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DOES INTERDEPENDENCY AFFECT FIRM AND INDUSTRY PROFITABILITY? AN EMPIRICAL TEST

MICHAEL J. LENOX,[1] SCOTT F. ROCKART,[2]* and ARIE Y. LEWIN[2]
[1] *Darden School of Business, University of Virginia, Charlottesville, Virginia, U.S.A.*
[2] *Fuqua School of Business, Duke University, Durham, North Carolina, U.S.A.*

Strategy researchers have argued that heterogeneity in firms' practices and profitability within and across industries may derive from industry-level differences in the extent of interdependencies among firms' activities. Theoretical models have clarified how and why differences in the extent of the interdependencies faced by firms across industries may affect the distributions of firm profits, but the specific predictions from these models have not been empirically tested. In this paper, we present what we believe is the first large scale empirical analysis linking differences in the extent of interdependencies across industries to differences in the distribution of firm profits within and across those industries. We use survey data to measure interdependencies systematically across a wide number of industries, thus addressing the primary obstacle to incorporating interdependencies in larger scale empirical work, and find evidence consistent with the theoretical predictions: average profitability is highest in industries with moderate levels of interdependency; the dispersion of profits among firms is higher in industries with more extensive interdependencies; and industries with more extensive interdependencies have a more positively skewed performance distribution. We find that the effect of interdependencies on average industry profitability is similar in scale to the effect of patent protection and industry growth rates, placing interdependency squarely among the strategy field's central concepts. Copyright © 2009 John Wiley & Sons, Ltd.

INTRODUCTION

Recent research proposes that the potential for interdependencies among a firm's productive activities explains heterogeneity in firm and industry profitability (Lenox, Rockart, and Lewin, 2006). Interdependencies exist whenever the value of conducting one or more activities in a particular manner depends on how a firm conducts other activities (Levinthal, 1997).[1,2] Activities that are commonly thought to be subject to such interdependencies include elements of organizational form, aspects of production processes, and specific product characteristics. When there are many potential interdependencies, firms struggle to identify effective sets of activities leading to low efficiency and correspondingly low profits. However,

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*Correspondence to: Scott F. Rockart, Fuqua School of Business, Duke University, P.O. Box 90210, Durham, NC 27708, U.S.A. E-mail: srockart@duke.edu

[1] Complementarities (see Milgrom and Roberts, 1990) are a special case of interdependency where the marginal value of engaging in one activity is increased by engaging in another.
[2] For example, in semiconductor manufacturing, varying the technology for the mask (a high-tech stencil with the pattern for the semiconductor) may improve or worsen production performance depending on a variety of other factors such as the technology chosen to align the mask with the semiconductor (Henderson and Clark, 1990).

when there are many potential interdependencies there is also greater variety in firm performance (Levinthal, 1997; Rivkin, 2000), leading to industries dominated by a few firms earning high profits (Demsetz, 1973). Given that interdependencies may be argued to reduce or raise profits, recent theoretical models have attempted to clarify the relationship between interdependency and profitability. In particular, Lenox *et al*. (2006) have argued that average firm profitability should peak in industries where interdependencies are high enough that not all firms are efficient, but not so high that all firms are inefficient. In this paper, we test the three primary predictions from that study, providing what we believe is the first large, cross-industry empirical analysis of the effect of interdependencies on the distribution of firm and industry profits.

Despite extensive theoretical modeling efforts (Lenox *et al*., 2006; Lenox, Rockart, and Lewin, 2007; Rivkin, 2000, 2001), little empirical work has been conducted to test for the effect of interdependencies on the average profitability of firms within an industry or on variation in profitability among firms within an industry. The empirical work that has been done involves several individual case studies of firms and industries (Henderson and Clark, 1990; Siggelkow 2001, 2002; Ichniowski, Shaw, and Prennushi, 1997; Milgrom and Roberts, 1995) and studies of related questions such as knowledge flows (Sorenson, Rivkin, and Fleming, 2006) and research and development (R&D) activity (Zhao, 2006), which provide a rich understanding of interdependencies at work, but cannot speak directly to their effect on the distribution of firm profits.

One of the primary obstacles to larger-scale empirical work has been the difficulty in measuring interdependency systematically across a wide number of industries. Given the amount of theoretical investigation into the effects of interdependencies and their potential importance in understanding profit differences among firms, we believe that the challenges of measurement should not be allowed to stop empirical evaluation. This paper discusses the empirical issues involved in testing theories about interdependencies and employs survey data to provide one such test. Specifically, we make use of responses from R&D managers and directors to the 1994 Carnegie Mellon Survey (CMS) of Industrial R&D as proxy measures of interdependency in choices about product characteristics and production processes (Cohen, Nelson, and Walsh, 2002). We test for the predicted relationships between interdependencies and both the mean and dispersion of firm performance. Using our measure, which encompasses interdependencies at the product and process levels, we find evidence consistent with previous theoretical work: profitability peaks at moderate levels of interdependency; variance in profits increases with interdependency; and industries with higher interdependencies have a more positively skewed performance distribution.

THEORY AND HYPOTHESES

Research on the effect of interdependencies among firm activities has been growing in the strategy literature in recent years (Porter, 1996; Levinthal, 1997; Rivkin, 2000; Siggelkow, 2002; Zhao, 2006) and interdependencies in productive activities are increasingly seen as an important driver of heterogeneity in firm performance. Levinthal (1997) demonstrated with a conceptual model that, even when all firms are initially similar and engaged in similar search strategies for improvement, interdependencies cause substantial differences in firms' practices to arise. Rivkin (2000) demonstrated that interdependencies confound imitative efforts, allowing substantial differences in firms' practices and performance to persist. Since the publication of these papers, a growing literature has emerged exploring the effect of interdependencies on heterogeneity in firm practices and performance.

More recently, Lenox *et al*. (2006) continued this line of research by explicitly modeling the link between interdependency and the distribution of firm profits. Central to their conceptualization of the competitive environment was an industry's *potential for interdependency among activities*—the latent possibility of interdependency between activities in the industry's production function. In this conceptualization, while firms can affect the interdependencies they realize through their choices of activities, the underlying potential for interdependency is an industry attribute exogenous to the actions of firms. At the heart of their model is a representation of interdependencies where firms make binary decisions about how to conduct each of N activities (e.g., offer a piece-rate pay scheme or not), and the efficacy of each decision depends on how K of the other activities are conducted (e.g., the benefit of piece-rate pay systems depends on how quality control

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is conducted and bonuses are allocated). The combined set of activity decisions and their average individual efficacy then determines an overall efficacy score for the firm. The activities effectively constitute a firm's broadly defined production technology, making it natural to interpret the score as a firm's marginal cost or product quality. Often referred to as the Kauffman NK model (Kauffman, 1993), this underlying structure has been the basis for much of the modeling work on interdependencies and firm strategy.

Lenox *et al.*, 2006 note that the traditional NK model fails to capture the interfirm competitive interactions that condition the relationship between absolute firm performance and firm profitability. They interpret the NK model as a representation of the underlying production function and extend the model to include traditional game-theoretic models of competition among firms. This allows them to map firm production characteristics such as efficiency and quality to firm output decisions (including entry and exit), industry prices, and ultimately to firm and industry profits. Their analysis treated all competing firms as facing the same broadly defined technological opportunity set (the specific NK model specification), and they analyzed how firm profits would differ among industries with different latent potential for interdependency among activities. Analyzing their competitive-NK model at varying levels of interdependency (i.e., at varying levels of K) provided three primary results corresponding to the first, second, and third moments of the distribution of firm performance.

