firms, as measured by employment at the time of their proposals for their Phase II award to DOE. Firm sizes ranged from 1 to 451 employees. The mean number of employees was 32.6, with standard deviation of 59.0 employees.

Third, there is also heterogeneity in R&D investments (inclusive of the SBIR support for the project).[17] For our sample of projects, total R&D investments in constant year 2015 dollars averaged $2,353,115, with the standard deviation being $4,827,214 and the range being from $538,000 to $41,900,000.

4. Model, Descriptive Statistics, and Empirical Findings

In this section we formalize the framework from which we test our Schumpeterian firm-size hypothesis in the context of our sample of small, R&D-intensive firms. Specifically, we explore: 1) whether the research output from the sampled DOE SBIR projects is a function of the R&D investments in the projects; and 2) whether the effect of R&D investment on research output depends on the sizes of the firms that performed the R&D.

Our measure of the research output of each R&D project is, as illustrated by Figure 1, the number of patent applications, *P*, based on the knowledge that is generated by the project. The R&D investment, *R,* in the project is the total (private and public)

[17] In addition to the Phase II SBIR award, the total investment funding for the R&D project includes non-SBIR federal funds, private investment funds (U.S. venture capital, foreign investment, other private equity, other domestic private company), other sources of funding including state or local governments and colleges or universities, any own company funding, including borrowed funds, and personal funds.

R&D investment in the Phase II SBIR project; R is measured in constant dollars of the year 2015.[18]

We test the hypothesis that firm size significantly affects the relationship between R&D investment, R, in a project and the research output, as measured by the number of patent applications, P. The number of patent applications (hereafter, simply patents) is a count variable.[19] An appropriate model for our hypothesis test is the negative binomial model. The variables measuring the R&D investment for the project and the firm's size are entered as their natural logarithms because, as they increase, their effects on patenting are expected to diminish. Thus, we discuss each variable and the functional form for the expected number of patents, where that expected number for each project can be represented, with $\exp(x)$ denoting e^x, the base for the natural logarithms raised to the power x, with x denoting the collection of terms in the very long parenthetical expression that we will define, as:

$$P = \exp(\beta_0 + \beta_1 \ln R + \beta_2 \ln S \ln R + \beta_3 B \ln S \ln R + \beta_4 A \ln S \ln R + \beta_5 PhI \ln S \ln R$$
$$+ \beta_6 PhII \ln S \ln R + \sum_{j \neq 1} \tau_j T_j \ln S \ln R + \beta_7 B + \beta_8 A + \beta_9 PhI + \beta_{10} PhII + \sum_{j \neq 1} \alpha_j T_j$$
$$+ \beta_{11} NE + \beta_{12} MW + \beta_{13} South)$$

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[18] We follow the recommendation of Jankowski (1993, p. 204) and convert the nominal R&D expenditures for each sampled project to constant 2015 dollars by using the Gross National Product implicit price deflator (https://fred.stlouisfed.org; accessed July 6, 2016).

[19] We consider patent applications to be a better indication of the output developed in the projects of these small firms than patents received. Patent applications indicate results for which the firms considered intellectual property worthwhile and are not subject to the vagaries of the process of ultimately granting a patent. The two variables are similar in any case. For the 146 observations for which the data are available, the number of patents applications averaged 0.83 with standard deviation 1.62 and a range from 0 to 13; the number of patents received averaged 0.61 with a standard deviation of 1.19 and a range from 0 to 10.

Turning now to the discussion of the variables in the parenthetical expression, the expected number of patents from a project is represented as a function of the R&D investment *R* in the project, and the effect of that R&D investment depends on the size *S* of the firm as represented by interaction terms in the equation above. In our theory, the effect of firm size on R&D output results from firm size affecting the impact of R&D investment on R&D output, having a larger positive impact when the R&D project is more Schumpeterian in the cost and value senses. The size of the firm is measured by the firm's employment at the time that it applied for the Phase II SBIR award.[20]

The impact of firm size on the effect of R&D investment depends on the technology T_j of the project and on the extent to which the R&D project is Schumpeterian in the value sense and the cost sense. As we discuss below, the variables *PhI* and *PhII* capture technology effects; the variables *B* and *A* capture independent Schumpeterian effects. We explain these variables below. The variables *B*, *A*, *PhI*, *PhII*, and T_j enter the equation in both interaction terms (for slope effects) and as independent (intercept) effects. The model also controls for regional effects in the number of patents.

The technology effects are for the different technologies (T_j for the technology areas into which our DOE projects fall, with the technology area for "*Measuring & testing*" subsumed in the intercept). The classification of the DOE SBIR projects to technology classes was accomplished by comparing the project descriptions with the classification system used by the U.S. Patent Office (United States Patent and Trademark

[20] The firms were asked to provide the number of employees when the Phase II proposal was submitted. Some of the firms were just beginning their existence, and in some of those cases, the incipient firms reported zero employees. Knowing that someone was working for the young firm in its incipiency—someone wrote the proposal for the Phase II SBIR award—we have defined *S* as the reported number (at the time the firm applied for its SBIR Phase II award) of employees plus 1.

Office, 2016).[21] The regional effects are for the different geographic areas (the U.S. Census regions, Northeast, *NE*, Midwest, *MW*, South, *South*, and West, *West*, with the effect for the West subsumed in the intercept).

To explore the alternative circumstances associated with the impact of firm size on the effectiveness of R&D investment on patenting, we use the following variables. The variable *B* denotes business founders. It is 1 if the firm had founders with a business background and is zero otherwise. The variable *A* denotes academic founders. It is 1 if the firm had founders with an academic background and is zero otherwise.[22] The variable *PhI* denotes the number of previous related Phase I SBIR awards, and the variable *PhII* denotes the number of previous related Phase II SBIR awards.[23]

All of the variables are defined in Table 2.

INSERT TABLE 2 ABOUT HERE

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[21] Although the classification system is not good for defining meaningful industries, it is good for our purpose of assigning the projects to technology groups (see the discussion in footnote 4—we need to control for the differences in use and quality of patents across technologies). In addition to the technology area, "*Measuring & testing*," left in the intercept, the technology areas to which the DOE SBIR projects have been assigned are listed in Table 4.

[22] Of course, in some cases a firm will have founders with academic backgrounds and also founders with business backgrounds, and in such cases we anticipate the R&D projects would have characteristics that are associated with the human capital of each type of founder.

[23] Of course, the variables *PhI* and *PhII* are highly correlated: Their correlation coefficient is 0.808. However, although all related Phase II projects are expected also to have Phase I projects that the firm would report as related, not all Phase I projects succeed and result in a Phase II project. Thus, using the two variables, we have the variance across projects in the number of related Phase I projects, given the number of related Phase II projects. The number of related Phase I projects can be much more for some of our observed R&D projects because of many failures of Phase I projects for each Phase II award won. In fact, as seen in the descriptive statistics of Table 3, for our sample's R&D projects, the mean number of related Phase I projects is somewhat more than twice the mean number of related Phase II projects.

