A COUNT PANEL DATA STUDY OF THE SCHUMPETERIAN HYPOTHESIS

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ABSTRACT

This study estimates the patent-R&D relationship using count panel data. The data is an original panel of 318 firms making R&D investments and applying for patents during the period from 1984 to 1993. A negative binomial model with fixed effects is estimated, taking into account both the discrete nature of the count dependent variable and firm-specific unobserved heterogeneity as well as overdispersion in the data. Firm-level R&D capital, concentration ratios, and various firm size proxies are used as independent variables. Analysis of the data fails to reveal support for the basic tenets of the Schumpeterian Hypothesis. In particular, firm size has a significant negative impact on innovation while industry concentration is statistically insignificant. (JEL O3, L0, C0)

1. INTRODUCTION

A firm's economic environment is very likely to have a significant impact on its innovative activity. Schumpeter advanced the notion that innovative advantage belonged to large firms as opposed to small firms and to industries characterized by imperfect competition. These are the two main tenets of the Schumpeterian hypothesis. That is, market imperfections account for the relative innovative superiority of large firms over their smaller counterparts because they allow the larger firms to retain the returns from R&D. These larger firms may also have greater access to capital markets and a stronger ability to secure funding for their research endeavors.

Griliches (1979) explained the relationship between innovative output and innovative inputs in the context of the knowledge production function (KPF), which basically stated that innovative output is the product of innovative inputs. In many studies, patent applications have served as a measure of innovative output. The United States has experienced a surge in patenting uniformly distributed across technologies. Between 1900 and the mid-1980s, 40,000 to 80,000 patent applications were submitted per year. In 1995, however, more than 120,000 patent applications were submitted to the Patent Office. A firm's R&D expenditures are the most common innovative input to the KPF. It is reasonable to assume, however, that other forces affect the R&D relationship. In particular, the degree to which R&D expenditures produce innovative output is conditioned by the market structure characteristics of the industry in question.

Empirical studies of the relationship between market structure and innovation have found that large firms tend to have higher rates of R&D spending and innovation (e.g. Scherer, 1967). In general, the rationale is that the static efficiency losses associated with monopoly are offset by gains in dynamic efficiency. However, on the whole, the empirical work in this area has been inconclusive.

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Industry level studies (e.g. Geroski, 1990) suggest that concentration has a dampening effect on innovation. Blundell *et al.* (1993) find that, while higher market share firms innovate more, firms in competitive industries tend to have a greater probability of innovating. Thus, the lack of competition combined with a high level of industry concentration depresses the aggregate level of innovative activity.

Research by Gopinath and Vasavada (1999) on the U.S. food processing industry demonstrates a positive effect of market share on patenting, but a negative impact of concentration on it. Work by Blundell *et al.* (1995), and Acs and Audretsch (1987) also contradicts Schumpeter's belief by finding a similar dampening effect of industry concentration on innovation. Furthermore, Acs and Audretsch and others have shown that small firms do have an innovative advantage over large firms in some industries and under certain conditions.

Smythe (2001) obtained tentative support for the Schumpeterian Hypothesis studying electric power utilization at the turn of the century in the U.S. Higher degrees of industry concentration were found to be conducive to rapid innovation. Likewise, Hall and Ziedonis (2001) found that larger firms in the U.S. semiconductor industry submit more patent applications than smaller ones.

The issues surrounding the link between market structure and innovation need further investigation. Empirically, it has been found that while large firms are more innovative in a number of industries, the opposite is true in other cases. Coupling these findings with a lack of supporting evidence regarding the effect of industry concentration on innovation calls the Schumpeterian Hypothesis into question.

In this paper, the effect of market structure on patenting as summarized by the Schumpeterian Hypothesis is studied. The study borrows from Blundell *et al.* (1995) who used British firm-level panel data on the "technologically significant and commercially important" innovations commercialized during the period from 1972 to 1982, while controlling for market structure and firm size. It also widens the scope of Gopinath and Vasavada (1999) who employed U.S. firm-level panel data for the food processing industry to investigate the relationship between market structure and patent applications, and Hall and Ziedonis (2001) who investigated patenting behavior in the U.S. semiconductor industry using panel data.