With respect to the first moment, expected average firm performance peaks at moderate levels of interdependency (Hypothesis 1). In the model of Lenox *et al.*, 2006, this result occurs because profits are highest when the production decision problem is difficult enough to generate heterogeneity among firms, but not so great as to dramatically reduce the average efficacy (efficiency or quality) of firms. For example, at low levels of interdependency, most competitions will be able to determine the most efficient way of operating. High efficiency creates value that could be captured, but competition among similar competitors eradicates profits. In other words, low variance in performance means that high average performance is not translated into high profits. In contrast, at high levels of interdependency, it is rare for any firm to determine the most efficient ways of operating. Even though there is high variance in performance at high levels of interdependency (see second-moment predictions below), poor average performance reduces the value available to be captured as profits. Moderate levels of complexity, however, allow only a few firms to discover the most efficacious activity sets, leading to a few large competitors who create and capture substantial value (see Demsetz, 1973 for a similar argument).

Hypothesis 1: Mean firm performance rises then falls with rising potential for interdependency in activities.

With respect to the second moment, the competitive-NK model predicts greater variance in firm performance within industries with higher levels of interdependency. Greater numbers of interdependencies lead to more combinations of activities that are locally optimal (Weinberger, 1991). As a practical matter, this means that firms founded under different conditions (Stinchcombe, 1965), firms that explore opportunities in a different order, and firms that differ at any point for other reasons, are less likely to converge on the same activity sets in the presence of interdependencies (Levinthal, 1997). As a result, in industries with higher levels of interdependency, firms are more likely to be heterogeneous in their activities, leading to increased variance in performance among firms within the industry.

Hypothesis 2: Variance in firm profitability within industries rises with the potential for interdependency in activities.

Finally, the competitive-NK model predicts an increasingly positive skew in the distributions of firm performance within industries at higher levels of interdependency. At low levels of interdependency, there are few local optima among activity sets and the better activity sets have larger 'basins of attraction' meaning they are more likely to be selected. Thus, most firms find the best activity sets resulting in a large group of very good firms and few lower performing firms. This translates into a leftward skew in performance distributions at low levels of interdependency. As interdependency rises and local optima among activity sets proliferate, firms are more and more likely to end up with activity sets that reflect differences in founding conditions and vagaries in firm experiences rather than the potential of those activity sets. Thus, at

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higher levels of interdependency, the distribution of firms is more likely to reflect the normal distribution of locally optimal activity sets (Weinberger, 1991) with only a slight bias toward the right-hand side of the normal distribution (i.e., toward the better activity sets). As a result, we should expect a shift from leftward to rightward skew in firm profit distributions, which Lenox *et al.*, 2006 found to occur at a decreasing rate.

Hypothesis 3: The skew of firm performance distributions within industries will rise with the potential for interdependency in activities at a decreasing rate.

MEASURES AND METHODS

The main challenge in conducting empirical research on interdependencies is identifying appropriate measures of interdependency. Interdependencies appear in many forms (Zhao, 2006), and an ideal measure of interdependencies would capture interdependencies at multiple organizational levels. At the highest level, we expect interdependencies in organizational form and strategic decisions (Levinthal, 1997; Rivkin, 2000). Siggelkow (2001, 2002), for example, documents managerial choices at Vanguard and Liz Clairborne and how the value of each choice is affected by the other choices made. Porter (1996) gives examples of connections among the strategic and operational choices made by Southwest Airlines and several other companies. At the next level are potential interdependencies within firms' broadly defined production technology. Ichniowski *et al.* (1997) present evidence of interactions among compensation and other policies within steel finishing lines. Milgrom and Roberts (1990, 1995) discuss examples of similar interactions at Lincoln Electric and among a set of increasingly common modern manufacturing practices. At the most detailed level, substantial interdependencies may exist at the product and process levels (Zander and Kogut, 1995; Tyre and von Hippel, 1997). For example, Henderson and Clark (1990) refer to the interdependencies inherent in the product architecture, and Zhao (2006) shows that firms' R&D location choices depend on the strength of the internal linkages in their technologies.

However, most measures of interdependency operate at only one or two levels, and thus present a lower bound on interdependency as it affects firm and industry performance. Measures of interdependency at any level, however, must reflect two basic premises that drive the theoretical results in the literature: interdependencies are industry-level characteristics; and (relevant) interdependencies are non-obvious to industry participants so that they present a barrier to optimization and imitation. In the following section, we describe how we construct an industry-level measure using survey data that reflect the presence of interdependencies that are non-obvious to industry participants.

Interdependency measure

Recognizing the difficulty of observing and recording interdependencies that are inherently non-obvious *ex ante* to those operating in the industry, we measure the potential for interdependency through *ex post* managerial evaluations of the complexity of their products and processes. Specifically, we create proxy measures of the potential for interdependency in activities, *interdependency*, using items from the CMS developed by Cohen *et al.* (2002). The CMS was conducted in 1994 and was administered to a random sample of U.S. manufacturing R&D labs drawn from *Bowker's Directory of American Research and Technology* (Bowker, 1993). Of 3,240 labs surveyed, 1,478 R&D unit managers responded for an unadjusted response rate of 46 percent (see Cohen, Nelson, and Walsh, 2000 and Cohen *et al.*, 2002 for more survey details).

To measure the potential for interdependency in activities, we use responses to survey questions that elicit managers' perceptions of the complexity of their products and processes and, in particular, the ways in which complexity hampers the ability of others to imitate innovations. The term complexity has spawned many academic definitions. These generally correspond either to the difficulty of describing or creating an object or to the degree of organization (i.e., density of connections) apparent in some object (Lloyd, 2001). All of these measures of complexity correspond closely to some manifestations of interdependency. However, when it comes to using these survey items, the academic definitions of complexity are far less important than the natural language meaning that managers associate with complexity. Here the correspondence with interdependency is even

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stronger: the lead dictionary[3] definition of complexity refers to things 'composed of many interconnected parts.' This definition of complexity as many interconnected parts maps directly to the mathematical relationship hypothesized and represented in the NK model with N parts with K interconnections.

Specifically, the survey items we used to measure *interdependency* asked respondents to determine and report the percentage of their *product* innovations for which the 'competitive advantage from those innovations' (Cohen *et al*., 2000: 5) had been protected by each of eight possible sources—secrecy; patent protection; other legal mechanisms such as design registration or copyright; being first to market; complementary sales/service; complementary manufacturing facilities and know-how; product complexity; and other. The same question and list of response items was then repeated with respect to *process* innovations. Responses to the two questions were given on a one to five Likert scale signifying: below 10 percent; 10–40 percent; 41–60 percent, 61–90 percent; and over 90 percent (Cohen *et al*, 2000). We transform the five-point response scale to a measure ranging from zero to one to facilitate interpretation of the results. Using these converted values for the product complexity and process complexity items, we create an industry-level score by averaging across all respondents in the same four-digit standard industrial classification (SIC) code.[4] Since the CMS survey was conducted once in 1994, our measure derived from the survey is time invariant.

