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Market Concentration and Innovation:  
New Empirical Evidence on the Schumpeterian Hypothesis

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# **Market Concentration and Innovation: New Empirical Evidence on the Schumpeterian Hypothesis**

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## **Abstract**

This paper conducts a new empirical examination of the Schumpeterian hypothesis that more concentrated industries stimulate innovation. It is found that the lack of evidence for the hypothesized relationship in recent empirical work is largely due to the use of simple patent counts as the measure of innovative output. When citation-weighted patent count, arguably a more accurate measure of innovative output, is used, this paper finds empirical evidence in support of the Schumpeterian hypothesis.

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## **1. Introduction**

An important issue in economics is how market structure affects innovation. In his seminal contribution, Schumpeter (1942) claimed that society must be willing to put up with imperfectly competitive markets in order to achieve rapid technical progress. He argued that large firms in imperfectly competitive markets are the most conducive conditions for technical progress. To the extent that firms in more concentrated industries operate in a way that more closely approximates imperfectly competitive markets in which firms possess market power, this led to the long-standing and much debated hypothesis that more concentrated industries<sup>1</sup> are more conducive for innovation.

The Schumpeterian hypothesis challenged conventional economic thinking on the ideal market structure for optimal resource allocation and sparked a preponderance of both theoretical and empirical papers on the topic. A review of the empirical literature up to the late 70's by Kamien and Schwartz (1982) revealed an inconclusiveness of the relationship between market structure and innovative activity<sup>2</sup>

show that the empirical evidence supports the Schumpeterian hypothesis, even after controlling for both observable and unobservable industry and firm specific characteristics which includes technological opportunity, normally cited as critical in testing Schumpeter's hypotheses.

It is suggested that monopoly power interacts with a firm's decision to innovate via *anticipated* and *current* possession of monopoly power [Kamien and Schwartz (1982)]. Innovators will have more incentive to innovate the greater the anticipated monopoly power associated with the post-innovation industry. The promised extraordinary profits in the future will more than compensate for the current R&D investment. Thus it is not controversial in the literature that greater *anticipated* monopoly power stimulates greater innovative activity. Where controversy creeps in is whether *current* possession of monopoly power stimulates greater innovation. There are theoretical arguments that posit both positive and negative relations between current monopoly power and innovative activity.

There are several arguments why the current possession of monopoly power should result in greater innovative activities. First, monopoly power with respect to current products may be extendable to new products, for example, through a dominant firm's command over channels of distribution etc. With the ability to extend monopoly power to new products, a current monopolist should find innovation more attractive. Second, as suggested by Arrow (1962), due to moral hazard problems, there may be a need to finance innovation internally, which puts firms with monopoly power at an advantage since these firms may have supernormal profits. Third, firms with current monopoly power usually have more resources and thus more likely to hire the most innovative people. Of course the third reason is related to the imperfect capital market argument underlying the second reason.

There are also disadvantages to current monopoly power in performing innovation. First, monopoly may regard additional leisure as superior to additional profits. This may be due to the lack of active competitive forces and thus generates an x-inefficiency effect. Second, a firm realizing monopoly profits on its current product or process may be slower in replacing it with a superior product or process than a newcomer. This is because the firm realizing monopoly profits on its current product calculates the profit

from innovation as the difference between its current profits and the profits it could realize from the new product, whereas the newcomer regards the profits from the new product as the gain (see Kamien and Schwartz (1982)). As such, the larger current monopoly profits are, the less incentive the monopolist has to replace his own product or process.

Theoretical models comparing an incumbent's and an entrant's incentives to innovate also give mixed predictions about the impact of monopoly power on innovative effort. Gilbert and Newbery (1982) suggest that a monopolist has more incentive to win a patent race because its win avoids dissipation of rents that would occur if an entrant wins the patent race. Other theoretical models, including Reinganum(1983), Chen (2000), and Gayle(2001), suggest that factors such as uncertainty in the innovation process and the strategic relation between new and existing products may motivate entrants to spend more on R&D relative to incumbents.

