

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 is used to measure innovative output, this paper finds empirical evidence in support of the Schumpeterian hypothesis. Because citation-weighted patent count accounts for the well-known heterogeneity in technologies covered by patents, it is an improved measure compared to simple patent count. Further, the empirical model considers the nature of externalities in the R&D process; and compares the relative importance of firm level advertising and successful innovation in affecting a firm's market share.

JEL classification: L1; O31; C3

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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 industries¹ 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. Based on Schumpeter's argument, policies that seek to limit or eliminate imperfect competition could simultaneously reduce the amount of innovation that a society enjoys. 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 activity². Results ranged from finding that imperfectly competitive markets are better at stimulating innovative activity (support for Schumpeterian hypothesis), to finding the complete opposite. Subsequently, researchers such as Geroski (1990), Blundell, Griffith and Van Reenen (1995), Levin, Cohen and Mowrey (1985), and Cohen, Levin and Mowery (1987), among others, have found disproportionate evidence against the Schumpeterian hypothesis. These newer studies argued that technological opportunity, which varies across industry, is an

¹ The larger the percentage of industry output controlled by leading firms, the larger is industry concentration [see Tirole (1988), pp. 221, for measures of concentration].

important determinant of innovative activity and must be controlled for when investigating the relationship between market structure and innovation. They used various methods to control for these technological opportunities and point to this as the main reason that swung the evidence against the Schumpeterian hypothesis.

In this paper, I shall argue that the measure of innovative output plays a key role in testing the Schumpeterian hypothesis. The existing studies have relied heavily on the number of patents awarded (simple patent count) as a measure of innovative output³. One problem with simple patent count as a measure of innovative output is that it assumes that all technologies covered by patents are equal in their economic and social value. Major innovations usually require significant amount of resources that only large firms tend to have. These large firms are most likely to be located in concentrated industries, while less concentrated industries tend to have many small firms, who lack the resources to produce major innovations but can still produce minor innovations. In highly competitive industries where concentration is usually low, we often see a significant amount of product differentiation. Since product differentiation often leads to patenting of minor changes to existing technologies, we may observe extensive patenting in competitive industries that results from product differentiation. Given that simple patent count treats technologies covered by patents as equal in their economic and social value, this measure is likely to lead to empirical results suggesting that less concentrated industries produce more patents and thus more innovation (rejection of Schumpeterian hypothesis). This would not be an accurate conclusion however, because most of the

² Cohen and Levin (1989) provide another excellent review of the literature.

³ Other measures used include number of important innovations and sales of new products.

patenting in less concentrated industries would be for minor technologies possibly resulting from product differentiation driven by stiff competition.

In testing the Schumpeterian hypothesis, the contribution of this paper to the literature is to use a more accurate measure of innovation, citation-weighted patent count, that accounts for the heterogeneity of technologies covered by patents. A measure of innovative output that accounts for the heterogeneity of technologies covered by patents is not distorted by minor patenting and thus more reflective of true innovation. Using citation-weighted patent count, I 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 market power interacts with a firm's decision to innovate via *anticipated* and *current* possession of market power [Kamien and Schwartz (1982)]. Innovators will have more incentive to innovate the greater the anticipated market 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* market power stimulates greater innovative activity. Where controversy creeps in is whether *current* possession of market power stimulates greater innovation. There are theoretical arguments that posit both positive and negative relations between current market power and innovative activity.

There are several arguments why the current possession of market power should result in greater innovative activities. First, market 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 market 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 market power at an advantage since these firms may have supernormal profits. Third, firms with current market 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 market 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 (2002), 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 market 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. The Measure of Innovative Output

For a long time now, researchers have recognized that simple patent count is not a very accurate measure of innovative output⁴. Simple patent count as a measure of innovative output has been used extensively in the empirical literature, (for review see Griliches, 1990). As suggested before, one reason why simple patent count is not an

⁴ See Lanjouw, Pakes and Putnam (1998).