Table 3 provides descriptive statistics for the variables.[24] Observe the different range and levels for the variables for accumulated technical capital, *PhI* and *PhII,* and note the variance in the amount of R&D investment for the projects. Also, observe the wide range in the sizes of the sampled firms, all of which are small. In Section 5, we shall make detailed use of the range in the sizes of the firms.

TABLE 3 ABOUT HERE

We hypothesize that in some circumstances a larger firm size will be helpful for successful patenting by the R&D-intensive small firm, while in other circumstances size is associated with less success. In particular, following the discussion in Section 2 and the illustration in Figure 1, when the small firms' R&D projects are carried out in circumstances that are more Schumpeterian in the cost sense or the value sense, the elasticity of patenting with respect to firm size is expected to be greater than when circumstances are less Schumpeterian.

To explore alternatives, we hypothesize that when the founders of the small firms have business backgrounds, circumstances will be more Schumpeterian in the value sense because the R&D projects will tend to be those for which the marketing, sales, and distribution machinery of a larger firm would be especially helpful for increasing the marginal value of R&D output.[25] Business founders are likely to be more Schumpeterian when the R&D project is aimed at creating a new process for an established market that

[24] Instead of simply providing the descriptive statistics for only the 125 observations for which we have all of the variables needed for the estimation in Table 3, we have shown in Table 4 the descriptive statistics for the all of the observations for which the patent variable is available. The richness of the description of the sample thereby enabled comes with the cost of the intricate footnote to the table.

[25] Note that the business founders—the owners—still have access and control in these small entrepreneurial firms. Indeed, in our experience interviewing the principals of SBIR firms, the founders often "wear all the hats" and are deeply involved of all aspects of the small firm's operations.

can be advantageously exploited in-house with a firm's own production. This argument also holds for a new product where marketing is key.

In contrast, when the founders of the small firms have academic backgrounds, we hypothesize that marketing and sales and in-house exploitation are less important, and the projects entail more basic science with output that is more generic, with value less dependent on the size of the firm to exploit the R&D output. Thus, with academic founders, we expect the R&D projects will have output for which the small firm can readily get agreements with outsiders for marketing, sales, and distribution or for production. Thus, the small firm's own marketing, sales, and production expertise is not necessary, and the circumstances for the R&D projects will be less Schumpeterian in the value sense.[26]

We also hypothesize that, for projects with academic founders, the marginal cost of R&D output will fall less steeply as the R&D output increases; the *MC* curve in Figure 1 will be flatter, and the marginal cost of R&D output does not fall rapidly as that output increases. We hypothesize the flatter marginal cost curve in Figure 1 because the cost of finding additional knowledge with academic founders is less likely to be a simple matter of exploring different directions for knowledge already acquired and instead is the pursuit of more basic knowledge that opens up new areas of exploration.

Other things being the same, we further hypothesize that firms that have had many related Phase II SBIR projects have R&D projects that are more Schumpeterian in the cost sense than will be the case for firms with fewer related Phase II projects. The marginal cost of R&D output is expected to fall more rapidly as output increases because

[26] There are many different ways that the small, SBIR firms use agreements with outside firms and financiers to exploit commercially their innovations. See Link and Scott (2012, pp. 91-102).

the R&D project will be building on the firm's existing knowledge base and exploiting ideas established in earlier projects. An additional new increment to knowledge—and an additional new patent—will cost less for the firm with a larger number of related Phase II SBIR R&D projects.

Given the number of a firm's related Phase II projects, we expect that firms with a larger number of related Phase I projects will have R&D projects that are less Schumpeterian in the cost sense than will be the case for firms with fewer related Phase I projects. Other things being the same, having more related Phase I projects means that there have been more failures in the process of taking the first look at the possibilities for an R&D project. There are more exploratory looks at possibilities to find feasible Phase II R&D projects, and more costs to find the feasible projects imply that the marginal costs of R&D output do not fall as steeply as the output increases.

To help bring into focus the foregoing arguments, we summarize by observing that we hypothesize that the accumulated human capital of firms will matter. Firms with academic founders may—because of the nature of their projects and the firm's personnel—need to remain small and focused in order to have an R&D project succeed and lead to patents; their projects are expected to be less Schumpeterian in the value sense and in the cost sense. In contrast, firms with business founders are expected have R&D projects that are more Schumpeterian in the value sense.

Summarizing further, we hypothesize that accumulated technical capital—the firm's experience base that characterizes each project—will matter. Controlling for the number of previous Phase II projects in a technology area related to the current Phase II project, a larger number of related Phase I projects in that area necessarily implies larger

R&D portfolios with fewer successes in the sense of initial research developing into the Phase II R&D project.

Thus, in these cases, the R&D activities would be less Schumpeterian in the cost sense because the marginal costs of R&D efforts are declining less rapidly for the firms that are undertaking more Phase I projects to find the Phase II projects that are worth investing in. Controlling for the number of related Phase I awards won, firms with many related SBIR Phase II projects (hence, Phase I awards that were successful and generated the follow-on Phase II awards) may have the experience and portfolio of projects that imply that the marginal costs of R&D output fall more rapidly as that output increases. With many related Phase II awards, a firm's R&D activity would be expected to be more Schumpeterian in the cost sense.

Table 4 shows our empirical results. There are three specifications: the first with the technology effects' having only an impact on the intercept, and the second with the technology effects' having both intercept and slope effects. For the second specification, technology effects are estimated only for the technologies that have significant effects in the first specification, with any effects for the remaining technologies left in the intercept.[27] The third specification drops the regional effects because they are not significant; they are not significant individually, and the chi-squared statistics with three degrees of freedom for their joint significance are 2.91 (against the null hypothesis, the probability of a greater chi-squared = 0.406) in the first specification and 2.64 (probability of a greater chi-squared = 0.451) in the second. Studies of innovative small businesses have often anticipated and controlled for regional effects in the firms

[27] The technology effects as a whole are significant. The Wald test statistic against the null hypothesis that all of the effects are zero gives the chi-squared statistic with 12 degrees of freedom = 1684.31 with the probability of a greater chi-squared = 0.0000.

behavior, and so we present the specifications with those effects controlled as well as the specification without them. The standard errors are robust and are adjusted for clusters by firm because for some firms, multiple Phase II SBIR projects are sampled. The clustering allows for intra-group correlation in the errors for the multiple projects of a firm. The estimation also uses the sample weights (also called probability weights) that were explained and shown in Table 1.

For all of our specifications in Table 4, the results of the estimation are essentially the same. In Section 5, we report the magnitudes of the effects. Here we provide an overview of the directions for the effects in the context of our theory in Section 2.

First, the number of patents applied for increases with R&D investment in the project.[28]

Second, the positive effect of R&D on patenting is greater for larger firms.

