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Patents, R&D, and Market Structure in the U.S. Food Processing Industry

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This study investigates the effects of market structure and research and development (R&D) on the innovative activities of firms. Fixed and random effects count data models are estimated with firm-level data for the U.S. food processing industry. Results show a positive association between patents and R&D, and patents and market structure, suggesting that firms which exhibit noncompetitive behavior are likely to develop new products and processes. Significant intra-industry spillovers of knowledge are identified using industry R&D. For this industry, deadweight losses from imperfect competition may be offset by greater product variety and quality of food products for consumers.

Key words: food processing firms, innovative activity, market share, R&D, spillovers

Introduction

The purpose of this study is to analyze the effects of market structure and research and development (R&D) on innovations in the U.S. food processing industry. A number of studies have found that market structure in this industry is oligopolistic in nature, thereby causing welfare (deadweight) losses to society.[1] The focus on welfare losses has masked the possibility that at least a portion of the revenue (extra profits) earned by marking up prices over and above marginal costs may be reinvested to create new products and processes (Helpman and Krugman). When firms invest a portion of their extra profits toward development of new products and processes, the potential welfare losses due to noncompetitive behavior likely will be overstated because consumers eventually enjoy a payback in the form of greater product variety and better product quality.

The relationship between market structure and innovation is not completely understood because a problem arises with regard to the nature of the knowledge generated (i.e., new products and processes) (Baldwin and Scott). While knowledge is a nonrival good, a firm's incentive to generate new knowledge crucially depends on its (partial) excludability (Grossman and Helpman). If the new products and processes can be easily imitated by rival firms, then markets fail in the sense that innovators have difficulty

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[1] See Perloff for a survey of applications of the "new empirical industrial organization" (NEIO) approach to test for imperfect competition in different industries (Appelbaum).

obtaining the "full" returns to their innovations.[2] While market structure provides the resources, the magnitude of knowledge spillovers may be a crucial determinant of innovative activities.

The U.S. food processing industry indeed provides an interesting case study. This industry not only supplies a growing array of food of increasing variety and quality, but also is fraught with product imitations.[3] As mentioned earlier, the previous literature on this specific industry has not linked the three concepts of innovative activity, R&D investment, and market power in a single coherent framework. Toward this end, our analysis applies event count data models to evaluate the impact of both R&D and market structure on innovation counts in the U.S. food processing industry. Firm-level data, which have been used previously to identify the link between R&D and innovations (Pakes and Griliches; Hall), are utilized in our empirical analysis.

The contribution of this study is twofold, apart from identifying the link between R&D and innovations.[4] First, a firm's market share is used as a proxy for market power in the model describing innovative activities. Baldwin and Scott (rephrasing Schumpeter) argue that large-scale innovation may not be attractive unless some sort of insurance is available to the potential entrepreneur. Oftentimes, an insurance against the failure of an innovation is the ability to engage in a price strategy, and thus monopolistic power in existing products markets may be a precondition for innovation. While the endogenous growth/innovation literature has acknowledged the conceptual importance of market power in explaining a firm's innovative activity, very little empirical evidence has been offered to substantiate this assertion (an exception being Blundell, Griffith, and Van Reenen).

Second, our model identifies the contribution of the industry's stock of knowledge to the innovative activities of individual firms, i.e., knowledge spillovers. Spillovers are important because they point to the possibility that there is a market failure in the sense that firms are not able to realize all the benefits of their innovative efforts. Finally, an added feature of this model is its ability to distinguish the effects of overall industrial concentration from that of market share on patenting activity. While a higher market share for an individual firm may affect its innovative efforts, the resulting overall increase in industrial concentration may not necessarily be beneficial to society (Blundell, Griffith, and Van Reenen).

The remainder of the article proceeds as follows. In the next section, we offer a brief overview of the methodological underpinnings of the empirical model estimated later in the article. Next, we describe the data used in the analysis. The empirical findings of different versions of the model explaining innovative activity are then discussed and contrasted in the section on results. In the concluding section, we provide a discussion of policy implications and limitations of this research.