Since there are forces both in favor of and against a positive relation between monopoly power and innovative activity, the net result is an empirical matter. To the extent that pure monopoly is rare in the real world, existing empirical studies have focused on the relation between market concentration and innovation, with the underlying assumption that firms in more concentrated markets tend to have more market power. The present paper will take the same approach to revisit the empirical evidence on the Shumpeterian hypothesis.

The rest of the paper is organized as follows. Section 2 discusses the measurement of innovative output. I suggest that a more precise measure of innovative output, citation-weighted patent count, can be used to test the empirical relation between market concentration and innovation. Section 3 discusses the data, section 4 presents the empirical model, section 5 discusses estimation and results, and section 6 concludes.

## **2. Measure of Innovative Output**

For a long time now, researchers have recognized that simple patent count is not a very accurate measure of innovative output<sup>4</sup>

by the patent. As such, researchers have developed new and more precise measures of innovative output using patent citations. Once more, this idea is analogous to how we measure the relative importance of published research articles. The more citations that a research article receives the more likely it is that the cited article has made an important contribution to the literature.

The measure of innovative output used in this paper is citation-weighted patent counts, that is, each patent count is weighted by the number of citations received. A brief description of the construction of the citation-weighted patent count variable is as follows. Let  $n(t, s)$  be number of cites received at time  $s$  to patents applied for at time  $t$ .

Therefore,  $n(t) = \sum_{s=t}^T n(t, s)$  is the total number of cites to patent applied for at time  $t$ .

Thus the time interval over which cites are counted for patents applied for at time  $t$  is  $T-t$ . The same length time interval is used to count citation information for each patent, irrespective of application date, in order to allow for comparable measures. For example, if an interval of ten years is used, then the citation measure is number of cites received by a patent within ten years after application date. The variable  $n(t)$  is citation-weighted patent count. This measure of innovative output treats each patent as if it is worth the number of citations received. Thus a measure of total innovative output in a given year is the sum of citations over all the patents applied for in that year.  $n(t)$  is calculated for each firm for each year in the dataset.<sup>5</sup>

### 3. Data

The dataset used in this paper is the NBER-Case-Western University R&D patents data set [see in references, Trajtenberg, Manuel, Adam Jaffe, and Bronwyn Hall (2000)]. This is a new and comprehensive dataset containing over 4800 U.S. Manufacturing firms over the period 1965 to 1995. The dataset contains usual firm specific data (2-digit industry code, sales, R&D expenditure, advertising expenditure, capital stock, assets, Tobin's  $q$  etc.) along with firms' patenting activities. Firm specific patenting information includes number of patents applied for in a given year that were

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<sup>5</sup> For a more detailed derivation of the citation-weighted patent stock measure used in this paper see Hall, Jaffe and Trajtenberg (2000).

eventually granted and the total number of cites received by those patents. The dataset contains citation information starting only from 1976. As such, the sample used for



**Table 2**  
**Correlation Matrix**

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Firm	Firm	Patents	Cites	Industry	Market	Industry	Advertising
R&D	Sales			R&D	Share	concentration	Expenditure

posited a direct rather than indirect relationship between industry concentration and innovation. The theoretical structure of the model in this paper posits an indirect relationship between industry concentration and innovation as suggested by the data. The last point I want to mention before moving on to the next section is that advertising expenditure is positively correlated with firm's market share as expected, but the correlation between firms market share and innovation is even higher. This seems to suggest that successful innovation could be a stronger determinant of market share compare to advertising expenditure.