The comparative survey question used to construct our proxy measure is focused on the ability to protect innovations. As such, there is a risk that respondents simply score protection mechanisms higher whenever they have been able to protect innovations, creating a spurious positive link between complexity measures and profitability. Fortunately, as noted earlier, the questions offer respondents several alternative explanations for protection of innovations, specifically: legal barriers to appropriation (e.g., patents and trademarks); the control of scarce resources (e.g., complementary production and sales capabilities); and a catchall 'other' category. This primes the respondent to consider the relative contribution of interdependency and provides alternative explanations for innovation protection, thus decreasing the odds of such an overall halo effect on the complexity question. This also allows us to test the idea that such a halo effect occurred. We find that the correlations among the protection mechanisms in some cases are negative, suggesting no such halo effect occurred, and that controlling for these alternative mechanisms has insignificant effects on the reported results.

A basic issue with measuring group properties from individual survey respondents, made more severe by measuring a latent property, is that respondents' views will vary. Variance can originate from differences in the way the question is interpreted and from differences in the experiences and understanding of respondents. For example, some firms in a highly complex industry may have explored only a narrow range of the potential variants in product or process characteristics. These firms are unlikely to recognize the range of alternative combinations of characteristics or how extensively the product or process characteristics are interconnected. The resulting variance in responses within industries raises the question of whether observed industry-level differences reflect real differences among industries or simply random variation in responses. We use the Kruskal-Wallis equality of populations rank test to reject ($P(H_0)<0.0002$) the null hypothesis that random selection from a homogenous population produced the observed industry differences (Kruskal and Wallis, 1952).

Profitability measures

To test our three hypotheses, we adopt a measure of profitability that controls for differences in the scale of investments needed across industries. Tobin's q provides such a measure. Tobin's q is derived from the assumption that firms' market values reflect the cash flows generated by invested assets (both tangible and intangible) and that these cash flows depend in turn on industry characteristics. Specifically, the calculation of Tobin's q begins with the assumption that the market value (M) of firm (i) in time period (t) is a function

[3] http://dictionary.reference.com/search?q=complex (accessed 15 January 2007)

[4] We experimented with various constructions of our *interdependency* measure including using nontransformed responses (i.e., 1–5) and independent product- and process-based measures. In all cases, the measures are highly correlated (>90%) and lead to similar empirical estimates in our models.

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of the scale of its tangible (*Vp*) and intangible (δVi) assets and of additional factors (α, X_{it}), such as interdependency among activities, that magnify or reduce the return that firms can generate with assets invested in those industries:

$$M_{it} = (Vp_{it} + \delta Vi_{it})e^{(\alpha+\beta X_{it})} \quad (1)$$

Tobin's q thus provides a way to see how various factors beyond investment scale influence the flow of firm profits. In addition, compared to pure accounting measures of profitability, Tobin's q has the advantage of reflecting market expectations of the discounted stream of future cash flows accruing to a firm and its industry. Accounting-based measures are often more subject to the vagaries of accounting practices that may lead to idiosyncratic fluctuations in reported firm and industry profitability

In order to use this equation to estimate the effect of interdependency and other firm and industry influences on profits (i.e., the terms α, X_{it}) at the firm level, we use the standard transformation and approximations to derive the following linear equation (Griliches, 1981):[5]

$$\log Q_{it} = \alpha + \delta Vi_{it}/Vp_{it} + \beta X_{it} + \varepsilon_{it} \quad (2)$$

where ε_{it} is a disturbance term and Q_{it} the ratio of the market valuation of the firm to the value of tangible assets ($Q_{it} = M_{it}/Vp_{it}$) commonly referred to as Tobin's q.

Similar transformations allow the derivation of a linear estimation equation for the average Tobin's q at an industry level. The industry-level derivation differs from the firm-level derivation only in that that one calculates the mean of firm values within an industry for M_{it}, Vp_{it}, and Vi_{it}, before making the same transformations made in the firm-level derivation, such that:

$$\log \overline{Q_{it}} = \alpha + \delta\overline{Vi}_{it}/\overline{Vp_{it}} + \beta X_{it} + \varepsilon_{it} \quad (3)$$

Following Chung and Pruitt (1994) and DaDalt, Donaldson, and Garner (2003), we calculate *FirmQ* as the sum of firm market value (share price multiplied by outstanding shares) and the book value of long-term debt, preferred stock, and net current liabilities all divided by the total asset value of the firm for each firm in each year of our sample. To be consistent with Equations 2 and 3, we create a measure of the natural log of *FirmQ*, which we refer to as *LogQ*, and a measure of the natural log of the average *FirmQ* within each four-digit SIC code industry, which we refer to as *MeanQ*. All data for these calculations of Tobin's q are taken from Standard & Poor's Compustat North America Industrial Annual Dataset. We do not adopt the more complicated measure of q proposed by Lindenberg and Ross (1981), which attempts to correct for the replacement value of assets, because previous empirical studies have found that data limitations associated with that measure can introduce sample biases and produces little qualitative difference (Chung and Pruitt, 1994). To test our hypotheses concerning the two higher moments of q at the industry level, we create two variables (*VarQ* and *SkewQ*) that represent the second (variance) and third (skew) moments respectively of q for all firms within the same four-digit SIC industry for each year in our panel.[6]

Controls

Referring to the specifications in Equations 2 and 3, we need to control for the ratio of intangible to tangible assets, Vi_{it}/Vp_{it}. Following previous work on intangibles, we use R&D expenditures (*RD*) and advertising expenditures (*ADV*) to form the primary measures of intangible assets (*Vi*). Thus:

$$\frac{Vi_{it}}{Vp_{it}} = \beta_{RD}\frac{RD_{it}}{Vp_{it}} + \beta_{ADV}\frac{ADV_{it}}{Vp_{it}} \quad (4)$$

Prior research has shown that the flows of R&D and advertising expenditures are highly correlated with any stock measures that might be constructed by accumulating and discounting the flows of these expenditures (Hall, 1993). Given the substantial persistence in firms' expenditure patterns, such high correlations are to be expected. The high correlation precludes the inclusion of both stock

[5] This standard derivation assumes that the observed range of intangible to tangible asset ratios is small enough that $\delta Vi_{it}/Vp_{it}$ is a reasonable proxy for $\log(1 + \delta Vi_{it}/Vp_{it}$.

[6] *VarQ* is calculated as the standard deviation of *FirmQ*, that is, the square root of the variance of *FirmQ*. While our estimation equations for the first moment of q (Equations 2 and 3) can be derived directly from Griliches (1981) model, our estimation equations for the higher moments are not directly derived from that equation, and are more appropriately understood as using Tobin's q as a proxy for profitability.

and flow variables. We follow Villalonga (2004) in using Hall's (1990) method to interpolate missing values for R&D, replace missing values that cannot be interpolated with zeroes, and calculate stocks. For firm-level regressions, we divide the R&D stocks and advertising expenditures by the tangible assets of the firm (Vp) creating two measures: *R&D intensity* and *advertising intensity*.[7] For industry-level regressions, we first sum R&D stocks, advertising flows, and tangible assets of all firms in the industry, then calculate the ratios of the sums. Data for both measures were gathered from the Compustat dataset. For our industry-level analyses, we simply create industry average measures of both *R&D intensity* and *advertising intensity* by summing the R&D (or respectively advertising) reported by all firms in an industry in a given year and dividing that by the sum of all tangible assets reported for all firms in that industry year.