accurate measure of innovative output is that the technologies covered by patents are very heterogeneous in their economic and social value while, simple patent count values all patented innovations equally. Recognizing this problem, Pakes (1986), Pakes and Schankerman (1984), and Schankerman (1991), among others, attempted to measure the quality rather than quantity of innovative output using patent renewal data. In many patenting regimes, patent holders must pay an annual renewal fee in order not to forfeit the patent before its statutory limit of protection (approximately 20 years). The patent renewal literature posits that information on the value of patents can be extracted from patent renewal patterns since rational agents will only renew patents if the benefit of renewal is greater than the cost. This literature finds that a substantial number of patents were not renewed to the full statutory limit. Estimation of these models required fairly lengthy time series to observe each cohort of patents and their respective dropout dates. The majority of these models were estimated on European data rather than U.S. data, probably because U.S. only started requiring patentees to pay a renewal fee in 1982. In other words, many of the patent cohorts in U.S. data were not observable for the full statutory limit.

Recently, using U.S. data, Jaffe and Trajtenberg (1996), Hall, Jaffe and Trajtenberg (2000), and Lanjouw and Schankerman (1999) have found more creative ways to measure the value of patents by using the number of citations received by a patent. An inventor must cite all related prior U.S. patents in the application process, much like how authors of journal articles must cite related previous research. A patent examiner is responsible for insuring that all appropriate patents have been cited. Again, this is analogous to the academic world where referees of journals are responsible for

ensuring that appropriate research has been cited. These citations help to define the rights of the patentee. Researchers have posited that the number of citations that a patent receives can be used to measure the relative value/importance of the technology protected 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 within time interval $T-t$, to patents applied for at time 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 data set.⁵

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

There exist empirical evidence that supports the hypothesized idea that patents that are frequently cited have made larger impact on technological improvements and thus more valuable. A review of the empirical literature that supports this idea can be found in Hall, Jaffe, and Trajtenberg (2000), however, I will briefly cite some specific examples discussed by them. Trajtenberg (1990) used patents related to a class of medical instruments, and related the flow of patents over time to the estimated social surplus attributed to scanner inventions. Trajtenberg found that simple patent counts have no correlations with estimated social surplus, but citation-weighted patent counts have extremely high positive correlations with estimated social surplus (0.5 and above). We can only conclude from this that citations are a measure of patent “quality” as indicated by the generation of social welfare. Using survey data, Harhoff et al (1999) find that more valuable patents are more likely to be renewed to full term and that the estimated value is positively correlated with subsequent citations to that patent. In other words, the patents that had the highest economic value based on survey data were also more highly cited. They estimated that a single U.S. citation imply on average more than \$1 million of economic value. Lanjouw and Shankerman (1999) also uses citations, together with number of claims and number of different countries in which an invention is patented to construct a measure of patent quality. They find that their measure of patent quality has significant power in predicting which patents will be renewed to full term, and which litigated.

3. Data

The data set 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 data set 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 eventually granted and the total number of cites received by those patents. The data set contains citation information starting only from 1976. As such, the sample used for analysis in this paper starts from 1976. Patenting information comes from the United States Patent Office while other firm-specific data are drawn from the Compustat file, which comprises all firms traded on the U.S. stock market [see Hall, Jaffe, and Trajtenberg (2000) for detailed description of data set]. Summary statistics and simple correlations of the variables used in this study are shown in tables 1 and 2. A list of broad industry categories covered by the data set is presented in table A.1 in the appendix.

Several points are worth mentioning about the correlations shown in table 2. First, a firm's R&D spending is positively correlated with both its simple patent count and citation-weighted patent count. In fact, these correlations are among the largest displayed in the matrix. Second, more concentrated industries, as measured by the

Herfindahl index⁶, are also more R&D intensive as exemplified with a correlation coefficient of 0.50. Third, industry concentration is slightly more highly correlated with firm level R&D expenditure than with innovative outputs (simple patent count and citation-weighted patent count). This suggests that industry concentration might influence innovation indirectly through R&D expenditure. Many empirical papers have posited a direct rather than indirect relationship between industry concentration and innovation. The theoretical structure of the model in this paper posits an indirect

Table 1
Descriptive Statistics
of the
NBER-Case-Western University R&D Patents Dataset