#### 4. The Empirical Model

The econometric model consists of three equations, one for research, one for innovation and one that takes account of the endogenous effect of innovation on market share. Each equation uses a different econometric treatment much like in Crepon, Duguet and Mairesse (1998). The first equation models the magnitude or intensity of research activities and is given by:

$$r_{it}^* = \mathbf{g}_{it} + \mathbf{b}'_1 x_{it} + \mathbf{m}_i + \mathbf{e}_{it} \quad (1)$$

where  $r_{it}^*$  is the true research intensity of firm  $i$  at time  $t$ ,  $s_{it}$  is firm  $i$  market share at time  $t$ ,  $\mathbf{g}$  is the corresponding coefficient,  $x_{it}$  is a vector of explanatory variables,  $\mathbf{b}_1$  the corresponding coefficient vector,  $\mathbf{m}_i$  controls for firm specific effect, and  $\mathbf{e}_{it}$  a random error term. In this equation the right hand side variables are firm and industry characteristics such as firm's market share, firm size, and industry concentration/competitiveness.

Having controlled for industry competitiveness and firms market share, we would

negative impact on innovation [Geroski (1990), Blundell, Griffith and Van Reem (1995), Levin, Cohen and Mowrey (1985)]. In the structural model of this paper I have posited that industry concentration directly influences firms' R&D intensity, which in turn affects firms' level of innovation (this will be more apparent when I specify equation 2). As



benefits from other firms' R&D through a “spillover” effect. As such, a firm's probability of success in innovation is enhanced by more R&D of other firms in the industry. This suggests a positive sign of the coefficient on industry level R&D in equation 2. Therefore, in general theory is inconclusive as to what sign we should expect for the coefficient on industry level R&D in equation 2.

Equation 3 models the effect of innovation on market share and is given by:

$$s_{it} = \mathbf{j} + \mathbf{b}_3 n_{it} + \mathbf{f} a_{it} + \mathbf{m}_{3i} + \mathbf{e}_{3it} \quad (3)$$

where  $s_{it}$  is firm  $i$  market share at time  $t$ ,  $\mathbf{j}$  is an intercept coefficient,  $n_{it}$  is citation-weighted innovation count from equation 3,  $a_{it}$  is the log of firm  $i$  advertising expenditure at time  $t$ ,  $\mathbf{m}_{3i}$  controls for firm specific effect, and  $\mathbf{e}_{3it}$  is a random error term. Equation 3 is estimated by the usual random effects procedure when the dependent variable is continuous and normally distributed. Specification of equation 3 is a direct attempt to model the endogeneity of the relation between innovation and market structure. From equation 1 we see that a firm's market share affects its R&D intensity which in turn influence the firm's probability of successful innovation as seen in equation 2. However, equation 3 recognizes that successful innovation in turn affects a firm's market share. We would expect that successful innovation increases a firm's market share. Also it is expected that a firm's market share should increase with its advertising expenditure since that's usually the goal of advertising. What is interesting is that we can use equation 3 to compare the relative importance of successful innovation to advertising in affecting market share.

Having specified each equation, I close this section by collecting all the equations that summarizes the full structural model as follows:

$$r_{it}^* = \mathbf{g}_{it} + \mathbf{b}'_1 x_{1it} + \mathbf{m}_i + \mathbf{e}_{1it} \quad (1)$$

$$E(n_{it} \mid r_{it}^*, x_{2it}, \mathbf{m}_{2i}, \mathbf{e}_{2it}; \mathbf{a}, \mathbf{b}_2) = \exp(\mathbf{a}'_{it} r_{it}^* + \mathbf{b}'_2 x_{2it} + \mathbf{m}_{2i} + \mathbf{e}_{2it}) \quad (2)$$

$$s_{it} = \mathbf{j} + \mathbf{b}_3 n_{it} + \mathbf{f} a_{it} + \mathbf{m}_{3i} + \mathbf{e}_{3it} \quad (3)$$