Third, as hypothesized, the effect of firm size on R&D investment's effect on patenting is less when the R&D activity is less Schumpeterian in the cost or value senses—discussed in Section 2 and illustrated in Figure 1—as indicated by the variables that we have used to characterize less Schumpeterian cases—namely, *A* and *PhI* reduce the impact of firm size on R&D's impact on patenting.

Fourth, as we hypothesized, R&D activity is more Schumpeterian when *PhII* is larger, other things being the same, and indeed, when *PhII* is larger, the impact of firm size on the effect of R&D on patenting is positive. However, contrary to our expectation, the hypothesized impact of *B* (a slope effect—that is, an impact on the effect that firm

[28] In personal correspondence (July 22, 2016), F.M. Scherer observes that although—for our sample of small firms—this result is unlikely to have been caused by the presence of in-house lawyers (available in a sense at zero marginal cost), possibly the somewhat larger small firms have more experience with patent law and lawyers and hence bear a smaller psychological cost in applying for patents.

size has on the relationship between R&D investment and patenting) is not positive. Via its intercept effect, *B* does have a positive impact on patenting, but the hypothesized positive impact of *B* on firm size's effect is not supported because the slope effect for *B* is negative.

The hypothesized slope effects for *B*, *A*, *PhI*, and *PhII* are grounded in the hypothesis that the responsiveness of R&D output to R&D investment will be greater as firm size increases when the R&D project is more Schumpeterian in the value and cost senses. The responsiveness will be less as firm size increases when the project is less Schumpeterian.

The estimation results in Table 4 support the hypothesized effects, except for the variable *B*. The intercept effect for these variables is what we would expect. The human capital associated with founders with experience in business or academics is associated with an intercept effect that shows more patenting, other things being the same. Thus, apart from any relationship between human capital and the effect of a firm's size on the R&D-patenting relationship, more human capital, whether from business experience or academic experience, is associated with more patents.

The technical capital that is associated with more related Phase I projects has a positive intercept effect, as would be expected, because for the knowledge input into the R&D project there will have been more research at the basic, exploratory end of the research spectrum to inform patentable ideas from the Phase II project's R&D. The negative intercept effect for more related Phase II projects might be expected because, at the applied end of the research spectrum, the additional technical capital from numerous related Phase II projects will make it more likely that patentable ideas have already been patented.

TABLE 4 ABOUT HERE

5. Comparison with Findings in the Literature

Using the estimated models in Table 4, we next present examples to show the magnitudes for the elasticities that have been estimated.[29]

Our model for the expected number of patent applications is:

$$\begin{aligned} P = \exp(&\beta_0 + \beta_1 \ln R + \beta_2 \ln S \ln R + \beta_3 B \ln S \ln R + \beta_4 A \ln S \ln R + \beta_5 PhI \ln S \ln R \\ &+ \beta_6 PhII \ln S \ln R + \textstyle\sum_{j \neq 1} \tau_j T_j \ln S \ln R + \beta_7 B + \beta_8 A + \beta_9 PhI + \beta_{10} PhII + \textstyle\sum_{j \neq 1} \alpha_j T_j \\ &+ \beta_{11} NE + \beta_{12} MW + \beta_{13} South) \end{aligned}$$

The elasticity of patent applications with respect to R&D investment is:

$$\left(\frac{\partial P}{\partial R}\right)\left(\frac{R}{P}\right) = \beta_1 + \beta_2 \ln S + \beta_3 B \ln S + \beta_4 A \ln S + \beta_5 PhI \ln S + \beta_6 PhII \ln S + \textstyle\sum_{j \neq 1} \tau_j T_j \ln S$$

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[29] The literature has developed alternative ways to look at the count variable for patents in a model estimating elasticities, given that for many observations the number of patents is zero. For example, Bound et al. (1984, p. 39) observe that they want to include the zero observations in their estimation and will treat the issue in two ways. One (p. 39) is to "set log patents to zero for all zero patent observations and allow those firms to have a separate intercept" in the regressions. The other is (1984, p. 41): "Second, we model the patents properly as a counts (Poisson) variable, taking on values 1, 2, 3, etc. . . ." In our paper we use the negative binomial model, which is a generalization of the Poisson model. Bound et al. actually use the negative binomial because it is needed given the "overdispersion" present for the patent count variable. Observe that with the formal treatment of the dependent variable as a count variable in the negative binomial (Poisson) context, there is no need to take the log of the zero observations. Given the functional form of e^x in a maximum likelihood estimation, the constant and the coefficients for the explanatory variables are chosen so that the "x" for the zero patent observations is sufficiently negative that the predicted patents can be close to zero and even essentially so if that outcome for the choice of the constant and other parameters maximizes the likelihood function. Scherer (1983a) provides another alternative—cubic equations, linear in the parameters estimated but nonlinear in the variables—that estimates the elasticities without the need to use the natural logarithms of the variables.

Observe several points about the functional form for patents. With its interaction terms for the logarithms of firm size and R&D investment, it implies that the elasticity of patents with respect to R&D investment is a function of firm size, and also the effects of the other variables depend on firm size. The cross-partial effects of firm size on the elasticity of patents with respect to R&D are diminishing. Further, the elasticity of patents with respect to firm size (that we examine subsequently) is a function of R&D investment, and in this case the effects of the other variables will depend on R&D investment, and the cross-partial effects of R&D on the elasticity of patents with respect to size are diminishing. There is a direct effect of R&D on patenting, but firm size affects patenting only through its (value and cost) effects on the impact of R&D investment on patenting. Depending on the parameters estimated, these elasticities may be large or small, and the logarithmic metric for R&D investment and for firm size limits the influence of unusually large R&D investments or unusually large firms (there are some very large observations for the two variables as seen in the descriptive statistics in Table 3) in our sample of small firms. Once we have estimated the model, we observe its predictions for various firm sizes or R&D investments using the actual values of all of the variables for observations with those various sizes or investments.

To estimate the elasticity of patent applications with respect to R&D investment using the second specification in Table 4 and the actual observations in the sample, we calculate the elasticity for each R&D project as:

$$0.472 + 0.0330\times\ln S - 0.0279\times B\times\ln S - 0.0302\times A\times\ln S - 0.00494\times PhI\times\ln S + 0.0156\times PhII\times\ln S + 0.0323\times Calculators\times\ln S - 0.0368\times Electro\text{-}mechanical\times\ln S$$

$– 0.123×Motors×\ln S + 0.0302× Synthetic\ resins×\ln S$.[30]

Table 5 shows the resulting estimated elasticity of patenting as a function of R&D for firms of various sizes in our sample. The elasticity averages somewhat less than 0.5 for the entire sample (n=125), and across the firm sizes ranges between 0.41 and 0.55. [31]

With reference to the pioneering work, discussed next, of Scherer on this topic, our calculated patenting elasticities follow, with respect to firm size, an inverted-U relationship.