Variable	Mean	Std. Dev.	Min	Max
Year	-	-	1976	1992
Firm R&D expenditure (M\$)	15.92	81.58	0	2224.498
Firm advertising expenditure (M\$)	14.28	76.94	0	2693
Industry level R&D expenditure (M\$)	2439.68	2831.11	2.077	13187.46
Firm sales (M\$)	723.15	2741.19	0.001	59946
Capital stock (M\$)	550.34	2310.25	0.045	47911.38
Number of Patent application	6.83	31.58	0	775
Number of Cites to patents	32.37	163.5	0	3713
Market share	0.011	0.032	2.36e-08	0.638
Industry Concentration (Herfindahl index)	0.122	0.098	0.024	0.478

N=33121

⁶ The Herfindahl index is calculated by $C_t = \sum_{i=1}^n s_{it}^2$ where s_{it} is firm i market share at time t , and n is the number of firms in the particular industry [see Tirole (1988), pp. 221 for more on concentration indices]. Industry subscripts are suppressed for notational convenience but note that the index is calculated for each industry at each time period.

Table 2
Correlation Matrix

	Firm R&D	Firm Sales	Patents	Cites	Industry R&D	Market Share	Industry concentration	Advertising Expenditure
Firm R&D	1							
Firm Sales	0.71	1						
Patents	0.68	0.58	1					
Cites	0.56	0.49	0.90	1				
Industry R&D	0.13	-0.02	0.06	0.03	1			
Market Share	0.62	0.73	0.51	0.48	-0.12	1		
Industry Concentration	0.07	-0.01	0.02	0.05	0.50	-0.01	1	
Advertising Expenditure	0.40	0.52	0.31	0.26	-0.02	0.47	-0.025	1

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:

$$r_{it}^* = \gamma s_{it} + \beta_1' x_{1it} + \mu_i + \varepsilon_{1it} \quad (1)$$

where r_{it}^* is the true research intensity of firm i at time t , s_{it} is firm i 's market share at time t with γ being the corresponding coefficient, x_{1it} is a vector of explanatory variables with β_1 being the corresponding coefficient vector, μ_i controls for firm specific effect, and ε_{1it} is 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 firm's market share, we would expect larger firms to be more R&D intensive as is well documented in work by Cohen and Klepper (1996) and Scherer (1965a, 1965b). As such, the sign of the coefficient on firm size is expected to be positive. As stated previously, more recent empirical literature swung the balance of evidence against the Schumpeterian hypothesis. That is, recent evidence suggests that industry concentration either have no effect or have a 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 such, the effect of industry concentration on innovation is indirect.

Following Crepon, Duguet and Mairesse (1998), and Blundell, Griffith and Van Reem (1995), I also include firm's market share since these previous studies found that market share is a significant determinant of innovative effort. A firm's market share can also be viewed as a measure of dominance and thus theoretically should affect a firm's R&D intensity. Crepon, Duguet and Mairesse (1998) found a positive and statistically significant coefficient for the effect of market share on R&D intensity. Blundell, Griffith and Van Reem (1995) also found a positive and statistically significant coefficient but this is for the effect of market share on innovative output. As will be explained later, the structural parameters of equation 1 will not be estimated because we are more interested in the resulting parameters when equation 1 is combined with equation 2.

Equation 2 is the innovation equation and is modeled as a random/fixed-effects negative binomial regression given by:

$$E(n_{it} \mid r_{it}^*, x_{2it}, \mu_{2i}, \varepsilon_{2it}; \alpha, \beta_2) = \exp(\alpha r_{it}^* + \beta_2' x_{2it} + \mu_{2i} + \varepsilon_{2it}) \quad (2)$$

where n_{it} is citation-weighted patent count of firm i in year t . Since the dependent variable falls in the category of count data (only integer values), we specify the equation as a heterogeneous count data process conditional on research intensity and other variables. Recall that r_{it}^* is our R&D intensity variable from equation 1. x_{2it} is a vector of explanatory variables, μ_{2i} controls for firm specific effect (heterogeneous ability to innovate), and ε_{2it} is a random error term. Since x_{2it} only contains one variable which is industry level R&D, the right hand side variables in equation 2 are firm level R&D spending and industry level R&D spending. Based on previous studies such as Crepon,

Duguet and Mairesse (1998), Pakes and Greliches (1984), Lanjouw and Schankerman (1999), we expect firm's R&D spending to be positively correlated with innovation. As such, the sign of the coefficient on firm level R&D intensity should be positive.