This paper is presented in six sections: Section 2 presents the data, its main characteristics, and the construction of some variables. Section 3 explores the econometric models for count data, using the basic Poisson as a benchmark model. Past research is presented in Section 4. The empirical findings are presented in Section 5. Section 6 provides a brief conclusion.

2. DATA

The data are an original panel of 318 U.S. manufacturing firms with concentration ratio data available for their SICs, which invested in R&D and applied for patents between 1984 and 1993. The relevant explanatory variables for this analysis include firm-level R&D capital, firm size proxies, and industry-level concentration ratios. The dependent variable is patent application counts serving as a proxy for innovative output.

Patents are assumed to be an indicator of innovative output or the “success” of R&D rather than just the input of R&D. The validity of this assumption has been investigated by Pakes (1985) and Griliches (1981) using the market value of the firm as an additional indicator of R&D success. In regressions of the rate of return of market value on the R&D history of the firm, contemporaneous patenting is moderately significant. Although the results are somewhat inconclusive, their result suggests that patents measure something more than the input of R&D, which can be considered the “success” or output of R&D.

Patents have been criticized as a measure of innovative output because not all patented inventions prove to be innovations and many innovations are never patented. Nevertheless, Schmookler (1966, p. 56) states, “We have the choice of using patent statistics cautiously and learning what we can from them, or not using them and learning nothing about what they alone can teach us.”

In addition, the findings of Ernst (2001) support the significance of patent data as an objective output indicator for R&D efforts. The paper also points out that patent data are easily obtained. Patent data provide an aggregate indication of patenting activity by R&D-conducting firms even though the information conveyed by a single patent may be very inconsequential. Further, they provide a long time series for study in contrast to the Innovation Citation Database published by the U.S. Small Business Administration in 1984, which only included data for innovations in 1982.[1]

Concentration ratios were collected as measures of market structure. They were taken from the Census of Manufacturing bulletin, *Concentration Ratios in Manufacturing*. The ratios are defined as the percentage of total industry sales accounted for by the largest 4, 8, 20, or 50 firms.

Controlling for market structure is important because various changes, such as mergers and acquisitions, in the composition of an industry over the course of a ten-year period can have an impact on the patenting activity of firms. In addition, the Schumpeterian Hypothesis asserts that firms in industries characterized by imperfect competition tend to be more innovative than firms in industries more closely resembling the competitive model. Industry concentration ratios can be used to measure the competitiveness of an industry and help control for the role of market structure.

The information collected for each firm from Standard and Poor’s Compustat includes its corporate name, primary SIC code, annual R&D expenditures, assets, capital expenditures, employment, market value, and net sales. In addition, the capital expenditure-employment, the R&D-sales, and the R&D-employment ratios were created. The total number of patent applications submitted by year and U.S. Patent Office company codes were collected from the PATSIC file on CD-ROM from the United States Patent and Trademark Office. The Compustat and patent data were matched by company code for each firm. The R&D investments at the firm level and all other firm-level dollar amount variables have been converted to constant 1990 dollars.

Following Crepon and Duguet (1997a, b), the firm’s own R&D capital was created as an input to the KPF. The formula for the variable is

$$k_{it} = (1-\delta)k_{it-1} + r_{it} \qquad \textbf{(1)}$$

where k_{it} is R&D capital for firm *i* at time *t*, δ is the annual depreciation rate, and r_{it} is real R&D for firm *i* at time *t*. The depreciation rate was set at 15 percent in line with Crepon *et al.* (1998), Crepon and Duguet (1997a, b), Klette (1996), and Encaoua *et al.* (1998). All of these studies used depreciation rates in the range of 15-20 percent. Rates of 20 percent, 25 percent, 30 percent, and 50 percent were experimented with, but the exact depreciation rate made very little difference in the results as discovered by Blundell *et al.* (1995).

The descriptive statistics reported in Table 1 indicate that the mean number of patent applications submitted by a firm in a given year in this sample is 15.5. The overdispersion typical of count data is evident in the variance-to-mean ratio of 174.45 for the patent count variable. The minimum and maximum for this variable also reveal a skewed distribution, which is characteristic of non-negative data.