The final element of our specification in Equations 2 and 3 is a vector of firm and industry-level effects (X_{it}) that magnify the profits firms earn on invested assets. This paper, of course, is focused on how interdependency affects the profits firms earn on investments (tangible and intangible) in an industry. However, interdependency is not the only influence on those profits. In line with previous empirical models of Tobin's q, we include other variables that may affect profitability independently from interdependency (see Montgomery and Wernerfelt, 1988; Cockburn and Griliches,1988; Ceccagnoli, 2009). Therefore, in the vector X_{it}, we include several industry-level factors beyond our measure of interdependency. For example, Tobin's q should be greater on average as an industry grows, reflecting both the expansion in net income as revenues increase and the decrease in price competition in the presence of capacity constraints. Thus, we calculated *industry growth* (change in industry sales over the prior year sales) by using the U.S. Census of Manufactures input-output tables at the four-digit SIC level.

[7] Almost two-thirds of the observations have unreported advertising. We report regressions assuming the unreported values are zero. Attempts to apply prior techniques for interpolating R&D values and calculating R&D stocks to the advertising data produced unrealistic results. We found that the estimates of the effects of interdependency were similar whether we simply assumed unreported values were zero, omitted advertising from the model entirely, or assumed unreported values were zero and included a dummy variable to indicate where missing values had been replaced by zero.

Previous work has argued and found evidence that appropriability has a significant positive effect on the relationship between R&D expenditures and Tobin's q (Cockburn and Griliches, 1988; Ceccagnoli, 2009). For example, the more effective patents are, the greater a firm's ability to appropriate the returns to R&D. To control for other drivers of appropriability, we construct measures for all of the primary response categories included in the CMS from the same product and process appropriability questions used to construct our *interdependency* measure (*patent effectiveness, secrecy, other legal, first mover, complementary sales, complementary manufacturing*). As with *interdependency*, we create industry-level scores for each of the primary response categories, which range from zero to one after averaging across all respondents in the same four-digit SIC code and normalizing.[8]

Finally, to control for potential sources of unobserved heterogeneity, we include year-effect dummy variables, dummy variables for the two-digit industry classification where those dummy variables provide a considerable boost in explanatory power beyond the measured time-invariant variables, and random effects at the level (firm or industry) at which the model is specified.

Data

To construct the sample for our analyses, we combine firm-level data from Standard & Poor's Compustat North America Industrial Annual Dataset, industry-level data from the Census of Manufacturers, and industry-level data from a survey of R&D managers and R&D directors (CMS) (Cohen, Nelson, and Walsh 2002). In order to bracket the time period reflected in the CMS (the survey was conducted in early 1994 and asked respondents to reflect on conditions during the period 1991–1993) the Compustat data are taken for the period from 1988 to 1996. Compustat data are limited to publicly-traded firms and thus do not provide a full census of industry participants. In addition, any measure of firm-level performance will often reflect activity beyond the firm's primary reported industry. These two limitations are difficult to overcome and introduce error into our

[8] Some studies also include market share, but for these firms we know only their total size, thus market share estimates are likely to reflect diversification at a firm level more than relative performance within an industry.

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measures of the distribution of firm performance. However, errors in the measurement of dependent variables in an estimation equation are well accommodated by the standard statistical techniques we apply, and we see no *a priori* reason to expect the errors to be correlated with our independent variables of interest. We thus proceed with Compustat as the best available data on financial performance across industries.

Using the historical SIC code data reported in Compustat, we appended the Compustat data to that from the CMS and from the Census of Manufacturers using four-digit SIC codes. We limit the study to manufacturing industries (SIC codes 2000 to 3999, see Hall, 1990) appearing in both the CMS (the CMS was focused on manufacturing industries) and in the Census of Manufacturers shipments data records. We restrict the records to those for which we can calculate our dependent variable, Tobin's q, resulting in a dataset of 16,615 observations for 3,462 firms in 109 industries. We then remove observations where advertising or R&D expenditures were more than five times the total reported book value of assets, as well as observations with negative estimated q values or q values greater than three standard deviations above the mean, which reduces the dataset to 16,501 observations for 3,452 firms in 109 industries.[9]

ANALYSIS AND RESULTS

Table 1 includes information on our measures of interdependency and the first three moments of q (mean, variance, and skew) by industry.

Table 2 includes summary statistics and pairwise correlations for each of our variables. The central tendency for *LogQ* is 0.38, which is equivalent to an average *FirmQ* of 1.46, and similar to the average value calculated in prior studies using Tobin's q. *R&D intensity* and *advertising intensity* are 23 percent and one percent on average, respectively. The much higher values for *R&D intensity* reflect several factors: the R&D measure is an accumulated stock, which, when expenditures are fairly constant, will represent about seven years of the flow; the sample favors industries with identifiable R&D labs included in the CMS; and as noted earlier, advertising is more likely to be underreported. *Industry growth* is six percent on average with a maximum observed growth rate of 48 percent. *Patent effectiveness* and *interdependency* range from zero to one (as constructed) and have means of 0.29 and 0.41, respectively. We observe, as expected, significant positive correlations between *LogQ* and *R&D intensity, advertising intensity, industry growth, patent effectiveness, secrecy, other legal*, and *interdependency*. While we observe a positive pairwise correlation between *interdependency* and several measures of the factors that protect innovation (*secrecy, other legal, first mover, complementary sales, and complementary manufacturing*) we also observe a negative pairwise correlation between *patent effectiveness* and *interdependency* (−0.05). The variation in these relationships, along with our inclusion of these variables as controls and the curvilinear shape of the predicted relationship between interdependency and Tobin's q, should help allay concerns that higher survey responses simply reflect success in protecting innovations.

All of the models are specified as random-effects models—with those effects at the firm or industry level depending on the level of the dependent variable—with year dummies and robust standard errors. Concerned about possible heteroskedasticity resulting from differing numbers of survey respondents by industry, we also ran ordinary least squares (OLS) models with clustered standard errors using weights based on the square root of the number of respondents. Those weighted least squares models provided very similar results to the random-effects models reported in the tables.

We also included additional dummy variables for two-digit SIC codes in models where they improved the quality of the estimation. The inclusion of industry dummy variables has the potential to improve or obscure estimates of the time-invariant variables of interest. To the extent that these dummies account for variation unrelated to the variation explained by the observed variables, they will improve the estimates of time-invariant

[9] We were concerned that such outlying values represented simple misreporting of data and would overly influence our estimates. Clearly, removal of these observations alters our calculation of the moments of performance (mean, variance, and skew) for a given industry. However, we believe their removal will tend toward a conservative analysis by leading to, at worst, understatement of underlying moments and reducing the likelihood of finding statistically significant coefficient estimates. As a robustness test, we reestimated our empirical models on a less restrictive sample and found consistent results.