We want to emphasize the importance of μ_{2i} in equation 2. Empirical studies have found that industries vary with respect to their technological opportunities and appropriability conditions. Technological opportunities include factors such as the technological base of an industry, that is, what is the body of scientific knowledge relevant to research in an industry and how easily can this knowledge be accessed. Geroski (1990), Levin, Cohen and Mowrey (1985), Cohen, Levin and Mowery (1987), Blundell, Griffith and Van Reenen (1995), stress the importance of controlling for technological opportunities and appropriability conditions when testing the Schumpeterian hypothesis. In fact, these papers show that whether you control for these factors makes the difference between accepting and rejecting the Schumpeterian hypothesis. The problem is that these factors are generally not observable. Levin, Cohen and Mowrey (1985), and Cohen, Levin and Mowery (1987) made an attempt to measure these factors via survey data. Geroski (1990) controlled for these effects via the usual fixed effect procedure applicable to panel data. Without good measures for these factors, he argued that the usual fixed or random effect procedures done with panel data are appropriate. Therefore, this explains the importance of μ_{2i} in equation 2, which is also a feature of the empirical model found in Geroski (1990) and many other papers. In fact, it is a general theme in all of our equations to control for unobservable specific effects.

Following Crepon and Duguet (1997), industry level R&D is used to measure R&D externalities among firms in the same industry. According to Katz and Ordover

(1990), two main types of externalities have been reported in the theoretical literature: a “competitive” externality and a “diffusion” one. Theoretical models by Loury (1979), Lee and Wilde (1980), Delbono and Denicolo (1991), and Gayle (2002), all incorporated competitive externalities via a patent race, where firms invest in R&D aiming to be the first to discover an innovation. In these models, winning depends on both individual and competitors’ R&D investment: a rise in a firm’s R&D spending, *ceteris paribus*, increases its probability of winning and lowers that of its competitors. This would suggest a negative sign for the coefficient on industry level R&D in equation 2. Other theoretical models such as Katz (1986) examine diffusion externalities. In these models a firm 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:

$$s_{it} = \varphi + \beta_3 n_{it} + \phi a_{it} + \mu_{3i} + \varepsilon_{3it} \quad (3)$$

where s_{it} is firm i 's market share at time t , φ is an intercept coefficient, n_{it} is citation-weighted innovation count from equation 3, a_{it} is the log of firm i 's advertising expenditure at time t , μ_{3i} controls for firm specific effect, and ε_{3it} is a random error term. Equation 3 is estimated by the usual fixed/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 influences 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 is 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:

$$r_{it}^* = \gamma s_{it} + \beta_1' x_{1it} + \mu_{1i} + \varepsilon_{1it} \quad (1)$$

$$E(n_{it} \mid r_{it}^*, x_{2it}, \mu_{2i}, \varepsilon_{2it}; \alpha, \beta_2) = \exp(\alpha r_{it}^* + \beta_2' x_{2it} + \mu_{2i} + \varepsilon_{2it}) \quad (2)$$

$$s_{it} = \varphi + \beta_3 n_{it} + \phi a_{it} + \mu_{3i} + \varepsilon_{3it} \quad (3)$$

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:

$$E(n_{it} | C_t, s_{it}, x_{2it}, \mu_{2i}, \varepsilon_{2it}; \varpi, \lambda, \beta_2) = \exp(\varpi C_t + \lambda s_{it} + \beta_2' x_{2it} + \mu_{2i} + \varepsilon_{2it}) \quad (2')$$

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 ϖ is our main interest⁷. If $\varpi > 0$, then there is support for the Schumpeterian hypothesis but $\varpi \leq 0$ 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 and 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 information system estimator. In both approaches we can find estimators that are

⁷ 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, ϖ 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.