TABLE 5 ABOUT HERE

The literature has often presented descriptive statistics for the elasticity of R&D output—as measured by patenting—with respect to firm size. We can complement those observations by calculating an elasticity of patenting with respect to firm size where the

[30] Recall from the discussion of the specification of Table 4 that the technology categories not included in the elasticity equation here did not have an effect on the relationship between firm size and the impact of R&D on patents.

[31] Scherer (personal correspondence, July 22, 2016) has an insightful observation about the elasticities that we observe for our small firms: "I'm puzzled by the strong tendency toward diminishing R&D – patent returns, with elasticities in a range around 0.5. I wonder if the following metaphor is plausible? When one undertakes an SBIR project, one seems to be working on the technological and commercial working out of a particular idea. In a sense, one is doing R&D on a more or less bounded technological set, and when one applies more resources to a bounded objective, diminishing returns almost surely apply. When on the other hand firms, large or small, decide what technological objectives they will pursue with their R&D, the set is virtually unbounded, and a tendency toward diminishing returns is much less compelling. This could explain the difference between your results and my own earlier finding for samples of typically larger firms toward more or less constant returns." We find the metaphor plausible, although we note also that Bound et al. (1984), discussed below, find essentially the same elasticities as ours for their small firm sample while observing their patenting and R&D at the level of the firm. Perhaps the R&D portfolios of their small firms are more like a focused R&D project than a collection of projects. See also the discussion in Griliches (1990, pp. 1674-1677) about the different elasticities for samples of small firms versus those for large firms. In particular, observe that we do not have the selection problem for our sample of small firms that Griliches discusses for the sample of small firms in Bound et al. (1984) where all of the small firms were successful in the sense that they were publicly traded firms, yet our elasticity estimates are essentially the same as the ones found there (and discussed by Griliches, 1990, p. 1675) for the small firms.

calculated elasticity is grounded in Section 2's *theory* of how firm size affects R&D output.

From our model, the elasticity of patent applications with respect to firm size is:

$$\left(\frac{\partial P}{\partial S}\right)\left(\frac{S}{P}\right) = \beta_2 \ln R + \beta_3 B \ln R + \beta_4 A \ln R + \beta_5 PhI \ln R + \beta_6 PhII \ln R + \sum_{j\neq 1} \tau_j T_j \ln R$$

Now, to estimate this in sample using the second specification in Table 4, again using the actual observations in the sample, we form the elasticity for each R&D project as:

$0.0330 \times \ln R - 0.0279 \times B \times \ln R - 0.0302 \times A \times \ln R - 0.00494 \times PhI \times \ln R + 0.0156 \times PhII \times \ln R + 0.0323 \times Calculators \times \ln R - 0.0368 \times Electro\text{-}mechanical \times \ln R - 0.123 \times Motors \times \ln R + 0.0302 \times Synthetic\ resins \times \ln R$.

Table 5's last column shows the resulting estimated elasticity of patenting as a function of firm size for firms of various sizes in our sample.

Observe in Table 5's last column that the elasticity of patenting with respect to firm size is "all over the place" even within size classes. That is exactly what theory tells us to expect, because the effect of firm size depends on the degree to which the R&D project is Schumpeterian in the cost or value senses. For example, for the eight projects that are not particularly Schumpeterian in the cost or value senses because the underlying variables that we use to distinguish Schumpeterian projects are not characteristics of the projects (i.e., $A = B = PhI = PhII = 0$ and the project is not in one of the four significant technologies that affect the impact of firm size), we have $(\partial P/\partial S)(S/P) = 0.445$ with standard deviation = 0.00889 and a minimum of 0.433 and a maximum of 0.455.

Turning to cases with various mixtures of Schumpeterian characteristics, for the 45 projects where $A = 1$ and $B = 0$ and therefore we hypothesized the R&D would be less

Schumpeterian, we find that elasticity of patenting with respect to firm size is especially low; its mean equals 0.198 (and exhibits skewness, with standard deviation = 0.298).

When *PhII* is high relative to *PhI*, we hypothesized that the R&D would be more Schumpeterian. Forming the ratio of *PhII* to *PhI* plus 1 in order to have a metric for relatively high *PhII*, for the 48 projects where the ratio exceeds its mean, the elasticity of patenting with respect to firm size averaged 0.384, with standard deviation = 0.345. For the 77 cases where the ratio is less than its mean, the elasticity averages –0.0501, with a large standard deviation of 0.484. For the 17 projects where the ratio is between its mean and a standard deviation more than its mean, the elasticity averages 0.247, with standard deviation = 0.331. For the 31 projects where the ratio is more than a standard deviation above its mean, the elasticity averages 0.459 with standard deviation 0.334.

For the actual observations in our sample, the elasticity of patenting with respect to firm size decreases as the projects become less Schumpeterian and increases as they become more Schumpeterian.

We now compare our results for the elasticity of patents with respect to R&D investment for firms of different sizes to prominent results in the literature about the elasticity of patents across the distribution of firm sizes. Table 6 provides an overview of selected articles, with descriptions of their samples and their findings to which we compare our own sample and results.

TABLE 6 ABOUT HERE

Scherer (1965, pp. 1110-1111) provides a careful assessment of the various possibilities for differences in the propensity to patent across the size distribution of firms, and he succinctly explains (1965, p. 1103) the literature's focus on the elasticity of patenting with respect to firm size:

> Does patenting increase more than proportionately with firm size, less than proportionately, or is the relationship essentially linear? Disciples of Schumpeter argue that inventive output ought to increase more than proportionately with firm size due to the scale economies and more effective incentives associated with bigness. Others have postulated the opposite relationship, pointing mainly to the stultifying effects of bigness on incentives and initiative.

Scherer (1965, pp. 1110) finds:

> Where significance is doubtful by traditional standards, one may incline toward the Scotch verdict that corporate patenting has not been shown to increase either more or less than proportionately with sales. But if the regressions are accepted as best estimates of some true behavioral pattern, it would appear that after a stage of slightly increasing returns extending to 1955 sales of approximately $500 million, corporate patenting tends to increase less than proportionately with sales, except in the case of a few giant firms which lead their two-digit sectors in sales. The least vigorous patent recipients relative to their size appear to be non-leader firms with sales over $500 million.

Then, Scherer (1965, p. 1114) makes this inference relevant for antitrust policy:

> In conclusion, the evidence does not support the hypothesis that corporate bigness is especially favorable to high inventive output. If anything the results show that firms below the half-billion dollar sales mark generate more inventions relative to their size than do giant firms. . . [T]he observed tendencies are less than completely uniform. It is also possible that large size does confer advantages for the development and integration of complicated "systems"—activities less likely to yield patentable inventions. Small firms at the same time may enjoy a comparative advantage at inventing and developing the more readily patentable component parts for such systems. My results do suggest, however, that a heavy burden of proof must be sustained by firms emphasizing research and development potential as a justification (i.e., in merger cases) for bigness.