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[2] The nonrival and partially nonexcludable nature of knowledge often results in technological externalities. Market failure is thus the failure to internalize these externalities (Grossman and Helpman).

[3] *New Product News* reports that the U.S. food processing industry introduces about 20,000 new products per year. The preponderance of fat-free, cholesterol-free processes and flavors in almost all types of food suggests the prevalence of product imitation practices.

[4] A survey by Griliches (1995) identifies three styles of research on the contribution of R&D to productivity: case studies, event count (patent) analysis, and econometric studies. The literature relating R&D and productivity growth in agriculture mostly falls under the last category, with few insights into private R&D and its motivation. There are a few exceptions (Moschini and Lapan, and others), but their focus is on the benefits of private agricultural R&D rather than its sources and motivation.

A Count Data Model of Patents, R&D, and Market Structure

In order to analyze the effects of R&D capital and market structure on innovations, we adopt a knowledge-production function framework similar to the methods employed by Hausman, Hall, and Griliches; Cameron and Trivedi; Cincera; and others. These authors consider patents as a function of both current and lagged R&D expenditures. Following Crepon and Duguet, our initial specification of the knowledge-production function is as follows:

(1) $$\ln(\lambda_{it}) = \alpha_0 + \beta_1 \ln(k_{it}),$$

where λ_{it} is the mean patent count, and k_{it} is R&D capital owned by firm i at time t. Data on patents constitute a nonnegative integer valued random variable. The failure of classical linear models for this type of data has been well established in the literature. Several authors have discussed alternative count data models (Hausman, Hall, and Griliches; Cameron and Trivedi), where event counts are the primary variables of interest. Examples other than patent counts include the number of visits to health practitioners, and takeover bids received by targeted firms. In our analysis, we consider two models within the linear exponential family, the Poisson and the negative binomial, for analyzing patent counts. In what follows, we digress briefly on the description of the Poisson and negative binomial models before presenting the estimated model.

The Poisson Model

Typically, the Poisson parameter, λ_{it}, is represented as $\ln(\lambda_{it}) = \mathbf{X}_{it}\beta$, where $\mathbf{X}_{it}$ is a set of regressors [e.g., $\ln(k_{it})$ in equation (1)] which describe the characteristics of a cross-sectional unit in a given time period. If n_{it} is the observed event (patent) count for the ith unit during time period t, then

(2) $$E(n_{it} \mid \mathbf{X}_{it}) = \lambda_{it} = e^{\mathbf{X}_{it}\beta}.$$

Note that λ_{it} is deterministic, while the randomness comes from the Poisson specification for n_{it}. The basic probability density function for the Poisson model is given by:

(3) $$\mathrm{pr}(n_{it}) = f(n_{it}) = \frac{e^{-\lambda_{it}}\lambda_{it}^{n_{it}}}{n_{it}!}.$$

The Negative Binomial Model

The Poisson specification imposes the restriction that the mean of n_{it} is equal to its variance, which is a testable hypothesis. The negative binomial model, which is more flexible, does not impose this restriction. Here, λ_{it} is assumed to follow a gamma distribution with parameters (γ, δ), where $\gamma = e^{\mathbf{X}_{it}\beta}$, and δ is common both across firms and across time. Then, the gamma distribution for λ_{it} is integrated by parts to obtain:

(4) $$\mathrm{pr}(n_{it}) = \int_0^\infty \frac{1}{n_{it}!} e^{-\lambda_{it}} \lambda_{it}^{n_{it}} f(\lambda_{it})\, d\lambda_{it} = \frac{\Gamma(\gamma_{it} + n_{it})}{\Gamma(\gamma_{it})\Gamma(n_{it} + 1)} \left(\frac{\delta}{\delta + 1}\right)^{\gamma_{it}} (1 + \delta)^{-n_{it}},$$

which is the negative binomial distribution with the parameters (γ_{it}, δ). Previous empirical studies (Hausman, Hall, and Griliches; Blundell, Griffith, and Van Reenen; Cincera) using both of these models reject the absence of serial correlation in the residuals due to unobserved heterogeneity of the individual units. The fixed and random effects versions of the Poisson and negative binomial models developed by Hausman, Hall, and Griliches have attempted to correct for firm-specific heterogeneity that is either observable or unobservable. In the Poisson model, the specification of the parameter changes to $\overline{\lambda}_{it} = \lambda_{it}\alpha_i$, where α_i is either a random firm-specific effect or is conditioned to provide fixed effects. Similarly, the parameter δ in equation (4) is allowed to vary across firms to develop fixed and random effects versions of the negative binomial models. (For specific details on extension and application of these models to the case of fixed and random effects, see Hausman, Hall, and Griliches.)