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Table 1. Interdependency and Tobin's q moments for all industries

SIC4	Industry description	N	Interdependency	MeanQ	VarQ	SkewQ
3679	Electronic components, NEC	8	0.67	1.47	1.63	4.11
3567	Industrial process furnaces & ovens	5	0.64	0.90	0.57	2.44
2052	Cookies & crackers	5	0.60	1.66	0.83	1.00
3663	Radio & TV broadcasting & communications equipment	16	0.57	2.00	2.14	3.30
3845	Electromedical & electrotherapeutic apparatus	29	0.54	3.29	3.65	3.10
2891	Adhesives & sealants	21	0.54	2.40	2.38	3.14
3674	Semiconductors & related devices	26	0.52	2.03	1.96	3.91
3827	Optical instruments & lenses	7	0.50	2.12	2.20	2.31
2835	In vitro & in vivo diagnostic substances	11	0.48	3.84	3.51	2.35
3443	Fabricated plate work (boiler shops)	5	0.48	1.16	0.86	2.41
3728	Aircraft parts & auxiliary equipment, NEC	14	0.47	1.36	1.04	2.07
3523	Farm machinery & equipment	8	0.47	1.11	0.81	2.59
3826	Laboratory analytical instruments	7	0.47	1.99	1.49	2.37
3577	Computer peripheral equipment, NEC	12	0.47	2.69	3.44	3.49
3572	Computer storage devices	11	0.46	2.20	2.69	3.45
3812	Search, detection, navigation, guidance aeronautical, & nautical systems and Instruments	40	0.45	0.98	0.82	4.02
2821	Plastics material, synthetic resins & nonvulcanizable elastomers	33	0.45	1.74	2.17	4.85
3672	Printed circuit boards	7	0.45	1.44	0.94	1.66
3841	Surgical & medical instruments & apparatus	33	0.44	3.23	3.03	2.96
3721	Aircraft	11	0.44	1.75	2.15	3.38
3714	Motor vehicle parts & accessories	33	0.44	1.57	1.87	5.36
3861	Photographic equipment & supplies	13	0.43	1.62	1.49	3.29
3661	Telephone & telegraph apparatus	15	0.43	2.33	2.40	3.29
2836	Biological products, except diagnostic substances	19	0.43	4.49	4.07	2.69
2834	Pharmaceutical preparations	43	0.43	3.97	3.63	2.62
3842	Orthopedic, prosthetic, & surgical appliances & supplies	10	0.41	2.36	2.46	3.94
2851	Paints, varnishes, lacquers, enamels	32	0.41	1.41	0.46	0.65
3571	Electronic computers	8	0.41	1.64	1.65	4.45
3089	Plastics products, NEC	8	0.41	1.90	2.64	4.55
3949	Sporting & athletic goods, NEC	4	0.41	1.57	1.43	2.61
3537	Industrial trucks, tractors, trailers, & stackers	5	0.40	0.96	0.54	2.39
3829	Measuring & controlling devices, NEC	13	0.40	1.82	2.40	5.36
2844	Perfumes, cosmetics, & other toilet preparations	18	0.39	2.05	2.01	2.88
3559	Special industry machinery, NEC	24	0.39	1.61	1.55	4.06
3651	Household audio & video equipment	8	0.38	1.95	3.11	5.25
3081	Unsupported plastics film & sheet	8	0.38	1.44	1.10	2.69
2086	Bottled & canned soft drinks & carbonated waters	5	0.38	2.26	3.12	5.68
3621	Motors & generators	13	0.37	1.87	2.78	4.22
3724	Aircraft engines & engine parts	12	0.37	0.88	0.47	2.82
3669	Communications equipment, NEC	6	0.35	1.79	2.07	3.24
2621	Paper mills	10	0.35	1.09	0.52	2.84
3312	Steel works, blast furnaces (including coke ovens), & rolling mills	9	0.35	0.87	0.45	3.03
3711	Motor vehicles & passenger car bodies	6	0.33	1.64	2.77	4.64
3823	Industrial instruments for measurement, display, & control of process variables; & related products	8	0.32	1.50	1.25	2.55
3825	Instruments for measuring & testing electricity & electrical signals	14	0.32	1.47	1.60	4.52

Table 1. (*Continued*)

SIC4	Industry description	N	Interdependency	MeanQ	VarQ	SkewQ
2911	Petroleum refining	12	0.31	1.02	0.29	1.71
3569	General industrial machinery & equipment, NEC	8	0.30	1.71	1.47	2.86
2082	Malt beverages	6	0.29	1.62	1.09	1.84
3011	Tires & inner tubes	4	0.28	1.71	1.05	0.51
3585	Air-cond & warm air heating equip & comm & industrial refrig equip	16	0.27	1.77	3.09	5.10
3433	Heating equipment, except electric & warm air furnaces	6	0.27	2.38	2.84	2.37
3612	Power, distribution, & specialty transformers	5	0.25	1.00	0.46	2.10
3541	Machine tools, metal cutting type	4	0.25	0.79	0.29	0.32
3532	Mining machinery & equipment,(no oil/gas field machinery/equipment	4	0.25	2.43	3.05	1.75
2033	Canned fruits, vegetables, preserves, jams, & jellies	4	0.25	1.45	0.89	1.20
3533	Oil & gas field machinery & equipment	5	0.23	1.37	0.62	2.21
3944	Games, toys, & children's vehicles, except dolls & bicycles	4	0.22	1.36	1.38	3.31
3613	Switchgear & switchboard apparatus	9	0.21	1.36	0.76	1.96
3531	Construction machinery & equipment	6	0.17	1.18	0.87	4.10
3561	Pumps & pumping equipment	5	0.15	1.31	0.63	3.04
2842	Specialty cleaning, polishing, & sanitation preparations	4	0.13	2.06	3.04	5.21
3743	Railroad equipment	4	0.09	1.27	0.73	1.29
3211	Flat glass	*	*	0.80	0.10	0.00
2273	Carpets & rugs	*	*	1.05	0.51	1.77
3578	Calculating & accounting machines, except electronic computers	*	*	2.56	2.91	2.80
2211	Broadwoven fabric mills, cotton	*	*	0.84	0.34	1.06
3678	Electronic connectors	*	*	1.85	2.75	6.13
3555	Printing trades machinery & equipment	*	*	1.88	2.96	4.31
3357	Drawing & insulating of nonferrous wire	*	*	2.09	2.35	3.12
2522	Office furniture, except wood	*	*	1.41	0.84	0.31
2013	Sausages & other prepared meats	*	*	1.18	0.98	3.02
3821	Laboratory apparatus & furniture	*	*	2.20	2.92	2.80
2015	Poultry slaughtering & processing	*	*	1.03	0.28	0.37
2531	Public building & related furniture	*	*	0.84	0.47	1.83
2085	Distilled & blended liquors	*	*	1.52	0.45	0.21
2011	Meat packing plants	*	*	1.43	2.05	6.24
3843	Dental equipment & supplies	*	*	3.16	3.95	3.30
3241	Cement, hydraulic	*	*	1.07	0.57	1.31
3411	Metal cans	*	*	0.96	0.30	0.80
2711	Newspapers: publishing, or publishing & printing	*	*	1.55	0.71	2.27
3824	Totalizing fluid meters & counting devices	*	*	1.15	0.56	1.65
3579	Office machines, NEC	*	*	1.54	1.07	1.62
2721	Periodicals: publishing, or publishing & printing	*	*	2.22	1.71	1.78
2024	Ice cream & frozen desserts	*	*	2.04	1.32	1.28
3713	Truck & bus bodies	*	*	1.16	0.75	2.26
3452	Bolts, nuts, screws, rivets, & washers	*	*	0.84	0.36	1.98
3086	Plastics foam products	*	*	1.44	1.19	2.87
3564	Industrial & commercial fans & blowers & air purification equipment	*	*	2.19	2.95	3.74
3562	Ball & roller bearings	*	*	1.29	0.82	1.93
3524	Lawn & garden tractors & home lawn & garden equipment	*	*	0.90	0.23	0.88