One possibility to be considered in antitrust policy applications is the following: For a given amount of R&D, a larger firm may be able to apply its R&D-generated knowledge to greater output (and hence spread its R&D cost over more output) than would a smaller firm; thus, less than proportional increases in R&D output as firm size increases are consistent with increasing private and social returns to the R&D conducted by the larger firms (Cohen and Klepper, 1992, 1996a, 1996b).[32] As seen in Kohn and Scott (1982, p. 248), when the relations between the various elasticity propositions are set out, the fact that the elasticity of patents with respect to firm size is less than 1.0 does not imply that the elasticity of the R&D value added with respect to firm size is also less than 1.0.

Observe first that our results in Table 5 complement Scherer's results by examining the elasticities for a sample of small R&D-intensive firms in 2005, whereas Scherer's classic study from 50 years earlier examined a sample of very large firms, all of which were in the *Fortune 500* list of the largest U.S. corporations in 1955. Across the distribution of firm sizes for our small firms, the elasticity of patenting with respect to R&D is largest—that is the elasticity roughly peaks in an inverted-U sense—when the firms are in the middle of the range of sizes for the small firms.[33] As with Scherer's (1965) study of large firms, beyond a point, size does not appear to confer an advantage for inventive output, despite the fact that our measure of firm size—the firm's employment—is the measure that most favors finding support for the Schumpeterian firm-size hypothesis.[34]

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[32] This would be the case for R&D investments in process innovations if such innovations are more effectively used in-house by the firm—for example, because licensing or sale of the technology are less effective—and if smaller firms cannot grow to take advantage of a larger size when exploiting their innovations.

[33] The inverted-U relationship here should not be confused with Scherer's inverted-U in the relationship between R&D activity and seller concentration. For Scherer's description—both the seminal theory and the seminal empirical observation—of that inverted-U, see Scherer (1967a, p. 530, 1967b, pp. 391-392) and Scherer (1980, p. 437) with explicit reference to the "$\cap$-shaped relationship" at Scherer (1980, note 116, p. 437).

[34] Scherer (1965, p. 1103) observes: "[T]he neo-Schumpeterian bigness contention receives greatest support when total employment is chosen as the scale measure and least when assets are chosen." Scherer then uses the sales measure because of its more neutral

Second, as observed earlier, we emphasize that our elasticity estimates are remarkably similar in magnitude to those found by Bound et al. (1984) in a study of "as complete a cross section as possible of U.S. firms in the manufacturing sector which existed in 1976" for which "[t]he final sample consists of 2595 firms, of which 1492 reported positive R&D in 1976" (Bound et al., 1984, pp. 21, 24). For our sample of small R&D-intensive firms, from Table 5 we see that the elasticity of patenting with respect to R&D ranged from 0.41 to 0.55. Bound et al. (1984, Table 2.10, p. 49) divide (on the basis of R&D expenditures) their sample into small (n = 2102) and large (n = 480) firms and use the negative binomial model. They report that the elasticity was 0.37 for the smaller firms and 0.53 for the largest firm within the small firm group. Thus, for their small firm group, their estimates are very close to our own estimates for the small firms in our sample.

For the Bound et al. (1984) group of large firms, the elasticity was 0.85 for the smallest of the large firms and 0.59 for the very large firms; the latter had R&D that was 50 times greater than the smallest of the firms in the large firm group. Bound et al. (1984, p. 48) tentatively conclude that patenting increases more or less proportionately with R&D over the range of sizes from the smallest (R&D > $2 million) to those with $100 million in R&D, and then, at some point after that size, diminishing returns sets in for the firms in the group of large firms.

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characterization of firm size. As explained earlier, we use the employment measure of firm size because we can observe employment for our small R&D-intensive firms at the time of the proposal for the Phase II project—before any sales ultimately resulting from the project's R&D output will be observed (and for many of our young entrepreneurial firms before they have established sales). The small firms in our sample are special in many ways (as discussed in Section 3), and certainly they are very different from the very large firms in Scherer's seminal study.

To complete the comparisons of our findings with those in the literature, the analysis in Scherer (1983a; 1984a, pp. 227-235; 1984b) provides the elasticity of patenting with respect to the size of the line of business (a firm's operations in a particular industry, distinguished from the other industries in which the firm produces). Scherer worked with the U.S. Federal Trade Commission's Line of Business (LB) Program's data for 443 large manufacturing corporations with their operations in 1974 observed across 276 standardized industry categories (reduced to 249 for Scherer's purposes).

On average, each of the 443 firms operated in 9.6479 of the 276 standardized industries; thus, together they provided reports on 4,274 individual lines of business (LBs). With allowance made for multiple LBs of origin, because of central research labs having inventions applicable to multiple LBs, Scherer linked patents to LB R&D expenditures by observing the U.S. invention patents obtained by each firm from June 1976 through March 1977. In that period, the companies obtained 15,112 U.S. invention patents (more than 60 percent of all patents issued to U.S. industrial corporations during the period). The patents linked to each company's 1974 R&D expenditures were then linked to the specific LBs in which they originated, making the aforementioned allowance for multiple LBs of origin.

Scherer estimates both nonlinear patenting on R&D regressions and nonlinear patenting on sales regressions (Scherer, 1984a, pp. 229-230):

> The dependent variable is the count of patents received by a line of business . . . . The size of an LB (i.e., the independent variable) is measured by its 1974 sales (in millions of dollars). To take into account the fact that some industries enjoy richer opportunities to perform R&D and make patentable inventions than others, each industry category (of 249) with five or more nonzero observations on the dependent variable was allowed to have its own best-fitting regression equation.

"There were 124 industries in which five or more LBs had nonzero patenting" (Scherer, 1984a, p. 234). For those 124 industries, Scherer finds (1984a, Table 11.4, p. 234) no significant departure from the constant returns case with unitary elasticity for the elasticity of patenting on line of business sales for 73.4 percent (n = 91) of the industries. Increasing returns appeared for 11.3 percent (n = 14), while decreasing returns appeared for 15.3 percent (n = 19) of the industries.

Examining the patenting on R&D regressions, he found (1984a, Table 11.5, p. 235) the elasticity of patenting with respect to R&D to be insignificantly different from 1.0 for 59.7 percent of the industries, greater than 1.0 for 15.3 percent, and less than 1.0 for 25 percent. Scherer (1983a, p. 115) concludes: "Thus, the preponderant pattern is toward essentially constant returns in the patent output — R&D input relationship. To the extent that there are deviations, they tend to be more on the side of diminishing rather than increasing returns."[35]

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[35] Cohen and Klepper (1996a) use Scherer's patent data linked to the FTC Line of Business Program's data to develop support for "the basic idea that larger firms have an advantage in R&D because of the larger output over which they can apply the results and thus spread the costs of their R&D" (1996a, p. 241). Note this point is the one discussed above with caveats about the antitrust policy implications of the diminishing returns observed in the patenting to R&D relationship. Cohen et al. (1987) examine R&D expenditures as a function of a firm's sales in a line of business and also firm-wide sales. They use the FTC Line of Business Program's data and replicate the dominant result in Scherer (1984a, Table 11.3, p. 233, 1984b). Scherer controls for appropriability and technological opportunity conditions by estimating the elasticity of R&D with respect to line of business sales separately for each industry. He finds that the elasticity is unity for over seventy percent of the industries. Cohen et al. eliminate outliers from the FTC sample, examine the sample a whole, and find that controlling for industry effects, or instead controlling for the variance in conditions of appropriability and opportunity with their interesting industry-level variables, R&D intensity (the ratio of R&D to line of