In our empirical specification of the parameter λ_{it}, two additional determinants of technology are included. These variables are the market share of a firm and total industry R&D capital:

(5) $$\lambda_{it} = \exp(\mathbf{X}_{it}\beta) = \exp\big(\beta_0 + \beta_1 \ln(M_{it-1}) + \beta_2 \ln(K_{it-1}) + \eta_i + \upsilon_t\big),$$

where M_{it-1} is a set of market structure variables (industry- and firm-level variables),[5] K_{it-1} is a set of firm's and industry's knowledge capital variables (R&D stock), η_i is a firm-specific effect, and υ_t is a time- (t) specific effect.[6]

The role of a firm's R&D capital in explaining its innovation process has been well established in the literature (see Griliches 1990, for a survey). In addition, the research activity by other firms in the same industry also can generate potential benefits for a particular firm (Griliches 1992). This is captured by the inclusion of total industry R&D in our knowledge-production function.

The market share of the ith firm (w_{it-1}) indicates the extent of market power exercised by a particular firm.[7] As it reflects a firm's ability to mark up prices over the marginal cost of producing output, we hypothesize that the effect of market power on innovations is positive. Moreover, this variable can provide, to an extent, a feedback from past experiences in the market.

The question of fixed versus random effects has been addressed extensively in the literature on panel models. For instance, Greene (1993) states that "it might be appropriate to view individual specific constant terms as randomly distributed across cross-sectional units. This would be appropriate if we believed that the cross-sectional units

[5] The NEIO studies of market power estimate the conjectural variation elasticity, which is often equal to the market share of a firm under certain conditions (Appelbaum).

[6] We also report the results from simple Poisson and negative binomial specifications.

[7] The market share is the ratio of firm sales to industry sales, $p_i y_i / \Sigma_i p_i y_i$.

were drawn from a large population" (p. 469). Mundlak argues that we should always treat the individual effects as random, because the fixed effects model is simply analyzed conditionally on the effects present in the observed sample. In addition, the fixed effects model is costly in terms of degrees of freedom lost. Conversely, there is no justification for treating the individual effects as uncorrelated with other regressors, as is assumed in the random effects model. Hence, in our empirical analysis, we use a Hausman test to identify any misspecification resulting from the use of the random effects models.

Description of Data

Data for the analysis were obtained from three sources: the U.S. productivity panel, 1960–90 (Hall); "patpan85" patents data at the individual firm level (Hall et al.); and the National Bureau of Economic Research (NBER) manufacturing productivity database (Bartelsman and Gray).

The large U.S. productivity panel is unbalanced and contains firm-level data, identified by Compustat id and the four-digit Standard Industrial Classification (SIC) codes, for sales, employment, R&D expenditures, and R&D stock.[8] This database was searched for four-digit SIC codes between 2000 and 2099 for all firms in the food processing sector. Based on this search, there were 1,358 observations, with over 110 firms under the SIC 2000–2099 code span. These data formed an unbalanced panel for 1965–81, but most of the firms have data only for 1970–81. The "patpan85" database contains firm-level data on patents applied for and granted in each year—again identified by Compustat id. Data on total patent applications and total grants for the firms are available for the periods 1965–79 and 1965–81, respectively.