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Table 1. (*Continued*)

SIC4	Industry description	N	Interdependency	MeanQ	VarQ	SkewQ
3444	Sheet metal work	*	*	0.94	1.20	5.15
2221	Broadwoven fabric mills, manmade fiber & silk	*	*	0.98	0.20	0.39
3715	Truck trailers	*	*	1.43	0.67	0.86
3341	Secondary smelting & refining of nonferrous metals	*	*	1.74	1.71	3.27
2673	Plastics, foil, & coated paper bags	*	*	1.77	1.62	1.62
2631	Paperboard mills	*	*	1.18	0.50	1.24
3851	Ophthalmic goods	*	*	2.62	2.42	2.68
3272	Concrete products, except block & brick	*	*	0.64	0.42	3.44
3221	Glass containers	*	*	0.87	0.14	0.48
2511	Wood household furniture, except upholstered	*	*	0.92	0.48	2.87
2111	Cigarettes	*	*	1.95	1.65	3.09
3695	Magnetic & optical recording media	*	*	1.26	0.65	0.70
2092	Prepared fresh or frozen fish & seafoods	*	*	1.53	0.66	1.48
3317	Steel pipe & tubes	*	*	0.94	0.40	1.88
3281	Cut stone & stone products	*	*	1.69	.	.
3677	Electronic coils, transformers, & other inductors	*	*	0.99	0.61	2.60
3822	Automatic controls for regulating residential &commercial environments appliances	*	*	1.35	1.50	3.55
2833	Medicinal chemicals & botanical products	*	*	4.01	2.35	0.73
2611	Pulp mills	*	*	0.92	0.30	1.86
	Total	847				
	Maximum		1.00	4.49	4.07	6.24
	Minimum		0.00	0.64	0.10	0.00
	Mean		0.38	1.66	1.51	2.68

* To protect respondent confidentiality, CMS data have been excluded from the tables when there were fewer than four survey respondents.
[a] N is the number of survey respondents.
[b] For clarity, MeanQ in this table is the actual mean of Q rather than the mean of the log of Q as used in our analysis.

variables; and, to the extent that they pick up on the same sources of variation as the included time-invariant variables, they will reduce the quality of the estimates of those variables.

To determine how the inclusion of dummy variables affects the estimates in each panel, we estimated four versions of each panel. One version had only the time-varying variables, one had the time-varying variables and the two-digit industry fixed effects, one had the time-varying variables and the time-invariant independent variables, and one had all the variables and the two-digit fixed effects. We compared the increment to adjusted r-square across models relative to the base model, which includes only the time-varying independent variables. In order to be able to compare adjusted r-square values, each model was regressed in OLS with clustered standard errors.

For the regression of *LogQ*, we found that the adjusted r-square of the base model (0.125) improved a similar amount with either the inclusion of the measured time-invariant independent variables or the two-digit industry dummies (to 0.182 and 0.208 respectively), but the improvement when both were added was far less than additive of the two increments (to 0.225). This similar increment in model fit—and much less than additive improvement when dummies and time-invariant measured variables were all included—led us to conclude that the dummies were picking up on a similar source of variation to the estimated variables, and thus we exclude them from this model. In the case of the models of *MeanQ, SDQ*, and *SkewQ*, the increments were quite different and nearly additive, so we included the two-digit dummies along with the time-invariant variables of interest. Specifically, comparing the models with (a) only time-varying variables with (b) those with dummies as well, with (c) those with time-invariant variables as well, and with (d) those with both, we found the *MeanQ models* had adjusted r-squares of 0.250, 0.359, 0.379,

Table 2. Descriptive statistics and pairwise correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. LogQ	1												
2. VarQ	0.40*	1											
3. SkewQ	0.10*	0.49*	1										
4. R&D intensity	0.29*	0.25*	0.12*	1									
5. Advertising intensity	0.01*	0.01	−0.03*	−0.04*	1								
6. Industry growth	0.14*	0.14*	0.04*	0.08*	−0.04*	1							
7. Patent effectiveness	0.23*	0.34*	0.15*	0.17*	0.00	0.10*	1						
8. Secrecy	0.17*	0.26*	0.05*	0.14*	0.08*	0.06*	0.43*	1					
9. Other legal	0.05*	0.17*	0.10*	0.03*	0.08*	−0.02*	0.25*	0.13*	1				
10. First mover	−0.08*	−0.02*	0.11*	0.00	−0.04*	0.01	0.03*	0.01	0.32*	1			
11. Complementary sales	−0.06*	−0.07*	−0.01	−0.05*	−0.04*	−0.02*	−0.19*	−0.14*	0.27*	0.32*	1		
12. Complementary mfg	0.03*	0.02*	0.02*	0.01	−0.04*	0.05*	−0.17*	−0.05*	0.04*	0.16*	0.58*	1	
13. Interdependency	0.10*	0.21*	0.27*	0.10*	−0.07*	0.10*	−0.05*	0.16*	0.15*	0.31*	0.26*	0.37*	1

	1	2	3	4	5	6	7	8	9	10	11	12	13
Observations	16501	16477[a]	16477[a]	16501	16501	16501	16501	16501	16501	16501	16501	16501	16501
Mean	0.38	1.92	2.06	0.23	0.01	0.06	0.29	0.50	0.16	0.47	0.35	0.42	0.41
Standard deviation	0.81	1.34	1.22	0.50	0.05	0.09	0.15	0.14	0.10	0.12	0.12	0.13	0.12
Minimum	−4.82	0.01	−1.60	0	0	−0.37	0	0	0	0	0	0	0
Maximum	3.33	8.96	6.52	13.21	2.13	0.48	1	1	0.67	0.88	1	1	1

* $p < 0.05$.

[a] In some years, industries have too few participants to be able to calculate the variance and skew reducing observations.