Table 1. Descriptive Statistics

VARIABLE	MEAN	STD. DEV.	MINIMUM	MAXIMUM
PATENT APPLICATION COUNT	15.5	52.0	0.00	1139.0
R&D ($ millions)	57.1	152.5	0.00	1727.9
ASSETS ($ millions)	2152.1	10910.2	0.03	181416.6
CAPITAL EXPENDITURE ($ millions)	148.9	696.8	0.00	10541.2
EMPLOYMENT (thousands)	10.2	30.9	0.00	383.7
CAPITAL EXPENDITURE/EMPLOYMENT	8.9	13.0	0.00	214.7
MARKET VALUE ($ millions)	2342.3	8477.2	0.03	113061.1
NET SALES ($ millions)	2080.0	9113.7	0.00	112011.8
R&D/EMPLOYMENT	5598	6604.1	0.00	104820.0
R&D/NET SALES	27.45	2126.4	0.00	348014.7

3. ECONOMETRIC MODELS

The integer-valued patent data possess some unique attributes that must be addressed econometrically using models appropriate for count data. Due to the difficulties and uncertainties associated with R&D activities, firms do not always apply for patents, resulting in a nonnegligible number of zero values. Linear regression models are not recommended to analyze this type of data because it is unlikely that the basic assumptions of normal residuals and linearity will be satisfied.

3.1 Basic Poisson Model

The simplest non-linear regression model to accommodate the discrete, non-negative nature of the patent application count variable is the Poisson model. The Poisson model requires the first two conditional moments to be equal and allows for the straightforward treatment of the zero outcomes since they are a natural outcome of the Poisson specification. Estimation of unknown parameters is straightforward and proceeds by either an iterative weighted least squares (WLS) technique or maximum likelihood estimation (MLE). Since the log-likelihood function is globally concave, maximization routines converge rapidly. In addition, the heteroskedastic and skewed distributions natural to non-negative data are accounted for by the equality of the first two conditional moments (sometimes called the "equidispersion" property).

According to the Poisson regression model, each y_{it} is drawn from a Poisson distribution with parameter λ_{it} which is related to the explanatory variables x_{it}. The primary equation for this model is

$$\Pr(Y_{it} = y_{it}) = \frac{e^{-\lambda_{it}} \lambda_{it}^{y_{it}}}{y_{it}!}, y_{it} = 0,1,... \quad \textbf{(2)}$$

where

$$\lambda_{it} = \exp(x_{it}\beta) \quad \textbf{(3)}$$

The λ_{it} is a deterministic function of x_{it} and the randomness in the model comes from the Poisson specification for the y_{it}.[2] How the mean number of events changes as a consequence of changes in one or more of the regressors is the point of interest.

As mentioned before, the first two conditional moments for the Poisson model are equal. That is,

$$E[y_{it} \mid x_{it}, \beta] = Var[y_{it} \mid x_{it}, \beta] = \lambda_{it} \quad \textbf{(4)}$$

The log-likelihood function of a panel data sample for the Poisson model is

$$L(\beta) = \sum_{i=1}^{N} \sum_{t=1}^{T} [y_{it}! - \exp(x_{it}\beta) + y_{it}x_{it}\beta]. \quad (5)$$

The basic Poisson model with its "equidispersion" property suffers from some limitations, however. Overdispersion is a concern with patent data, where the conditional variance exceeds the conditional mean. Thus, the variance of the estimator will be larger than expected and a possible efficiency loss will result. In the case of patent data, unobserved effects such as the inherent uncertainty of R&D activities, different appropriability conditions, the ability of engineers to discover new products, strategies of secrecy, or the obvious commercial risk of selling an invention result in only a few successful firms applying for a large number of patents in a given period of time, while the majority of firms may find patenting holds little or no importance for them.

In addition, the "equidispersion" property does not allow for unobserved heterogeneity, i.e., individual firm-specific effects. This is definitely a concern with firm-level data where the heterogeneity is not necessarily fully represented by the observed individual characteristics summarized by the regressors. If this restriction is inappropriately imposed, spuriously small estimated standard errors of $\hat{\beta}$ may result.

3.2 Basic Negative Binomial Model

The negative binomial model represents a more general formulation than the Poisson model. It attempts to improve on the Poisson model by including a firm unobserved effect, ε_i, in the λ_{it} parameters. The negative binomial model arises from a natural formulation of cross-section heterogeneity and is essentially an "apparent contagion" model in which individuals have constant, but unequal probability of experiencing an event.[3]

Ideally, the negative binomial model would permit the variance to grow with the mean while simultaneously allowing a conditional fixed effect, which could be correlated with the independent variables, in particular R&D. In other words, firms, which are better at producing patents for unobserved reasons, may make larger R&D expenditures than others because their return to the expenditures is higher. Support for the existence of such a correlation can be found in Duguet and Kabla (1998), who analyze data from the French technological appropriation survey (EFAT). They point out that the highest R&D budgets belong to firms that possess a technical advantage in their industry, which enables them to patent a larger fraction of their innovations.