Acs and Audretsch (1988) use, instead of patents, a different measure of innovative output: the number of innovations in each four-digit SIC industry in 1982, as tabulated by the U.S. Small Business Administration based on information in technology, engineering, and trade journals. Examining the relationship between innovative output and R&D at the industry level, Acs and Audretsch find that the number of innovations increases with increased industry R&D expenditures but at a decreasing rate. They also find (1988, p. 687) ". . . *ceteris paribus*, the greater extent to which an industry is comprised of large firms, the greater will be the innovative activity, but that increased innovative activity will tend to emanate more from the small firms than from the large firms. Perhaps this indicates that, in industries comprised predominately of large firms, the existing small firms must resort to a strategy of innovation in order to remain viable."

6. Conclusion

This paper complements the extant literature about the Schumpeterian firm-size hypothesis by:

- examining the effect on R&D performance of different firm sizes across the distribution of sizes for small R&D-intensive firms

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business sales) is not affected by the size of line of business sales. In other words, the elasticity of R&D to line of business sales is unity, which is what Scherer found for 71.4 percent of the industries. The outliers that Cohen et al. eliminate are reminiscent of the very large firms that were also outliers (Scherer, 1965, p. 1110) in Scherer's original study, discussed above, some 20 years before his studies that use the FTC data. Cohen et al. add that the probability of doing R&D is greater when lines of business have greater sales. They also report that total size (an aggregation of all of a firm's lines of business) does not affect R&D intensity significantly either, given appropriate controls; in other words, R&D increases proportionately with firm size for the sample of very large firms absent the outliers, consistent with the finding of Bound et al. (1984) for their large firm sample, and moreover, consistent with Scherer's (1965, p. 1110) "Scotch verdict."

- examining R&D and patenting at the R&D project level rather than at the level of the line of business, the firm, or the industry
- controlling for the effects of rivalry by having a sample of R&D-intensive small firms with variance in their sizes but, as explained in Section 3, with all of the firms facing vigorous competition from many other firms that also use engineers and scientists and R&D resources more generally to provide commercial research services to develop new technologies in response to the requests for research from a single U.S. government agency
- controlling for the endogeneity of firm size (that would make it difficult to disentangle the impact of firm size on R&D activity) by using the information about the firm's size just before the beginning of each of the R&D projects
- providing a Schumpeterian firm-size hypothesis test of the theory that the elasticity of R&D output with respect to the size of the firm will be greater when the R&D activity is more Schumpeterian in the cost sense and in the value sense

We find that for small research-intensive firms the elasticity of patenting with respect to R&D investment is about 0.5—essentially what has been found in the earlier literature examining small R&D-intensive firms. Further, the estimated elasticity varies roughly in an inverted-U pattern across the different sizes for our small firms from 0.41 to 0.55. We also find that for our sample of firms the mean elasticity of patenting with respect to firm size for subsamples grouped by size is quite small for the research-intensive firms that we observe and does not vary systematically with firm size. Perhaps the finding is not, at least with hindsight, surprising given that all of our firms are small, R&D-intensive firms; consequently there is no observed advantage to size per se in such a sample. However, as explained by Kohn and Scott (1982) that traditional way of looking for the effect of firm size may be the wrong way, and, consistent with their theory that the elasticity will vary with the extent to which the R&D activity is

Schumpeterian in the cost and/or value sense, we do find that the elasticity of patenting with respect to firm size decreases as the projects become less Schumpeterian and increases as they become more Schumpeterian.

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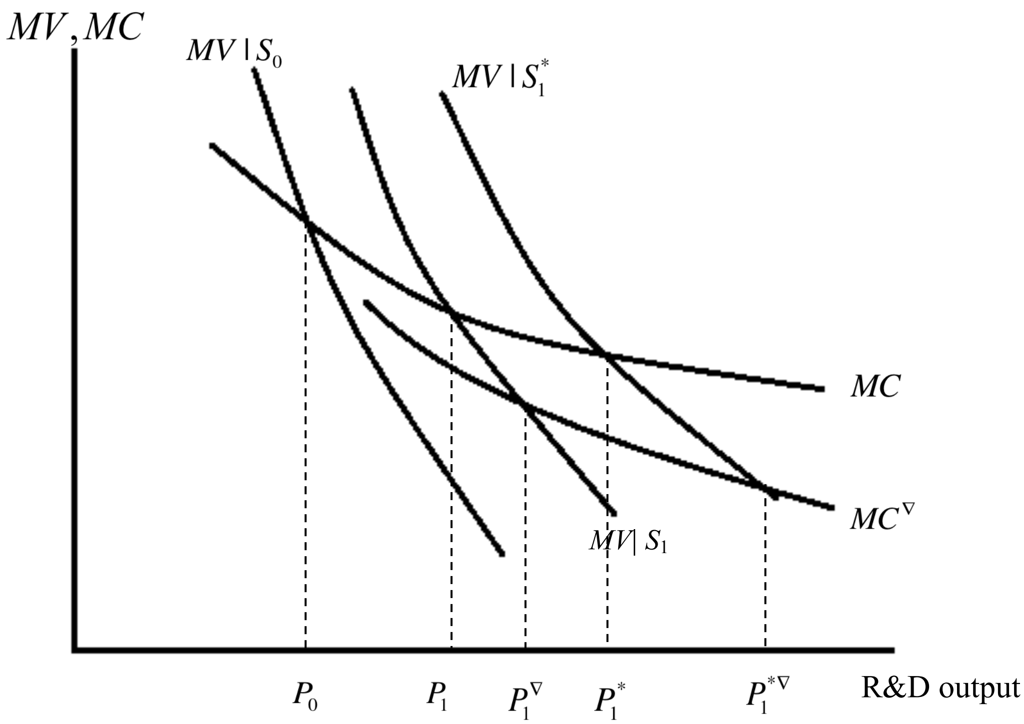
Figure 1. A R&D project can be more or less Schumpeterian in the cost sense and in the value sense.[a]



[a]Source: Adapted from Kohn and Scott (1982, pp. 246-247).