The above two databases were merged using the Compustat id, with only the data for food processing firms retained (SIC codes 2000–2099). Of the 538 observations for 50 firms, only 32 firms had both R&D and patents greater than zero (summed over the respective sample periods). In this analysis, firms that had neither R&D expenditures nor patents over the entire sample period are considered noninnovating firms; hence, the relationship between market structure and patents does not apply. Therefore, the final sample contained 311 observations for 32 firms (see Hausman, Hall, and Griliches for a similar characterization of data). The next step is to identify industry-level variables for each of these firms. Aggregate sales are available for each of the four-digit SIC industries from the NBER manufacturing productivity database. This information is merged with the firm-level data for the key variable—the market share of a firm (firm sales/industry sales).

Table 1 provides descriptive statistics on the 32 firms used in the analysis. The average for firm sales is $1,151.42 million, and average R&D expenditures is $3.14

[8] Unlike agriculture, innovations are more rapid in the manufacturing industries including the food processing industries, and so the R&D stocks derived by Hall et al. are utilized. Using the data on real R&D expenditures, the initial period stock of R&D capital is set to the R&D expenditures in the first year divided by the sum of the depreciation rate (15%) and an assumed presample growth rate of new R&D at 5% per year. Thus the initial stock is approximately five times the level of R&D expenditures. The stocks for subsequent periods are computed using the standard perpetual inventory equation, $K_t = (1 - \delta)K_{t-1} + R_t$, where K_t is the end of the period stock of R&D capital, R_t is the real R&D expenditures, and δ is the rate of depreciation. The major difference between the above computations and those of agricultural R&D, of course, is the long lag introduced in the latter (Huffman and Evenson).

Table 1. Descriptive Statistics for Firms Included in Analysis (N = 32)

Variables		Mean	Standard Deviation
Number of Patents:	Applied for	2.22	3.67
	Granted	2.81	4.41
Firm-Level R&D ($ mil.):	Expenditures	3.14	4.62
	Stock	18.83	23.37
Industry-Level R&D ($ mil.)		427.31	149.81
Average Sales ($ mil.):	Firm	1,151.42	1,381.24
	Industry	15,996.89	8,571.59
Market Share		0.09	0.12
No. of Establishments		2,931	1,027

million. Each firm has, on average, 2.22 patents applied for over the sample period, while the market share averages 9%. The standard deviations reported in table 1 suggest considerable variability in the data series.

Results

Most of the count data models described in Hausman, Hall, and Griliches can be fit using *GRBL: A Package of GAUSS Programs* (Hellerstein) and LIMDEP version 7.0 (Greene 1995).[9] Since the data formed an unbalanced panel, we created a *PDS* variable (which is equal to the number of observations for each firm) to identify the groups in the panel. The fixed and random effects options of the Poisson and negative binomial models are used to obtain all combinations of results. The results reported here are for patents applied for in a year that are eventually approved. Similar results are obtained for patents granted, and so they are not reported separately.

In the first two subsections below, we briefly address the results from the basic Poisson and negative binomial models, and examine the relationships between patents and R&D, and between patents and market structure—including a test on the validity of fixed versus random effects versions of the count data models. In the two remaining subsections, we offer discussions on intra-industry knowledge spillovers and the effects of overall industrial concentration.

[9] Negative binomial random effects models are estimated using LIMDEP. Convergence is not achieved for the Poisson random effects and negative binomial fixed effects models with LIMDEP. Therefore, these models are estimated using GRBL. The GRBL Gauss programs package offers more choices to compute the Hessian (Newton-Raphson, steepest descent, random search, and quasi-Newton). However, it does not have the option to estimate negative binomial random effects models (Hellerstein).

Table 2. A Comparison of Poisson and Negative Binomial Patent Models

	Poisson Models		Negative Binomial Models	
Variables	R&D Expenditures	R&D Stock	R&D Expenditures	R&D Stock
Current R&D	0.46*	0.73	0.76*	0.89
	(0.08)	(0.45)	(0.13)	(0.91)
Lag 1	-0.03		0.01	
	(0.04)		(0.05)	
Lag 2	-0.10*		-0.04	
	(0.04)		(0.27)	
Lag 3	0.55*		0.42	
	(0.06)		(0.28)	
Sum of R&D Coefficients	0.88	0.73	1.19	0.89
Time Trend	-0.10*	-0.33*	-0.06	-0.28
	(0.03)	(0.12)	(0.05)	(0.15)
Interaction (Time Trend and Current R&D)	-0.07*	0.04*	-0.12*	0.03
	(0.01)	(0.02)	(0.02)	(0.04)
Log-likelihood	-394.88	-359.23	-325.58	-311.05

Notes: An asterisk (*) denotes significance at the 5% level. Numbers in parentheses are standard errors of the coefficients.