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, reduced-form equations (equations that only have exogenous variables on the right-hand side) are 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 negative binomial model. The reduced-form parameters are used to get predicted values of n_{it} . Predicted n_{it} is then used in the estimation of equation 3 instead of using n_{it} . Likewise, before equation 2' is estimated we get predicted values of s_{it} from the reduced-form estimation of the s_{it} equation. Since s_{it} is a continuous variable, a normally distributed error term is assumed for the reduced-form estimation. Predicted s_{it} is then used in the estimation of 2'. Equation 2' is estimated as a fixed effects negative binomial model.

Having outlined the estimation strategy, let me briefly discuss identification issues. Each of the two equations in the system includes both endogenous variables. s_{it}

is on the right hand side of equation 2' while n_{it} is on the right hand side of equation 3. Equation 2' is identified if equation 3 has at least one exogenous variable that is not in equation 2'. The exogenous variable that identifies equation 2' is advertising expenditure found in equation 3. Equation 3 is also identified because there are several exogenous variables in equation 2' that is excluded from equation 3.

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. I report results for both random and fixed effects estimation. Columns 1 and 2 in both tables 3 and 4 display results based on random effects estimation while columns 3 and 4 show fixed effects estimation. It turns out that the Hausman test, reported in each table, always reject the random effects model as most appropriate and thus results from the fixed effects models are used to make conclusions. In both tables 3 and 4, the first and third columns display the negative binomial equation for innovation results, and the second and fourth columns display the effects of successful innovation and advertising on market share. However, from this point forward I will focus the discussion on the fixed effects models (columns 3 and 4) as suggested by the Hausman test.

Column 3 of tables 3 and 4 display the main result of this paper. In column 3 of table 3 we see that the coefficient on concentration is negative. This is consistent with the newer empirical findings when innovative output is measured by simple patent count.

This is evidence against the Schumpeterian hypothesis. That is, as industries become more concentrated innovation is reduced. If we turn to column 3 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 encourage innovation. It is worth emphasizing that estimation procedure and all the variables are the same in column 3 of tables 3 and 4 with the exception of the measure of innovative output.

The switch in sign on the concentration variable begs a plausible explanation. Since I argue that simple patent count is not an accurate measure of innovative output, why do we observe a statistically significant negative coefficient on concentration in table 3? In other words, simple patent count could be a fairly accurate measure of some process that is negatively related to industry concentration. While there might be several processes at work that drive the result, I will offer an argument that is both consistent with the data and traces back to the core of Schumpeter's argument as to why large firms in imperfectly competitive markets have an advantage in the innovative process.

One criticism of simple patent count as a measure of innovative output is that the measure captures patenting of minor technologies that can hardly be considered innovative and could have resulted from simple product differentiation. Significant innovations (innovations that have bigger impact), of which the citation-weighted patent count is a good measure, tend to require substantial resources that only large firms are likely to have. More concentrated industries tend to be characterized by large firms who

Table 3
Model Estimates Using Simple Patent Count

Model	Random Effects		Fixed Effects	
	Simple patent counts n_{it}	Market Share s_{it}	Simple patent counts n_{it}	Market Share s_{it}
	(1)	(2)	(3)	(4)
Industry Concentration, C_t	-0.93** (0.12)	-	-1.11** (0.13)	-
Market share, s_{it}	17.96** (4.37)	-	21.02** (4.76)	-
Firm size (log of Sales)	0.22** (0.03)	-	0.15** (0.03)	-
Industry level R&D expenditure (in logs)	0.13** (0.02)	-	0.07** (0.02)	-
Simple patent counts, n_{it}	-	0.00043** (7.09e-06)	-	0.0004** (7.12e-06)
Firm advertising expenditure (in logs)	-	0.0019** (0.0001)	-	0.001** (0.0001)
R-squared	-	0.41	-	0.41
Hausman:				
$H_o : E(u_{it} X_{it}) = 0$				
	$\chi^2(4) = 392.13$	$\chi^2(2) = 12868.63$		
	$prob\chi^2(4) = 0.0000$	$prob\chi^2(2) = 0.0000$		

Standard errors are in parentheses.