With the fixed effect specification, it is not necessary to assume away a correlation between the firm-specific effect and the right-hand-side variables because the individual effects are conditioned out and are not estimated. This is an especially attractive feature of the fixed effects approach.

The negative binomial model assumes that the Poisson parameter λ_{it} follows a gamma distribution with parameters (γ, δ) where $\gamma = exp\ (x_{it}\beta)$ with δ common both across firms and across time. With this specification, the mean and variance of λ_{it} are $E\ [\lambda_{it}] = exp\ (x_{it}\ \beta)/\delta$ and $Var\ [\lambda_{it}] = \exp\ (x_{it}\ \beta)/\delta^2$. Note that λ_{it} can still vary even if x_{it} remains constant for a firm over time.

3.3 Fixed Effects Negative Binomial Model

To add the firm-specific effects, assume the parameters of the underlying model are $(\gamma_{it}, \delta_i) = (e^{xit\beta}, \phi_i / e^{\mu i})$ where both ϕ_i and μ_i are allowed to vary across firms. The mean is

$$\tilde{\lambda}_{it} = \exp(x_{it}\beta + \mu_i)/\phi_i \qquad \textbf{(6)}$$

while the variance is

$$Var[\lambda_{it}] = \exp(x_{it}\beta + 2\mu_i)/\phi_i^2 . \qquad \textbf{(7)}$$

Here, the mean has been multiplied by $exp\ (\mu_i)$ and so has the standard deviation. With respect to the corresponding unconditional negative binomial model, calculate

$$E[y_{it}] = \exp(x_{it}\beta + \mu_i)/\phi_i \qquad (8)$$

with

$$Var[y_{it}] = \{e^{x_{it}\beta + \mu_i} / \phi_i\}\{1 + e_i^{\mu_i/\phi_i}\} \qquad \textbf{(9)}$$

so that the variance-to-mean ratio is $(e^{\mu i} + \phi_i)/\phi_i$. This allows for both overdispersion, which is lacking in the Poisson model, as well as a firm-specific variance-to-mean ratio, which the basic negative binomial model does not.

4. PREVIOUS WORK

Hausman *et al.* (1984) were the first to investigate differences in the propensity to patent across firms in the context of the patent-R&D relationship and explicitly account for the discrete, nonnegative nature of the patent count variable in a panel data setting. Their work reveals the importance and role of lagged R&D spending in the innovation process and develops the models for count panel data utilized in this study. Theirs was the seminal research of the patent-R&D relationship using count panel data.

The Schumpeterian Hypothesis emphasizes the importance of firm size in the production of innovations. In particular, large firms are supposed to be more innovative than small firms. Measuring firm size as a source of heterogeneity in the propensity to patent across firms is very important in this study since the firms are drawn from various manufacturing sectors.

To study the disparate effects of firm size and industry structure on innovation, Acs and Audretsch (1987) use cross-sectional data from the U.S. Small Business Administration's Innovation Citation Database to test a modified Schumpeterian Hypothesis. Specifically, they test the hypothesis that large firms hold an innovative advantage in markets characterized by imperfect competition while small firms have the innovative advantage in markets more reminiscent of the competitive model.

Acs and Audretsch find that large firms tend to have the relative innovative advantage in markets, which are capital-intensive, highly unionized, concentrated, and produce a differentiated product. On the other hand, their results indicate that small firms hold the innovative advantage over large firms in industries that are highly innovative, utilize a large component of skilled labor, and tend to be composed of a relatively high proportion of large firms. Thus, these results generally support the modified Schumpeterian hypothesis Acs and Audretsch posit.

Using the same data as in their previous paper at a more aggregated level, Acs and Audretsch (1988) test two more hypotheses related to the Schumpeterian Hypothesis. Specifically, that the degree to which R&D expenditures produce innovative output is tempered by market structure characteristics, and that the innovative activity of small firms and large firms responds to particular technological and economic regimes. They study 247 four-digit SIC industries bringing forth innovations in 1982.