## 5. Estimation and Results

Recall that the main interest of this paper is to explore how firm and industry characteristics, especially industry concentration, affects firms' innovation, where innovation can either be measured by simple patent count (standard in the literature) or citation-weighted patent count. To conduct this analysis we plug equation 1 into equation 2. This allows us to obtain an equation that expresses innovative output as a function of industry concentration among other variables. Having plugged equation 1 into equation 2, the main equation of interest is:

$$E(n_{it} | C_t, s_{it}, x_{2it}, \mathbf{m}_{2i}, \mathbf{e}_{2it}; \mathbf{v}, \mathbf{l}, \mathbf{b}_2) = \exp(\mathbf{v}C_t + \mathbf{l}s_{it} + \mathbf{b}'_2 x_{2it} + \mathbf{m}_{2i} + \mathbf{e}_{2it}) \quad (2')$$

where  $C_t$  measures industry concentration at time  $t$ ,  $x_{2it}$  is a vector of explanatory variables which includes firm size and industry level R&D. In equation 2' the sign of  $\mathbf{v}$  is our main interest<sup>8</sup>. If  $\mathbf{v} > 0$ , then there is support for the Schumpeterian hypothesis but  $\mathbf{v} \leq 0$  is a rejection of the hypothesis.  $n_{it}$  is measured either by simple patent count or by citation-weighted patent count. The full model to be estimated consists of equations 2' and 3. Thus there are now only two endogenous variables,  $s_{it}$  and  $n_{it}$ .

In any simultaneous equation system, two major concerns are the problem of simultaneity bias and the issue of identification. First, I discuss the problem of simultaneity bias then move on to the issue of identification.

Broadly speaking, there are two approaches to estimating the model that solves the problem of simultaneity bias. One approach involves estimating each equation separately, using a limited information estimator. Another approach is to use a full

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<sup>8</sup> We could have gone the route of specifying both a direct and an indirect effect of market concentration on innovative output by initially including the market concentration variable in both equations 1 and 2. After plugging equation 1 into equation 2,  $\mathbf{v}$  would then be interpreted as the total effect comprising both a direct and indirect effect. Note that the nature of the analysis would not change if this route had been chosen.

information system estimator. In both approaches we can find estimators that are consistent but, in general, full information estimation is more efficient. A full information system estimation of the model requires writing down a likelihood function for the system. As noted in Lee L.-F (1981), full maximum likelihood estimation of a simultaneous model with latent dependent variables are too complicated to be useful. To confound a full maximum likelihood estimation procedure of the model above, each equation has unobservable specific effect parameters and one of the endogenous variables is a count data variable.

Thus for practical purposes I am forced to consider a single-equation limited information approach that yields consistent estimates. The procedure used, suggested by Lee L.-F (1981), is analogous to two-stage least squares. First, the procedure requires the system to be expressed in reduced-form, that is, endogenous variables are expressed as functions of only exogenous variables. These reduced-form equations are then estimated and predicted values of the dependent variables recovered. For example,  $n_{it}$  is expressed as a function of all the exogenous variables in the model then reduced-form parameters are estimated using a random-effects negative binomial model. The reduced-form parameters are used to get predicted values of  $n_{it}$ .

Following standard estimation procedures that are usually used to reject the Schumpeterian hypothesis, this paper shows that using a more precise measure of innovative output (citation-weighted patent count) can overturn previous results (i.e. find support for the Schumpeterian hypothesis). The results when innovative output is measured by simple patent count are presented in table 3 while the results when the measure is citation-weighted patent count are presented in table 4. In both tables 3 and 4, the first column displays the negative binomial equation for innovation results, and the second column displays the effects of successful innovation and advertising on market share.

**Table 3**  
**Model estimates**

<b>Model</b>	<b>Simple patent counts <math>n_{it}</math> (1)</b>	<b>Market Share <math>s_{it}</math> (2)</b>
Industry Concentration, $C_t$	-1.17* (0.16)	-
Market share, $s_{it}$	13.96* (3.73)	-
Firm size (log of Sales)	0.244* (0.03)	-
Industry level R&D expenditure	0.00003* (5.43e-06)	-
Simple patent counts, $n_{it}$	-	0.013* (0.0004)
Firm advertising expenditure (in logs)	-	0.002* (0.0002)
R-squared	-	0.21

Standard errors are in parenthesis.