Choice of Models and Variables

There are two choices for expressing the relationship between patents and the R&D efforts of firms. Table 2 presents the results from fitting Poisson and negative binomial models with both R&D expenditures and R&D stock. While the choice of a flow variable over stock has been widely emphasized in economics literature, the R&D expenditures may not necessarily represent a flow due to lack of data on the composition of current R&D expenditures. Moreover, the use of a stock variable may mitigate the need for the long lag structures that are generally used with the R&D expenditures.

A comparison of the fit of R&D expenditures and stock variables in a Poisson model (columns 1 and 2 of table 2) shows that the standard errors of the coefficients from the R&D expenditures model are smaller.[10] However, the magnitude of the R&D coefficient in the stock model is close to those reported by Hausman, Hall, and Griliches, and the log-likelihood value is slightly larger. The negative trend is more pronounced in the Poisson stock model relative to the expenditures model. The improvement in the log-likelihood value of the negative binomial models (columns 3 and 4, table 2) suggests overdispersion, i.e., the variance exceeds the mean. Note that both R&D expenditures

[10] Unless the data are Poisson distributed, the estimated standard errors are inconsistent. Inappropriate imposition of the Poisson restriction may produce spuriously small estimated standard errors (Cameron and Trivedi).

models share the common feature of a "U"-shaped lag structure. In the Poisson model the mean equals variance, while the variance grows with the mean in the negative binomial models. However, both models fall short because of the failure to account for firm-specific heterogeneity that is either observable or unobservable (Hausman, Hall, and Griliches; Blundell, Griffith, and Van Reenen).

We report the results of Poisson random effects and negative binomial fixed and random effects models in table 3. As the mean of the patents is not equal to its variance in our sample, the Poisson fixed effects model is not considered here. The R&D stock variable is used in all of the models as opposed to R&D expenditures for reasons noted earlier. The market share variable w_i (the ratio of firm sales to industry sales) takes on values between zero and one. Its lag (w_{it-1}) is introduced into the model because we cannot account for the feedback mechanism between market power and innovation—a successful innovation is likely to lead to an increase in a firm's market share.[11]

In order to analyze the existence of intra-industry knowledge spillovers, the R&D stocks of all 32 firms in the sample are summed up for each time period (industry R&D) and introduced into the model. Since four firm concentration ratios are not available on a time-series basis at the four-digit SIC level, we use the number of establishments in the industry (SIC 20) to represent industrial concentration.[12] These data are available from census surveys and are interpolated using the linear techniques as suggested in Maddala.

Effects of R&D and Market Structure on Patent Counts

In the models of patent counts, if the association between patents and a particular variable is positive, then an increase in this variable has the tendency to increase the mean of the patent counts (table 3).

The association between R&D stock and patent count is positive in all three models (the Poisson random effects, and the negative binomial fixed effects and random effects) and highly significant in the two random effects models. The parameter estimate from the negative binomial random effects model (column 3 of table 3) is similar to the 0.45 estimate reported by Hausman, Hall, and Griliches for their broader sample (121 U.S. companies) but using an R&D expenditures variable. While the Poisson random effects model suggests a stronger relationship between R&D stock and patent counts (0.73), the negative binomial fixed effects model suggests a weaker relationship (0.22). The log-likelihood value of −289.8 for negative binomial fixed effects, however, is larger than that for the other two models. While these results reinforce earlier findings, they also suggest that the patent-R&D relationship in the U.S. food processing industry is similar to other industries. The use of the R&D stock variable reflects the need for incorporating a longer lag structure in the R&D expenditures variable.

[11] Blundell, Griffith, and Van Reenen used a large presample history of innovations activity, which is not available in our data series, to provide such dynamic feedback.