Acs and Audretsch conclude that the number of innovations increases with increased industry R&D spending, but at a decreasing rate. Innovation is also positively related to skilled labor and the degree to which large firms comprise the industry. Further, they find that industry concentration dampens industry innovation, and that unionization is negatively associated with innovation as well.

Smythe (2001) conducts a study of electric power utilization using a sample of 197 U.S. manufacturing firms over the years 1899-1909. Concerned with merger activity and the diffusion of electric power in the early 1900s, Smythe uses ordinary least squares (OLS) and instrumental variable (IV) estimation to reveal tentative support for the Schumpeterian Hypothesis. Specifically, the results indicate that a high degree of industry concentration fostered rapid innovation in U.S. manufacturing firms during the study period.

Duguet and Kabla (1998) analyze an international cross-section of 299 firms representing the U.S., Japan, and Europe. The number of patents is specified to be a function of R&D spending, sales, average Herfindahl concentration index, industry dummies, and other variables. They employ pseudo maximum likelihood estimation (PMLE) of a heterogeneous Poisson model in addition to other estimation routines.

The logarithm of average concentration does not achieve statistical significance in any of the regressions run by Duguet and Kabla. The sign of the coefficient on this variable is almost always negative throughout their study. The logarithm of sales has a positive sign, but is not statistically significant using pseudo maximum likelihood estimation of a heterogeneous Poisson model.

With a cross-section of 4,164 French manufacturing firms, Crepon *et al.* (1998) specify the number of patents per employee as a function of R&D capital, the number of employees, demand pull variables, and technology push variables. They estimate the patent equation using asymptotic least squares (ALS), and find a significant positive effect of R&D capital, but an insignificant negative impact of the number of employees as a firm size proxy. Crepon *et al.* conclude that firm innovative output increases with its research effort as well as demand-pull and technology push variables.

Van Cayseele (1998) criticizes the use of cross-sectional data to test the Schumpeterian Hypothesis, and attributes much of the inconclusiveness of the results of this research to the use of cross-sectional data. Van Cayseele calls for studies that, ideally, employ panel data in the study of innovation and market structure.

Blundell *et al.* (1995) use a panel of 375 British manufacturing firms to analyze the wide range of innovative activity across firms resulting, in part, from permanent unobservable differences across them. Concerned with the effects of market structure on innovation, Blundell *et al.* model innovation as a function of market structure measures at the firm and industry levels, tangible capital stock, knowledge capital stock at the industry level, the firms' accumulated knowledge stock, a firm-specific effect, and a time-specific effect.

Blundell *et al.* find a positive, significant effect for market share while concentration enters negatively (impact of competition on aggregate innovation is positive). Since the effects of the recession dummies are negative, they conclude that firms innovate more in booms to capture increased demand. With measured fixed effect variables, the effect of market share becomes smaller as does the effect of knowledge stock. Basically, controlling for unobserved firm heterogeneity indicates that dominant firms have a higher propensity to innovate, but competitive industries tend to generate higher aggregate number of innovations as an offsetting effect.

Gopinath and Vasavada (1999) study a panel of 32 U.S. food-processing firms over the period 1965-1981. Their aim is to investigate the impact of market structure and R&D spending on the number of patent applications submitted by firms using fixed and random effects Poisson and negative binomial models for count panel data. They consider patent applications to be a function of R&D expenditures, market share, and industry concentration variables, among others.

Gopinath and Vasavada discover a positive impact of R&D capital on patent applications using both Poisson and negative binomial models. When taking market structure into account, a positive and statistically significant coefficient for market share is obtained with the random effects Poisson model and the random effects negative binomial model. While positive, the coefficient is not significant at a 5 percent level with the fixed effects negative binomial model. Alternatively, a negative sign is obtained for the coefficient on the number of establishments variable, but it is only statistically significant with the random effects Poisson model. A Hausman test favors both random effects models over the fixed effects model indicating the absence of correlation between the firm-specific effect and the regressors.