**indicates statistical significance at the 5% level.

All regressions are fitted with a constant

Table 4
Model Estimates Using Citation-Weighted Patent Count

Model	Random Effects		Fixed Effects	
	Citation-Weighted patent counts n_{it}	Market Share s_{it}	Citation-Weighted patent counts n_{it}	Market Share s_{it}
	(1)	(2)	(3)	(4)
Industry Concentration, C_t	1.18** (0.15)	-	1.09** (0.15)	-
Market share, s_{it}	8.80* (4.66)	-	9.56** (4.82)	-
Firm size (log of Sales)	0.30** (0.03)	-	0.27** (0.031)	-
Industry level R&D expenditure (in logs)	0.10** (0.017)	-	0.065** (0.018)	-
Citation-Weighted patent counts, n_{it}	-	0.00008** (1.59e-06)	-	0.00006** (1.60e-06)
Firm advertising expenditure (in logs)	-	0.002** (0.0001)	-	0.001** (0.0001)
R-squared	-	0.41	-	0.41
Hausman:				
$H_o : E(u_{it} X_{it}) = 0$				
$\chi^2(4) = 360.28$				
$\chi^2(2) = 19660.49$				
$prob\chi^2(4) = 0.0000$				
$prob\chi^2(2) = 0.0000$				

Standard errors are in parentheses.

**indicates statistical significance at the 5% level.

*indicates statistical significance at the 10% level.

All regressions are fitted with a constant.

are more able to produce these innovations. On the other hand, less concentrated industries tend to have more small firms who tend to lack the resources for major innovation, but can still produce minor innovations. These minor innovations could be mere product differentiation by small firms in highly competitive industries. This reasoning fits the original idea behind Schumpeter's argument why more concentration would facilitate innovation, if what he thinks is that important innovations tend to require significant resources that only large firms tend to possess.

Based on the arguments above, a negative sign on the concentration coefficient when simple patent count is used as the measure of innovative output is not surprising. The simple patent count measure is picking up a lot of minor patenting (possibly driven by the need to product differentiate) that is more 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 for strictly positive simple patent counts. I proceed by selecting two industries that have contrasting levels of concentration from the data set. 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 industry⁸. This is a clear example where less concentrated industries tend to patent more minor innovations.

There are other interesting results in column 3 of tables 3 and 4. The positive sign of the coefficients on market share and firm size suggest that dominant and large firms tend to be more innovative. This finding is consistent with Blundell, Griffith and Van Reenen (1995). The sign of the coefficient on industry level R&D is positive in both tables 3 and 4. This is evidence in support of positive “spillover” effects present in the R&D process: a firm’s probability of success in innovation is enhanced by more R&D of other firms in the industry. As mentioned earlier, this is termed diffusion R&D externality in the theoretical literature [Katz (1986)].

Column 4 in both tables 3 and 4 also presents some interesting results. The coefficients on innovation and advertising are both positive across both tables. Not surprisingly, this suggests that both successful innovation and advertising are strategic tools that can be used to increase market share. Since innovation and advertising expenditure are measured in different units, both coefficients must be adjusted appropriately to facilitate a meaningful comparison of relative size. The standard

⁸ In the Textile, Apparel and Food Industry, approximately 17% of the observations had the citation-weighted patent count measure being less than the simple patent count measure. On the other hand, in the Motor Vehicle industry only a mere 6% of the observations had citation-weighted patent count being less than the simple patent count measure.

method⁹ to adjust these coefficients is given by $\hat{\beta}_i^* = \frac{\hat{\beta}_i s_{x_i}}{s_y}$, where $\hat{\beta}_i^*$ is the adjusted coefficient, $\hat{\beta}_i$ is the unadjusted coefficient that appears in the regression, s_{x_i} is the sample standard deviation of independent variable x_i (innovation and advertising expenditure), and s_y is the sample standard deviation of the dependent variable of the regression (which in this case is market share). After applying these adjustments to the coefficients in column 4 of table 4, the adjusted coefficients on innovation and advertising expenditure are 0.158 and 0.043 respectively. In table 3 the corresponding adjusted coefficients are 0.183 and 0.047 respectively. Thus across both tables the adjusted coefficient on innovation is larger than the adjusted coefficient on advertising. This implies that, on average, successful innovation is more powerful in increasing a firm's market share compared to advertising. This should be useful strategic information for managers.