\*indicates statistical significance at the 5% level.  
 All regressions are fitted with a constant

**Table 4**  
**Model estimates**

<b>Model</b>	<b>Citation- Weighted patent counts</b>	<b>Market Share</b>
	$n_{it}$	$s_{it}$
	(1)	(2)
Industry Concentration, $C_t$	1.45* (0.18)	-
Market share, $s_{it}$	9.39* (4.04)	-
Firm size (log of Sales)	0.29* (0.028)	-
Industry level R&D expenditure	-0.00001* (5.97e-06)	-
Citation-Weighted patent counts	-	0.02* (0.0004)
$n_{it}$		
Firm advertising expenditure (in logs)	-	0.002* (0.0002)
R-squared	-	0.25

Standard errors are in parenthesis.  
 \*indicates statistical significance at the 5% level.  
 All regressions are fitted with a constant.

Column 1 of tables 3 and 4 display the main result of this paper. In column 1 of table

This is evidence against the Schumpeterian hypothesis. That is, as industries become more concentrated innovation is reduced. If we turn to column 1 of table 4 where innovative output is measured by citation-weighted patent count, then we can see that the sign of the coefficient on industry concentration switches to positive. The results in table 4 are thus consistent with the Schumpeterian hypothesis that more concentrated industry

prevalent in less concentrated industries. Citation-weighted patent count is designed to purge simple patent count of patents that cover minor technologies that can hardly be considered innovative. As such, citation-weighted patent count should give us a more accurate measure of the relationship between industry concentration and innovation.

It is possible to further verify that the data is consistent with these arguments. Recall that the citation-weighted patent measure is obtained by summing up citations received by a patent. Thus the citation-measure of a patent that is never cited is zero. A sufficient condition to conclude that a firm has patents that are never cited is to check if the citation-weighted patent count is less than the corresponding simple patent count. I proceed by selecting two industries that have contrasting levels of concentration from the dataset. The first industry, Motor Vehicle, is consistently among the five most concentrated industries between 1976 and 1992, and the second industry, Textile, Apparel and Footwear, has consistently been among the least concentrated over the same period. It turns out that the rate at which minor patents are applied for is almost three times (2.83 times) higher in the Textile, Apparel and Footwear industry compared to the Motor Vehicle industry<sup>9</sup>



outliers, a total of 129 observations were deleted and the model re-estimated. Estimates based on this smaller sample are presented in tables A2. and A3. found in the a

## Appendix

**Table A1.**

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<b>2-Digit Industry code</b>	<b>Industry</b>
01	

**Table A2.**  
**Model estimates**

<b>Model</b>	<b>Simple patent counts <math>n_{it}</math> (1)</b>	<b>Market Share <math>s_{it}</math> (2)</b>
Industry Concentration, $C_t$	-0.76* (0.12)	-
Market share, $s_{it}$	18.65* (4.60)	-
Firm size (log of Sales)	0.23* (0.03)	-
Industry level R&D expenditure	0.00003* (5.46e-06)	-
Simple patent counts, $n_{it}$	-	0.013* (0.0003)
Firm advertising expenditure (in logs)	-	0.0014* (0.0001)
R-squared	-	0.28

Standard errors are in parenthesis.

\*indicates statistical significance at the 5% level.

All regressions are fitted with a constant

**Table A3.**  
**Model estimates**

<b>Model</b>	<b>Citation- Weighted patent counts</b>	<b>Market Share</b>
	$n_{it}$	$s_{it}$
	(1)	(2)
Industry Concentration, $C_t$	1.73* (0.14)	-
Market share, $s_{it}$	8.22** (4.93)	-
Firm size (log of Sales)		





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