Hall and Ziedonis (2001) utilize a panel of 95 U.S. publicly traded semiconductor firms for the period 1979-1995 to examine their patenting behavior. They attempt to explain the surge in semiconductor patenting since the mid-1980s, which contradicts more recent survey data claiming a lack of dependence upon patents to capture returns to R&D in the industry. Patent applications submitted by firms are modeled as a function of R&D spending, firm size, time dummies, firm age, and firm type.

Using Poisson models, their results show a positive and significant effect of R&D expenditures and firm size on the propensity of semiconductor firms to patent. Hall and Ziedonis conclude that a strengthening of U.S. patent rights in the 1980s has led to “patent portfolio races” and entry of specialized design firms.

In contrast to Blundell *et al.* (1995), Gopinath and Vasavada (1999), and Hall and Ziedonis (2001), this work utilizes U.S. firm-level panel data on patents from 1984 to 1993 for a variety of industries. It is well known that considerable merger and acquisition activity in the U.S. as well as the emergence of a plethora of innovations by firms of all sizes characterized the 1980s. As such, this data set provides a unique opportunity to analyze the Schumpeterian Hypothesis.

5. RESULTS

Since the regressors are taken in logs, the estimated coefficients of the R&D capital and the firm size proxies can be interpreted as elasticities. In the event that the regressors are not taken in logs then the parameters can be directly interpreted as semi-elasticities. Thus, the estimate gives the proportionate change in the conditional mean when the regressor in question changes by one unit. This is the case for the industry concentration ratios.

Likelihood ratio (LR) and Wald tests for overdispersion due to Cameron and Trivedi (1998) strongly reject the null hypothesis of equidispersion at the 1 percent level throughout the study.[4] The presence of overdispersion in the data supports the use of the negative binomial model for the analysis because its variance is proportional to the mean. In addition, the log-likelihood values obtained with the fixed effects negative binomial model are higher than those of the fixed effects Poisson model in all regressions, providing further support for the negative binomial model.

5.1 Industry Concentration

Using the four-firm concentration ratio as the measure of industry concentration in Table 2, the fixed effects negative binomial model finds R&D capital significant at the 1 percent level with an elasticity of 0.15. Gopinath and Vasavada (1999), Crepon *et al.* (1998), and Crepon and Duguet (1997 a, b) also obtained positive and significant estimates for R&D capital. In fact, Crepon and Duguet (1997a) obtained a coefficient on R&D capital of about 0.11. The concentration ratio estimate of 0.0009 is not statistically significant. Duguet and Kabla (1998) also found industry concentration to be insignificant in their analysis of French manufacturing data.

However, the estimate for the four-firm concentration ratio here disputes the findings of Blundell *et al.* (1995) as well as others. Using a British five-firm concentration ratio as an independent variable in their study, they found a significant, negative effect of industry concentration on innovation. On the other hand, Acs and Audretsch (1987), and Smythe (2001) obtained significant, positive coefficients for concentration.

Table 2. Fixed Effects Negative Binomial Regression with Four-Firm Concentration Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1508*	0.0073	20.691
CR4	0.0009	0.0015	0.577

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 3 shows that the eight-firm concentration ratio is not significant in the fixed effects negative binomial regression when used in place of the four-firm concentration ratio. Its elasticity of 0.0011 is only slightly larger than that of the four-firm concentration ratio. The twenty-firm concentration ratio also fails to show statistical significance in Table 4 with a coefficient of 0.0010. The effect of the fifty-firm concentration ratio is 0.0007 and insignificant in Table 5. The elasticity on R&D capital remains roughly 0.15 regardless of the concentration ratio used.

Table 3. Fixed Effects Negative Binomial Regression with Eight-Firm Concentration Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1490*	0.0081	18.479
CR8	0.0011	0.0014	0.804

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 4. Fixed Effects Negative Binomial Regression with Twenty-Firm Concentration Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1484*	0.0090	16.529
CR20	0.0010	0.0013	0.738

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 5. Fixed Effects Negative Binomial Regression with Fifty-Firm Concentration Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D	0.1491*	0.0010	15.505
CR50	0.0007	0.0012	0.571

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Clearly, the coefficient of R&D capital is considerably less than one, indicating decreasing returns to scale as discovered by Jaffe (1986), Crepon and Duguet (1997a), and Blundell *et al.* (2002). Specifically, a doubling of R&D capital leads to increases of about 15 percent in the number of patents. This can be expected, though, as investments in R&D do not always yield useful technologies. In addition, Encaoua *et al.* (1998) point out that only one-third of innovations are patented, on average.