[12] The new SIC classification is based on establishments rather than firms. However, when there is net exit, as is the case with the food processing industry, there is some confidence in the use of these data. In other words, holding the number of establishments per firm constant, net exit implies increasing concentration.

Table 3. Effects of R&D and Market Structure on Patent Counts

Variable	Poisson Random Effects	Negative Binomial Fixed Effects	Negative Binomial Random Effects
R&D Stock	0.73*	0.22	0.37*
	(0.41)	(0.71)	(0.17)
Lagged Market Share	0.79*	0.88	0.36*
	(0.30)	(0.67)	(0.09)
Industry R&D	1.22*	0.84*	0.49*
	(0.40)	(0.40)	(0.20)
No. of Establishments	-1.94*	-0.05	-0.63
	(0.82)	(0.39)	(0.50)
Time Trend	-0.42*	-0.21*	-0.36*
	(0.08)	(0.05)	(0.12)
Interaction (Time Trend and R&D Stock)	0.10*	0.01	0.03
	(0.04)	(0.02)	(0.02)
α	1.05*		
	(0.32)		
γ			7.36
			(4.94)
δ			1.45*
			(0.73)
Log-likelihood	-400.2	-289.8	-394.7
Correlation between observed and predicted	0.67	0.66	0.51

Notes: An asterisk (*) denotes significance at the 5% level. Numbers in parentheses are standard errors of the coefficients.

The association between patent count and one-period lagged market share is also very robust. All of our models yield a positive coefficient, although the size of the parameter estimate ranges from 0.36 to 0.88, with the coefficients from the two random effects models being highly significant (table 3). This suggests that the relationship between the market power of a firm and its innovative effort is positive, i.e., a rise in the market share of a firm increases its innovation counts. This finding also confirms our earlier claim that food processors may charge a higher price for their output, but a portion of the markup may be necessary to pay for the development of new products and processes.[13]

The negative time trend is significant in all three models (table 3) and suggests that there is a general tendency for the patent counts to fall among the food processing firms considered in this study. The coefficient on the interaction term between time trend and

[13] Note that our logarithmic specification for market share suggests that as a firm becomes a monopoly, its effect on innovation becomes zero; that is, if $w_i \rightarrow 1$, then $\ln(w_i) \rightarrow 0$ (Tirole).

R&D stock is positive, but insignificant in the negative binomial models. Nevertheless, the result from the Poisson random effects model contradicts earlier results that the effectiveness of R&D is declining over time (Hausman, Hall, and Griliches), at least in the food processing industry.

Of the three models considered for analyzing patent counts, the case for the random effects models is strongest. Blundell, Griffith, and Van Reenen claim that the difference between the majority of firms who make few innovations and the small group involved in high levels of innovative activity is unlikely to be solely attributable to observable differences across companies. Thus, unobservable permanent heterogeneity is an important feature of any empirical model of innovative activity. Although the qualitative results of the fixed and random effects models in our investigation are very similar, we tested for possible misspecification in the random effects models. The random effects models may be misspecified due to a correlation between panel-specific component of error and the explanatory variables—a problem not incurred by fixed effects models.

This can be verified by a Hausman test. The test statistic is given by $\hat{\mathbf{q}}^T V(\hat{\mathbf{q}})^{-1}\hat{\mathbf{q}}$, where $\hat{\mathbf{q}}$ is a vector of differences in coefficients between the fixed and random effects models, and $V(\hat{\mathbf{q}})^{-1}$ is the inverse of the differences between the covariance matrices of the fixed and random effects models (Hausman). The test statistic follows a χ^2 distribution with k (the number of exogenous variables in the model) degrees of freedom. Using this test, we failed to reject the null hypothesis of "no misspecification" in the random effects model, as the calculated χ^2 value (2.42) is less than the critical value at the 1% level of significance (six degrees of freedom).[14] An additional statistic validating the empirical results is the correlation between observed and predicted values. As reported in table 3, these correlations are in the range of 51% to 67% for our three models. Although caution is emphasized in the use of these types of statistics, in count-data panel models such as ours, computing measures similar to R^2 can be complex and sometimes misleading.