Table 3. Interdependency and the mean of Tobin's q

Model	1	2	3	4	5	6
Dependent variable	MeanQ	MeanQ	MeanQ	LogQ	LogQ	LogQ
Panel	Industry	Industry	Industry	Firm	Firm	Firm
R&D intensity[a]	0.333*	0.337*	0.330+	0.174**	0.173**	0.442*
	(0.169)	(0.170)	(0.170)	(0.020)	(0.020)	(0.201)
Advertising intensity[a]	1.049	1.139	1.130	0.438**	0.429**	0.380*
	(0.820)	(0.805)	(0.803)	(0.161)	(0.162)	(0.161)
Industry growth	0.306**	0.304**	0.305**	0.377**	0.375**	0.348**
	(0.116)	(0.117)	(0.116)	(0.047)	(0.047)	(0.047)
Interdependency (H1+)		0.421*	0.934+	0.450**	1.827**	1.866**
		(0.183)	(0.511)	(0.078)	(0.251)	(0.264)
Interdependency^2 (H1-)			−0.633		−1.693**	−1.481**
			(0.620)		(0.289)	(0.307)
Appropriability controls[b]						
Patenting						0.649**
						(0.082)
Secrecy						0.338**
						(0.081)
Other legal						0.337**
						(0.123)
First mover						−0.713**
						(0.095)
Complementary sales						−0.386**
						(0.107)
Complementary mfg						0.274**
						(0.098)
R&D interactions[b]						x
Year effects	x	x	x	x	x	x
Industry effects[c]	x	x	x			
Constant	0.235*	0.085	−0.003	0.156**	−0.100+	−0.211**
	(0.106)	(0.116)	(0.134)	(0.035)	(0.056)	(0.077)
Observations	953	953	953	16501	16501	16501
Industries	109	109	109			
Firms				3452	3452	3452
R-square	0.379	0.403	0.406	0.116	0.118	0.167
Wald χ^2	366.07***	378.99***	380.05***	969.24***	1016.11***	1333.29***

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$ (two-tailed tests of hypotheses).
[a] *R&D intensity* and *advertising intensity* represent industry annual averages (calculated by summing R&D and advertising expenditures across all firms in an industry then dividing by the sum of the tangible assets) in the industry panel and firm annual intensities in the firm panel.
[b] The appropriability controls in Models 6 were estimated with the entire set of controls (patenting, secrecy, other legal, first mover, complementary sales, complementary mfg) as main effects as shown and as interacted with R&D intensity (not shown). The interaction effect for patenting was positive as expected but not statistically significant. The statistically significant interaction effects at the five percent level were for interactions between R&D intensity and both complementary sales (0.725) and complementary manufacturing (−0.442).
[c] Two-digit industry effects are included as explained in the text and all models are estimated with random effects.

and 0.470, while the standard deviation models had adjusted r-squares of 0.145, 0.198, 0.153, and 0.215, and the skew models had adjusted r-squares of 0.082, 0.141, 0.106, and 0.174. Therefore, we included the two-digit industry controls in those regressions.

Table 3 presents estimates of models exploring the relationship between interdependency and average profitability (Hypothesis 1). Model 1 provides a baseline analysis not including *interdependency*. Our dependent variable is *MeanQ* and the sample is our industry panel leading to 953 industry-year observations of 109 industries. As explained earlier, we adopt a random-effects specification with year and industry fixed effects at the two-digit level. Robust standard errors and two-tailed tests of hypotheses are provided (as they are in all of our models). We estimate positive coefficients on each of the independent variables finding statistically significant estimates for *R&D intensity* and *industry growth*.

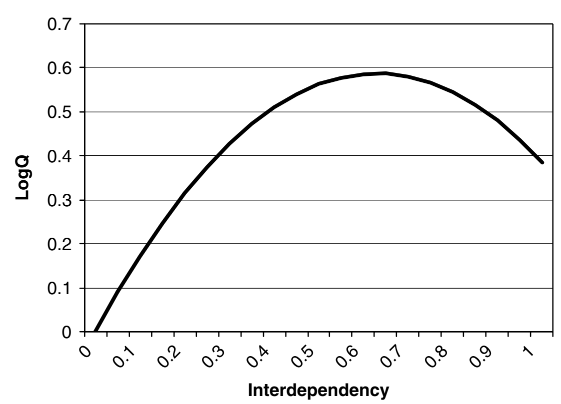
In Model 2, we add our measure of the potential for interdependency among productive activities within an industry to the specification in Model 1. We estimate a significant, positive coefficient on *interdependency*. We also continue to find significant, positive coefficients on *R&D intensity* and *industry growth*. Our explained variance (R^2) modestly increases from 38 percent to 40 percent, though that increase is relatively large when one considers that the other measured variables combined explain only three percent more than a model with only latent year and industry effects. In Model 3, we explore the nonlinear effect hypothesized in Hypothesis 1 by adding *interdependency* squared to our list of variables in Model 2. We estimate positive and statistically significant coefficient estimates for the linear term and a negative but not statistically significant coefficient for the quadratic term (*interdependency* and *interdependency*^{2}), apparently reflecting the linear relationship found in Model 2.

To better refine our coefficient estimates, we make use of our full dataset and reestimate our specification in Model 3 for our firm-level panel, increasing our sample to 16,501 firm-year observations of 3,452 firms in 109 industries. We adopt *LogQ* as our dependent variable and use firm-level measures of *R&D intensity* and *advertising intensity*. The estimation results for this specification are presented in Models 4 and 5. Consistent with Hypothesis 1, we find a significant, positive coefficient on *interdependency* and a significant, negative coefficient on *interdependency*^{2}.

In Model 6, we include our individual measures of appropriability (*patent effectiveness, secrecy, other legal, first mover, complementary sales, complementary manufacturing*). Previous work has argued for the use of interaction terms between firm R&D and appropriation mechanisms (Ceccagnoli 2009; Cockburn and Griliches 1988) and found evidence of their importance. Therefore, we include interaction terms for the appropriability controls that logically would affect the value of R&D more than the value of other assets. In the interest of space, the estimated coefficients for the interaction terms are not shown in the table. Those estimates show a positive coefficient for the interaction term on patenting, as expected, and statistically significant effects for interactions between *R&D intensity* and both *complementary sales* (0.725) and *complementary manufacturing* (−0.442).

We find that *patenting effectiveness, secrecy, other legal,* and *complementary manufacturing* protection mechanisms increase Tobin's q as previous research would lead us to expect. Interestingly, we find that when *first mover* and *complementary sales* advantages protect innovations, Tobin's q is lower. This may indicate that protecting innovations by moving quickly has negative repercussions, or that a firm can expect lower returns when moving quickly is the only way to protect innovations. Both with and without these controls, however, the findings support a concave relationship over the relevant range of *interdependency* (see Figure 1).[i]

As for the economic importance of *interdependency*, we estimate that the difference between a minimal interdependency industry (*interdependency* = 0) and a mid-interdependency industry (*interdependency* = 0.50) is approximately a difference in firm Tobin's q of 1.76.[10] This is more than moving half a standard deviation in the log of Tobin's q (0.81 in Table 2) above the average firm in our sample. As for the relative importance of interdependency, we find that the marginal



Note: The curve here is generated by applying the coefficient estimates on *Interdependency* (1.866), and *Interdependency* squared (-1.481), from Model 6 in Table 3.

Figure 1. Marginal effect of interdependency on Tobin's q

[10] Referring to Figure 1, the difference between minimal (0.0) and mid (0.50) interdependency leads to a difference in *LogQ* of 056. Taking the exponent gives 1.76.