Overall, the uniform lack of statistical significance of the concentration ratios in the regressions echoes the results of Duguet and Kabla (1998), and casts doubt on the Schumpeterian Hypothesis. From these results, it appears that industry concentration does not exert an appreciable influence on innovation. Perhaps market structure does not represent the important determinant of innovation that it did in the past. These findings run counter, however, to the work of Blundell *et al.* (1995) who discovered that greater concentration has a dampening effect on innovation, and Acs and Audretsch (1987), and Smythe (2001) who found a positive impact of concentration.

5.2 Firm Size

Using the fixed effects Negative Binomial model, different candidates for firm size measures are considered and their findings are reported in Tables 6-13. The firm size variable in question is included with R&D capital on the right-hand-side in each case. Most of the regressions show a small, negative effect of firm size on patenting significant at the 10 percent level. In fact, the elasticities for all of the statistically significant firm size proxies are in the vicinity of –0.03. The elasticities on employment, net sales, and the R&D-sales ratio are not significant. The capital expenditure estimate is the only proxy significant at the 5 percent level.

Table 6. Fixed Effects Negative Binomial Regression with Assets

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1998*	0.0190	10.532
LN ASSETS	-0.0342***	0.0182	-1.885

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 7. Fixed Effects Negative Binomial Regression with Capital Expenditures

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1921*	0.0141	13.590
LN CAPITAL EXP	-0.0346**	0.0169	-2.051

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 8. Fixed Effects Negative Binomial Regression with Employment

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1917*	0.0176	10.913
LN EMPLOYMENT	-0.0418	0.0267	-1.568

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 9. Fixed Effects Negative Binomial Regression with Capital Expenditure-Employment Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1960*	0.0153	12.830
LN CAP EXP/EMPL	-0.0402***	0.0210	-1.919

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 10. Fixed Effects Negative Binomial Regression with Market Value

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1920*	0.0213	8.998
LN MARKET VALUE	-0.0365***	0.0197	-1.853

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 11. Fixed Effects Negative Binomial Regression with Net Sales

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1698*	0.0134	12.708
LN NET SALES	-0.0025	0.0122	-0.207

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 12. Fixed Effects Negative Binomial Regression with R&D-Employment Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1879*	0.0127	14.804
LN R&D/EMPL	-0.0309***	0.0163	-1.896

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 13. Fixed Effects Negative Binomial Regression with R&D-Sales Ratio

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1823*	0.0118	15.485
LN R&D/NET SALES	-0.0229	0.0160	-1.437

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

The firm size results reflect the findings of other studies, including Duguet and Kabla (1998), Acs and Audretsch (1987), and Crepon *et al.* (1998). Duguet and Kabla used sales as their size proxy and obtained an insignificant coefficient for it. Crepon *et al.* (1998) found employment to be a statistically insignificant size proxy in their research. A negative impact of firm size on patenting in some industries was also obtained by Acs and Audretsch (1987). However, Hall and Ziedonis (2001), Blundell *et al.* (1995), and Gopinath and Vasavada (1999) found a positive effect of firm size on innovation.

Basically, the negative albeit small effects of firm size proxies on patenting indicate that larger firms are less innovative than smaller firms. This would seem to contradict the Schumpeterian Hypothesis view of innovation.

5.3 Industry Concentration and Firm Size

Since part of the Schumpeterian Hypothesis asserts that larger firms are more innovative than smaller firms, regressions are run adding the capital expenditure variable as a firm size proxy while controlling for market structure, and their results are reported in Tables 14-17.[5] The elasticity on R&D capital is consistently 0.19 throughout this analysis.

Table 14.

Fixed Effects Negative Binomial Regression with Four-Firm Concentration Ratio and Capital Expenditures

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1918*	0.0148	12.925
LN CAPITAL EXP	-0.0347**	0.0170	-2.045
CR4	0.0001	0.0017	0.062

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 15.

Fixed Effects Negative Binomial Regression with Eight-Firm Concentration Ratio and Capital Expenditures

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1934*	0.0151	12.777
LN CAPITAL EXP	-0.0344**	0.0170	-2.020
CR8	-0.0004	0.0016	-0.224

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 16.