Table 1. The DOE Sample of Phase II SBIR Projects[a]

Total Phase II projects for DoD, NIH, NASA, DOE, and NSF for 1992-2001	11,214
Total DOE Phase II projects, 1992-2001	808
Total DOE Phase II projects for firms with 1 project	136
Surveyed DOE Phase II projects for firms with 1 project	136
Did not respond	96
Did respond	40
Randomly sampled	136
Sample weight	1.00[b]
Total DOE Phase II projects for firms with 2 projects	86
Surveyed DOE Phase II projects for firms with 2 projects	85
Did not respond	62
Did respond	23
Randomly sampled	85
Sample weight	1.01[c]
Total DOE Phase II projects for firms with > 2 projects	586
Surveyed DOE Phase II projects for firms with > 2 projects	218
Did not respond	124
Did respond	94
Randomly sampled	215[d]
Sample weight	2.73[e]

NOTES:
[a]Total DOE projects = 136 + 86 + 586 = 808; total DOE surveyed = 136 + 85 + 218 = 439; total DOE randomly surveyed = 136 + 85 + 215 = 436; the 40 + 23 + 94 = 157 responses minus the 3 cases added to the sample = 154 responses from the random sample.
[b]136/136 = 1, and 1/1 = 1.
[c]85/86 = 0.9884, and 1/0.9884 = 1.01.
[d]After taking the random sample, 1 project was added to the sample at the request of the firm that received the award and then 2 projects were added by the National Research Council research team to ensure that known "big successes" (over $10 million in sales and subsequent investments) were in the sample. Hence, 218 – 3 = 215.
[e]215/586 = 0.3669, and 1/0.3669 = 2.73.

Source: Link and Scott (2012, Table B1, pp. 128-130).

Table 2
Definition of Variables

Variable	Definition
P	Number of patent applications as of 2005, the year of the NRC survey
R	R&D investment in the Phase II projects ($2015)
S	Firm employees at the time of its Phase II proposal to DOE
B	Binary variable if the firm had a founder with a business background
A	Binary variable if the firm had a founder with an academic background
PhI	Number of previous Phase I projects in a technology area related to the current Phase II project
PhII	Number of previous Phase II projects in a technology area related to the current Phase II project
T	Binary variable for the technology research area of the Phase II project
NE	Binary variable if the firm in located in the Northeast Census region
MW	Binary variable if the firm is located in the Midwest Census region
South	Binary variable if the firm is located in the South Census region
West	Binary variable if the firm is located in the West Census region

Table 3. Descriptive Statistics[a]

Variable	*n*	Mean	Standard deviation	Minimum	Maximum
P	146	0.829	1.62	0	13
R	143	2,353,115	4,827,214	538,002	41,900,000
S	146	32.6	59.0	1	451
B	141	0.426	0.496	0	1
A	141	0.610	0.490	0	1
PhI	143	2.01	5.81	0	65
PhII	143	0.923	1.60	0	12
Geographic Region					
NE	142	0.282	0.451	0	1
MW	142	0.141	0.349	0	1
South	142	0.162	0.370	0	1
West	142	0.415	0.495	0	1
Technology effects					
Calculators	135	0.111	0.315	0	1
Chemical Processing	135	0.289	0.455	0	1
Compositions	135	0.0444	0.207	0	1
Earth Working	135	0.0296	0.170	0	1
Electricity	135	0.0741	0.263	0	1
Electro-Mechanical	135	0.0296	0.170	0	1
Heating & Cooling	135	0.00741	0.0861	0	1
Life & Agriculture Science	135	0.00741	0.0861	0	1
Machine Elements	135	0.00741	0.0861	0	1
Measuring & Testing	135	0.230	0.422	0	1
Motors	135	0.0148	0.121	0	1
Nano-technology	135	0.0148	0.121	0	1
Software	135	0.00741	0.0861	0	1
Stock Materials	135	0.0519	0.223	0	1
Super-conductors	135	0.0519	0.223	0	1
Synthetic Resins	135	0.0296	0.170	0	1

[a]These summary statistics are for the subset of the observations for which we have the patenting variable. For example, we have more projects than 141 for which we know whether or not the project had academic founders, but there are only 141 projects with that information and also the information about patenting. For another example, of the 146 observations with the information for the variable *P*, only 135 have the technology classification variable, even though we have 143 observations that have technology classifications (8 of the 143 do not have the patent variable). Although we have the patent variable and the technology classifications variable for 135 observations (so, if we ran the model of *P* as a function of technology alone we would have *n* = 135), we have only 125 observations that have *P*, technology, and all of the other variables that we use in the models of Table 4.

Table 4. Negative Binomial Model for P.[a]

Variable	(1)	(2)	(3)
$\ln R$	0.446 (0.115)***	0.472 (0.0959)***	0.477 (0.0943)***
$\ln S \times \ln R$	0.0268 (0.0160)*	0.0330 (0.0140)**	0.0355 (0.0138)***
$B \times \ln S \times \ln R$	–0.0252 (0.0203)	–0.0279 (0.0168)*	–0.0295 (0.0169)*
$A \times \ln S \times \ln R$	–0.0251 (0.0169)#	–0.0302 (0.0150)**	–0.0336 (0.0156)**
$PhI \times \ln S \times \ln R$	–0.00473 (0.00278)*	–0.00494 (0.00224)**	–0.00534 (0.00249)**
$PhII \times \ln S \times \ln R$	0.0164 (0.00958)*	0.0156 (0.00852)*	0.0173 (0.00914)*
Calculators $\times \ln S \times \ln R$		0.0323 (0.0208)#	0.0315 (0.0211)#
Electro-mechanical $\times \ln S \times \ln R$		–0.0368 (0.0230)#	–0.0422 (0.0219)*
Motors $\times \ln S \ln R$		–0.123 (0.347)	–0.159 (0.350)
Synthetic Resins $\times \ln S \ln R$		0.0302 (0.0451)	0.0159 (0.377)
B	1.42 (0.753)*	1.46 (0.722)**	1.57 (0.743)**
A	0.779 (0.771)	0.997 (0.722)	1.11 (0.738)#
PhI	0.277 (0.167)*	0.295 (0.138)**	0.297 (0.158)*
$PhII$	–0.772 (0.429)*	–0.686 (0.409)*	–0.725 (0.444)#
Geographic Region[b]			
NE	0.0455 (0.334)	–0.0770 (0.342)	
MW	–0.883 (0.577)#	–0.847 (0.543)#	
$South$	–0.0754 (0.380)	–0.217 (0.419)	
Technology effects[c]			
Calculators	–0.758 (0.469)#	–1.86 (0.792)**	–1.86 (0.812)**
Chemical Processing	–0.217 (0.373)		
Compositions	0.444 (0.632)		
Earth Working	0.0566 (0.451)		
Electricity	0.572 (0.433)		
Electro-Mechanical	1.02 (0.448)**	2.64 (0.979)***	2.77 (0.799)***
Motors	–30.0 (0.800)***	–22.4 (10.9)**	–19.0 (11.0)*
Nano-technology	0.364 (0.535)		
Stock Materials	–0.0355 (0.570)		
Superconductors	0.0265 (0.633)		
Synthetic Resins	–1.69 (1.03)*	–2.42 (1.71)	–2.09 (1.59)
Miscellaneous[d]	–0.680 (0.709)		
Constant	–7.84 (1.69)***	–8.45 (1.27)***	–8.77 (1.29)***
Auxiliary parameter: alpha[e]	1.02×10^{-7} (6.98×10^{-8})	1.18×10^{-7} (1.16×10^{-7})	2.18×10^{-7} (2.41×10^{-7})
n	125	125	125
Log pseudo likelihood	–248.29	–250.62	–254.67
Wald chi-squared (df)	2781.7 (25)***	2164.9 (21)***	1783.9 (18)***

[a]The model is estimated with the sample weights (also called probability weights) shown in Table 1 and with standard errors adjusted for 98 clusters by firm; standard errors are in parentheses.. The significance levels for two-tailed tests are indicated as *** for 1%, ** for 5%, and * for 10%. To provide information about parameters that were marginally significant, # indicates p-values for the two-tailed test that were > 0.10 but < 0.15.