Before concluding, it is worthwhile to go through some comparative static exercises to better understand the economics behind some of the coefficient estimates. The estimates used for comparative-statics are taken from columns 3 and 4 of table 4. For a meaningful comparative-static exercise of the simultaneous system, we must take account of both direct and indirect effects of changes in exogenous variables. As such, I resort to elasticities based on total derivatives as oppose to partial derivatives. For example, interesting elasticities to analyze are: ξ_{nc} , ξ_{nR} and ξ_{sa} , where ξ_{nc} is the elasticity of innovative output with respect to industry concentration, ξ_{nR} is the elasticity

⁹ See Ramanathan (1989), "Introductory Econometrics with Applications", *Harcourt Brace Jovanovich, Inc.*, pp. 160

of innovative output with respect to industry level R&D spending, and ξ_{sa} is the elasticity of firm's market share with respect to its advertising expenditure. Formal derivations of these elasticities and total derivatives are shown in the Appendix. Given the non-linearity of the innovative output equation, derivatives must be evaluated holding each variable at some respective level. For this exercise I use the sample mean of each variable.

Since ξ_{nc} equals 0.13, this implies that for a one percent increase in industry concentration, on average, a firm's innovative output will increase by 0.13%. Activities such as mergers can lead to increases in industry concentration. Policy makers must take these potential benefits into account when deciding whether or not to prevent a merger.

As mentioned earlier, the positive coefficient on industry R&D expenditure suggest positive spillover effects to R&D. Further, the existence of these positive spillover effects provides a basis for government subsidization of R&D activities. Since ξ_{nR} equals 0.065, this implies that a one percent increase in industry level R&D will increase innovative output of the average firm by 0.065%.

As mentioned earlier, a positive coefficient on advertising expenditure in column 4 of table 4 implies that increases in advertising expenditure will increase a firm's market share. Since ξ_{sa} equals 0.09, this implies that a one percent increase in a firm's advertising expenditure will increase its market share by 0.09%.

6. Conclusion

This paper has revisited the empirical evidence on the relationship between market concentration and innovation. It has found that a more concentrated industry stimulates innovation, in support of the Schumpeterian hypothesis. It also shows that the

reason that this result has eluded recent empirical work is largely due to the use of an inaccurate measure of innovative output (simple patent count). Once innovative output is measured by citation-weighted patent count, arguably a more precise measure, a positive empirical relation between concentration and innovation is established. In addition, the empirical results support “diffusion” externalities in R&D; and suggest that, on average, successful innovation is more powerful than advertising at increasing a firm’s market share.

Even though this paper found empirical support for the Schumpeterian hypothesis, it does not advocate that policies should always seek to embrace imperfect competition. Based on the relatively large sample of industries used, the results are to be interpreted as “on average” relationships. This implies that some industries may operate in a manner inconsistent with Schumpeterian ideas while other industries fit the “Schumpeterian world” more closely. As such, a more accurate characterization of the main result in this paper is as follows: since a sufficiently large number of industries operate in a manner that make “on average” result consistent with Schumpeterian ideas, we need to approach antitrust policies with much more caution than previous results tend to support.

Based on the arguments above, a natural direction for future work is to extend the empirical analysis in specific industries. While analyzing industries individually for evidence of the Schumpeterian hypothesis is desirable, the data requirements for such analysis exceed even the relatively comprehensive data set used in this paper. Industry concentration does not vary much over time in any particular industry and thus, without very lengthy time series, precise estimation of the coefficient capturing the relevant

relationship is difficult. I remain optimistic however, because a decade ago, firm-level data as comprehensive as the data set used for this research was only an econometrician's dream.

Appendix

Appendix contains table A.1 and total derivatives based on econometric model

Table A1.