Fixed Effects Negative Binomial Regression with Twenty-Firm Concentration Ratio and Capital Expenditures

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1962*	0.0153	12.789
LN CAPITAL EXP	-0.0339**	0.0171	-1.976
CR20	-0.0008	0.0014	-0.576

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Table 17.

Fixed Effects Negative Binomial Regression with Fifty-Firm Concentration Ratio and Capital Expenditures

Variable	Coefficient	Standard Error	t-Statistic
LN R&D Capital	0.1939*	0.0154	12.566
LN CAPITAL EXP	-0.0343**	0.0173	-1.983
CR50	-0.0003	0.0013	-0.240

* Significant at 1%; ** Significant at 5%; ***Significant at 10%.

Looking at the results for firm size, the elasticities on capital expenditure are consistently significant at the 5 percent level across models with a magnitude of approximately –0.03. Alternatively, the concentration ratios are never significant, regardless of model. The signs on all concentration ratio estimates are negative except for that of the four-firm concentration ratio.

From these results, it appears that firm size does have a significant dampening effect on patenting. Industry concentration, however, does not significantly influence innovative activity. Thus, this study does not yield support for the Schumpeterian Hypothesis.

6. CONCLUSION

The Schumpeterian Hypothesis is called into question in this analysis. An insignificant effect of industry concentration on innovation is discovered in agreement with Duguet and Kabla (1998). This runs counter to the work of Blundell *et al.* (1995) who found a significant and negative impact of concentration, and Acs and Audretsch (1987), and Smythe (2001) who estimated significant, positive effects of concentration. Thus, more concentrated industries, which are characterized by less competition, do not foster more patent applications, according to this work.

Turning to another tenet of the Schumpeterian Hypothesis – firm size – this paper finds that larger firms tend to have fewer patent applications than smaller firms. Acs and Audretsch (1987) echo this finding in certain industries. This effect is most significant when firm size is measured by capital expenditure. It is remarkable that, regardless of measure, the coefficients on the firm size proxies are in the neighborhood of –0.03. This means that doubling the value of a particular firm size proxy will result in 3 percent fewer patent applications submitted on average.

The government should consider channeling R&D funds to small firms in an effort to maximize the return on its investment. These firms could complement the government financing with their own R&D resources in the pursuit of innovations and, possibly, secure more patent applications as a result. The magnitude of the changes indicated by this analysis, though, are relatively small, and it is not clear that enough additional patenting would be fostered for such programs to be worthwhile. If sufficient patenting activity occurs and the estimated value of the benefits from these innovations exceed the costs of R&D grants, then such policies should be implemented.

In considering the impact of market structure and firm size on patent applications, as summarized in the Schumpeterian Hypothesis, evidence contradictory to Schumpeter's assertions is obtained. Firm size has a negative role in the promotion of innovation, while industry concentration plays no significant role at all based on these results. Thus, smaller firms are found to hold the innovative advantage over larger firms in this study. Coupling these findings with those of Hall and Ziedonis (2001), Gopinath and Vasavada (1999), and Blundell *et al.* (1995) who obtained opposite results, however, dilutes the relevance and strength of the Schumpeterian Hypothesis in the modern era.

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ENDNOTES

1. See Edwards and Gordon (1984) and Acs and Audretsch (1988) for a description of this data.
2. The exponential function is used to ensure the non-negativity of y_{it}.
3. There are also the "true contagion" model in which all individuals have the same probability of experiencing an event initially, but this is modified by prior occurrences of events; the "proneness" model in which individuals are heterogeneous in terms of their proneness to certain events, with the heterogeneity attributed to individual or environmental effects; and the "spells" model in which events occur in clusters and are dependent.
4. The LR test statistic is calculated as 2[Poisson log-likelihood – Negative Binomial log-likelihood]. Its critical value was $\chi^2_{0.98}(1) = 5.41$. The Wald test statistic is calculated as the t-statistic for α in the Negative Binomial model. Its critical value was $z_{0.99} = 2.33$. Test statistics of 71143 and 28 for the LR and Wald tests, respectively, were typical in the analysis.
5. The results of fixed effects Negative Binomial regressions using assets as the firm size proxy provide estimates fairly comparable in size and significance to these. The same is also true of regressions run using the capital expenditure-employment ratio and the R&D-employment ratio. However, the latter two obtained a negative and statistically insignificant coefficient for the four-firm concentration ratio.