Intra-Industry R&D Spillovers

The introduction of industry R&D in the count data models is to test the hypothesis that knowledge, as embodied in the R&D stock variable, is likely to exhibit some of the public good properties (nonrivalness, partial nonexcludability) which result in technological externalities (Romer). Existence of spillovers will suggest that firms in the food processing industry are subject to a market failure problem in the sense that they are not able to realize the "full" benefits of their innovative efforts. The most often cited consequence of market failure is underinvestment in R&D by innovating firms.

The results showing the effects of industry R&D on patenting are provided in table 3. Overall, the findings suggest the existence of spillovers because the coefficients on industry R&D are positive and significant in all three models. Although the magnitude of the coefficients varies from 0.49 to 1.22, the case for knowledge spillovers is strong. While previous studies have focused on inter-industry spillovers (Mansfield; Bernstein and Nadiri), the results here point to significant intra-industry spillovers of knowledge

[14] A similar test for Poisson fixed effects (not reported) versus random effects provided inconclusive results.

as embodied in the industry R&D stock.[15] The presence of both intra- and inter-industry knowledge spillovers suggests that knowledge generated by firms in the U.S. food processing industry has public good properties, and so there may be a market failure problem.

Effects of Overall Industrial Concentration

The market share variable adequately represents the incentives for a firm to innovate. However, as the market share of a firm increases, it is likely that the overall industry's concentration increases, because gains to one firm are losses to another firm or group of firms. Moreover, at both ends [i.e., competitive markets (market share $\rightarrow$ 0) and monopoly (market share $\rightarrow$ 1)], the incentives for an individual firm to innovate are smaller than in the case of oligopoly (Tirole). Table 3 also presents the results relative to the effects of industrial concentration on innovative activities in the U.S. food processing industry for all three models. The coefficient on the number of establishments is negative as expected in all three cases, but not significant in the case of the negative binomial models. Although a firm's share of its market is shown to have positive effects on patenting, the overall increase in concentration in an industry appears to dampen innovative activity in the food processing industry (see Blundell, Griffith, and Van Reenen for a similar result).

In sum, this study found that the innovative activities of U.S. food processing firms (as represented by patents) is positively associated with internal characteristics such as the market share of a firm and its R&D investment. Innovation is also related to broader industry-level variables, cumulative R&D investment by all firms (positive), and the overall industrial concentration (negative).

Summary and Conclusions

In this analysis we have explored two research themes within a single economic model of firm behavior. Results obtained reinforce the finding reported in the literature of a positive association between R&D and patents in the U.S. food processing industry. A second conclusion, which is of greater interest, is that market share is positively associated with patents. This latter finding has interesting implications. The traditional focus of the literature on imperfect competition has been on measurement of welfare losses due to departures from perfect competition. Results obtained here suggest that those losses may be partially offset by the positive impact of a higher market share on innovative activity. Firms that are likely to exhibit noncompetitive behavior are also likely to produce new products and processes, leading to a greater variety and better quality of food products for consumers. However, results also suggest that there are significant intra-industry spillovers of knowledge, as embodied in the R&D stock, which likely may cause underinvestment in R&D in the food processing industry.

[15] This is consistent with the observed product imitation practices (preponderance of fat-free, cholesterol-free processes and flavors in almost all types of foods).

A limitation of this study is the claim by some authors (Acs and Audretsch) that patents may not necessarily represent the innovative efforts of firms. Use of trade secrets and the differences in the values of patents to firms provide support for this claim. However, as Griliches (1992) notes, patents continue to represent a credible measure of the innovative activities of firms, until better alternatives are found.

Further research may focus on the net gains/losses from price markups and the counteracting benefits from innovative activities, possibly in a general equilibrium framework. This is important from the perspective of federal regulatory policies that do not discriminate between innovating and noninnovating firms. Such policies likely may lower the incentives to innovate, and thus hinder economic growth. Additionally, the divergence between private and social benefits to R&D in the food processing industry may be investigated further to ascertain a role for public policy to mitigate market failure.

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