2-Digit Industry code	Industry
01	Food & Tobacco
02	Textile, apparel & footwear
03	Lumber & wood products
04	Furniture
05	Paper & paper products
06	Printing & publishing
07	Chemical products
08	Petroleum refining & products
09	Plastics & rubber products
10	Stone, clay & glass
11	Primary metal products
12	Fabricated metal products
13	Machinery & engines
14	Computer & com. Equipment
15	Electrical machinery
16	Electronic inst. & comm. Equipment
17	Transportation equipment
18	Motor vehicle
19	Optical & medical instruments
20	Pharmaceuticals
21	Misc. manufacturing
22	Soap & toiletries
23	Auto parts

Total Derivatives Based on Econometric model

The two main equations in the simultaneous system are:

$$\bar{n}_{it} = \exp \left(\varpi C_t + \lambda \bar{s}_{it} + \beta_1 \tilde{Z}_{it} + \theta \tilde{R}_t \right) \quad (1)$$

$$\bar{s}_{it} = \varphi + \beta_3 \bar{n}_{it} + \phi \tilde{a}_{it} \quad (2)$$

where \bar{n}_{it} is expected (equilibrium) innovative output of firm i at time t , \bar{s}_{it} is equilibrium market share of firm i at time t , \tilde{Z}_{it} is the size of firm i at time t , \tilde{R}_t is the log of industry level R&D at time t , C_t is industry concentration at time t , and \tilde{a}_{it} is the log of advertising expenditure of firm i at time t . For comparative-statics I am interested in solving for $\frac{d\bar{n}_{it}}{dC_t}$, $\frac{d\bar{n}_{it}}{dR_t}$ and $\frac{d\bar{s}_{it}}{da_{it}}$. From equation (1):

$$\frac{d\bar{n}_{it}}{dC_t} = \lambda \exp(\bullet) \frac{d\bar{s}_{it}}{dC_t} + \varpi \exp(\bullet) \quad (3)$$

From equation (2):

$$\frac{d\bar{s}_{it}}{dC_t} = \beta_3 \frac{d\bar{n}_{it}}{dC_t} \quad (4)$$

If we plug equation (4) into equation (3) and rearrange terms, we get:

$$\frac{d\bar{n}_{it}}{dC_t} = \frac{\varpi \exp(\bullet)}{1 - \lambda \beta_3 \exp(\bullet)} \quad (5)$$

Further, we can use equation (5) to calculate the elasticity of \bar{n}_{it} with respect to C_t :

$$\xi_{nc} = \frac{C_t}{\bar{n}_{it}} \frac{d\bar{n}_{it}}{dC_t} = \frac{\varpi C_t}{1 - \lambda \beta_3 \exp(\bullet)} \quad (6)$$

From equation (1):

$$\frac{d\bar{n}_{it}}{dR_t} = \lambda \exp(\bullet) \frac{d\bar{s}_{it}}{dR_t} + \theta \frac{1}{R_t} \exp(\bullet) \quad (7)$$

Note that the “~” is no longer above R_t , which implies that R_t is expressed in levels not logs. From equation (2):

$$\frac{d\bar{s}_{it}}{dR_t} = \beta_3 \frac{d\bar{n}_{it}}{dR_t} \quad (8)$$

If we plug equation (8) into equation (7) and rearrange terms, we get:

$$\frac{d\bar{n}_{it}}{dR_t} = \frac{\frac{\theta}{R_t} \exp(\bullet)}{1 - \lambda\beta_3 \exp(\bullet)} \quad (9)$$

Equation (9) can then be used to calculate the elasticity of \bar{n}_{it} with respect to R_t :

$$\xi_{nR} = \frac{R_t}{\bar{n}_{it}} \frac{d\bar{n}_{it}}{dR_t} = \frac{\theta}{1 - \lambda\beta_3 \exp(\bullet)} \quad (10)$$

Analogous to the process in finding equations (6) and (10) we can also show that the elasticity of market share with respect to advertising expenditure is:

$$\xi_{sa} = \frac{a_{it}}{\bar{s}_{it}} \frac{d\bar{s}_{it}}{da_{it}} = \frac{\frac{\phi}{\bar{s}_{it}}}{1 - \lambda\beta_3 \exp(\bullet)} \quad (11)$$

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