[b]The effect for the region *West* is left in the intercept.

[c]The effect for the technology *Measuring and testing* is left in the intercept.

[d]This category is composed of the four technologies (*Heating and cooling*, *Life and agriculture science*, *Machine elements*, and *Software*) that each have only a single observation in the sample; for one of the projects P= 1, and the other three projects have P= 0.

[e] Because alpha is essentially 0 (the 95% confidence interval for alpha is 0.0000000265 to 0.000000390 for the first specification, 0.0000000172 to 0.000000811 for the second), and 0.0000000248 to 0.00000191 for the third), the Poisson estimator would do just as well as the negative binomial. The Poisson distribution is a special case of the negative binomial distribution with alpha equal to zero.

Table 5. Mean Patenting Elasticities with respect to R&D and Firm Size[a]

Firm Size, S	n	$\left(\frac{\partial P}{\partial R}\right)\left(\frac{R}{P}\right)$	$\left(\frac{\partial P}{\partial S}\right)\left(\frac{S}{P}\right)$
$0 < S < 10$	61	0.488 (0.0515) [0.00659] {0.475-0.501}	0.168 (0.409) [0.0523] {0.0628-0.272}
$9 < S < 20$	14	0.471 (0.112) [0.0298] {0.407-0.536}	–0.00944 (0.627) [0.168] {–0.372-0.353}
$19 < S < 30$	13	0.520 (0.112) [0.0309] {0.453-0.588}	0.200 (0.514) [0.142] {–0.111-0.510}
$29 < S < 50$	14	0.545 (0.0761) [0.0203] {0.501-0.588}	0.267 (0.294) [0.0786] {0.0970-0.437}
$49 < S < 100$	8	0.493 (0.102) [0.0361] {0.408-0.578}	0.0795 (0.367) [0.130] {–0.227-0.386}
$99 < S < 200$	11	0.408 (0.232) [0.0701] {0.252-0.565}	–0.202 (0.730) [0.220] {–0.692-0.288}
$199 < S \leq 451$	4	0.446 (0.258) [0.129] {0.0353-0.856}	–0.0634 (0.640) [0.320] {–1.08-0.954}
$0 < S \leq 451$	125	0.488 (0.110) [0.00983] {0.468-0.507}	0.117 (0.483) [0.0432] {0.0311-0.202}

[a]Standard deviation in parentheses; standard error in brackets and 95% confidence intervals in curly brackets, for the estimated mean in the classical normal model

Table 6. Selected Descriptive Evidence about the Nexus of Patents, R&D, and Firm Size

Article	Sample	Aggregation Level	Findings
Scherer (1965)	Sample of the largest U.S. corporations (all from the *Fortune 500*) in 1955 (*n* = 448); each firm's patents received in 1959, and its sales, R&D employment and total employment in 1955.	firm; firms examined together, grouped by broad (2-digit SIC) industries, and also in broader groupings	Patenting (patents received in 1959) increases slightly more than proportionately with firm size (measured by sales in 1955) up to a point, and then increases less than proportionately except for a few giant firms.[a]
Bound, et al. (1984)	Sample of U.S. firms in the manufacturing sector in 1976 (*n* = 2595 firms); each firm's 1976 patent applications and its 1976 R&D expenditures	firm; firms examined together, grouped by broad (roughly 2-digit SIC) industries	Elasticity of patents with respect to R&D = 0.55 at $100 thousand in R&D and = 0.66 at $1 billion in R&D (*n* = 2582) (p. 46). Dividing the sample into small and large firms by their R&D, for the small firms (R&D less than $2 million or missing, *n* = 2102), the elasticity = 0.37 at $100 thousand in R&D and = 0.53 at $2 million in R&D; for the large firms (R&D greater than $2 million, *n* = 480), the elasticity = 0.89 at $2 million in R&D and = 0.59 at $100 million in R&D (p. 49).[b] "[T]entative conclusion is that there are nearly constant returns to scale in patenting throughout the range of R&D above $2 million, with decreasing returns setting in some place above $100 million." (p. 48)
Scherer (1983a; 1984a, pp. 227-235; 1984b)	U.S. Federal Trade Commission Line of Business Program sample of the largest U.S. corporations in 1974 (*n* = 443); 4,274 line of business (LB) observations for the 1974 R&D expenditures for the firms; 15,112 U.S. invention patents from June 1976 to	Line of business (LB); LBs grouped by industries (at the 3-digit to 4-digit SIC industry level of aggregation)	"[T]he preponderant pattern is toward essentially constant returns in the patent output — R&D input relationship. To the extent that there are deviations, they tend to be more on the side of diminishing rather than increasing returns." (1983a, p. 115)

	March1977 linked to the 1974 LB R&D expenditures		
Present paper (Link and Scott)	Sample of individual R&D projects begun 1992-2001 for small U.S. R&D-intensive firms (n = 125); for each project, total R&D investment in 2015 dollars and patent applications resulting as of 2005	R&D project; the projects are for firms that all compete to apply science and engineering resources to perform contract research for the DOE SBIR program; technology dummies control for different intercepts and slopes across technologies	Across the distribution of firm sizes, the elasticity of patenting with respect to R&D ranged from 0.41 to 0.55 with the elasticities being largest for intermediate levels of firm size and also varying directly with the extent to which the projects are Schumpeterian in the cost or value senses.

[a]Also, from Table 3, p. 1104, with firms ranked by sales, patenting increases somewhat more proportionately with R&D (measured as R&D employees) than with firm size, although still with some suggestion of diminishing returns.

[b]These results are for the negative binomial model; Bound et al. also examines the data with other models without the treatment of the patent variable as a count variable, including OLS with dummy variables to handle the cases of zero patents and zero R&D. The negative binomial results for Bound et al. are for all firms grouped together and without the industry dummies. After carefully examining the OLS results with the industry dummies, Bound et al. (1984, p. 42) observe: "Although we believe that there are significant differences in the relationship of R&D and patenting at the detailed industry level from inspection of the distribution of the two variables by industry, these differences do not affect the basic results of this aggregate study. We have therefore omitted the industry dummies for the sake of simplicity in what follows."