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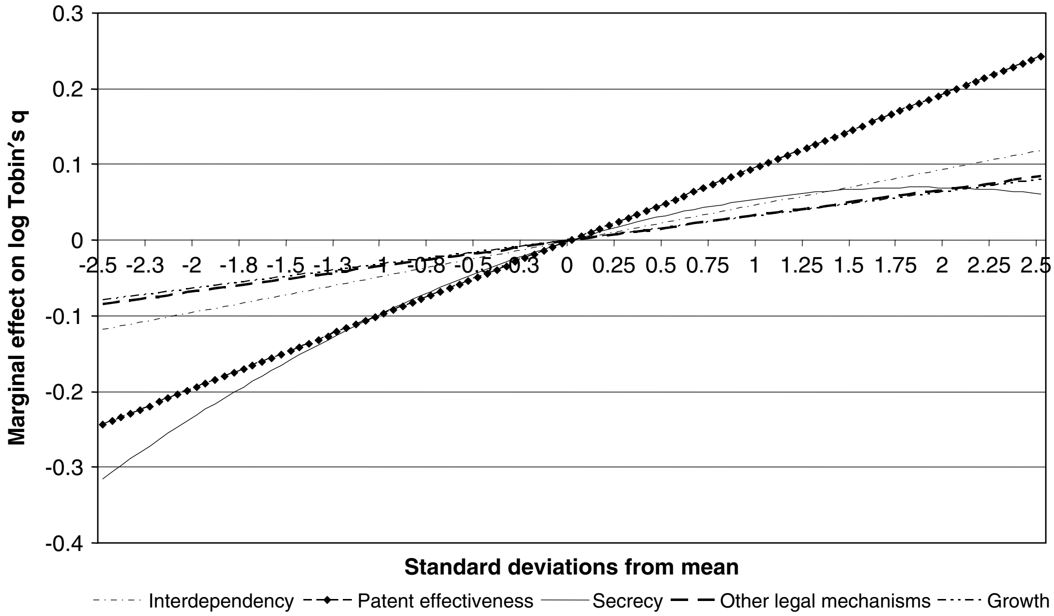

Note: The effects are shown as variations around their mean effects in order to highlight the relative effect of variation in these variables rather than the scale of their main effects. The figure is constructed using the main effect coefficient estimates from Model 6 in Table 3.*

*To further test that profitability really turns down within the data, we repeated the analysis using a spline regression. We broke the measure of interdependency into three equal parts: 0 to 0.33, 0.34 to0.67, and 0.68 to 1.0. These breaks isolated the estimate for interdependency at higher levels from the estimate for interdependency at lower levels. The highest of the three segments had a negative slope (statistically significant p<0.01) consistent with a drop in profitability at high levels of interdependency.

Figure 2. Relative marginal effect of interdependency on Tobin's q

effect of *interdependency* on industry profitability is comparable to the main effects of *patent effectiveness, secrecy, other legal* mechanisms and *industry growth* over most of the relevant range of each of these variables (see Figure 2).

Next we turn our attention to an analysis of the effect of interdependency on the distribution of firm profitability within an industry (see Table 4). In Model 7, we adopt *VarQ* as our dependent variable and use our full panel of industry-year observations.[11] As noted earlier, we adopt a random-effects specification with year and industry fixed effects. In Model 8, we introduce the measure of interdependency and, consistent with Hypothesis 2, we estimate a positive, significant coefficient on *interdependency* suggesting that industry variance in profitability increases with interdependency.

Finally, we analyze the effect of interdependency on the skew of firm profitability within an industry (see Table 5). In Model 9, we adopt *SkewQ* as our dependent variable and use our industry panel of industry-year observations. Consistent with our hypotheses, we estimate a positive, significant coefficient on *interdependency* indicating that industry skew in profitability increases with interdependency.

To test the nonlinear relationship in Hypothesis 3, we reestimate our specification in Model 9 adding the square of *interdependency* (see Model 10). Consistent with Hypothesis 3, we estimate a positive, significant coefficient on *interdependency* and a negative, significant coefficient *interdependency*^{2} thus suggesting that industry skew in profits is increasing with greater interdependency at a decreasing rate. Interestingly in Model 11, over the relevant range of interdependency we predict a decrease in *SkewQ* at high levels of interdependency. We leave consideration of this to the discussion.

[11] In some years, industries have too few participants to be able to calculate the variance and skew reducing the sample from 953 to 929 industry-year observations in which 107 industries have multiple observations.

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Table 4. Interdependency and the variance of Tobin's q

Model	7	8
Dependent variable Panel	VarQ Industry	VarQ Industry
R&D intensity[a]	1.029[+]	1.039[+]
	(0.535)	(0.534)
Advertising intensity[a]	2.891	3.287
	(3.231)	(3.181)
Industry growth	0.114	0.103
	(0.436)	(0.436)
Interdependency (H2+)		1.056**
		(0.409)
Year effects	x	x
Industry effects[b]	x	x
Constant	0.648*	0.268
	(0.282)	(0.283)
Observations	929	929
Industries	107	107
R-square	0.211	0.229
Wald χ^2	171.78***	189.88***

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$ (two-tailed tests of hypotheses).
[a] *R&D intensity* and a*dvertising intensity* represent industry annual averages calculated by summing R&D and advertising expenditures across all firms in an industry then dividing by the sum of the tangible assets.
[b] Two-digit industry effects are included as explained in the text and all models are estimated with random effects.

Table 5. Interdependency and the skew of Tobin's q

Model	9	10	11
Dependent variable Panel	SkewQ Industry	SkewQ Industry	SkewQ Industry
R&D intensity[a]	−0.348	−0.331	−0.309
	(0.392)	(0.385)	(0.382)
Advertising intensity[a]	0.200	0.600	0.512
	(2.512)	(2.489)	(2.456)
Industry growth	−0.657*	−0.665*	−0.626*
	(0.313)	(0.311)	(0.304)
Interdependency (H3+)		1.344**	6.318**
		(0.451)	(1.142)
Interdependency^2 (H3-)			−6.176**
			(1.255)
Year effects	x	x	x
Industry effects[b]	x	x	x
Constant	0.748**	0.267	−0.580[+]
	(0.246)	(0.285)	(0.320)
Observations	929	929	929
Industries	107	107	107
R-square	0.137	0.172	0.226
Wald χ^2	52.38***	61.30***	87.28***

$^+ p < 0.10$, $^* p < 0.05$, $^{**} p < 0.01$, $^{***} p < 0.001$ (two-tailed tests of hypotheses).
[a] *R&D intensity* and *advertising intensity* represent industry annual averages calculated by summing R&D and advertising expenditures across all firms in an industry then dividing by the sum of the tangible assets.
[b] Two-digit industry effects are included as explained in the text and all models are estimated with random effects.

DISCUSSION

Overall our analyses support the hypotheses derived from previous theoretical models concerning the relationship between interdependency and the first three moments of industry profitability. In particular, we find that 1) Tobin's q is higher in industries with moderate levels of interdependency (Hypotheses 1); 2) variance in Tobin's q among firms in an industry is increasing with the level of interdependency of the industry (Hypothesis2); and 3) skew in Tobin's q among firms in an industry is increasing at a decreasing rate with the level of interdependency of the industry (Hypothesis 3). Our results were robust across a number of specifications including the inclusion of year, industry, and firm effects. We found similar results when testing a number of alternative specifications including some using different methods for constructing our measure of interdependency.

A peak in profitability at moderate levels of interdependency is consistent with predictions made by other models and researchers. Rivkin (2001) argued that profits peak in a middle range of interdependency where the production decision problem is sufficiently difficult to limit imitation by new entrants, but not so difficult as to forestall replication by incumbents. Lieberman (1987) employed game-theoretic models incorporating experience curves to show that the profit potential generated by different entry times is small when improvements can be made either quite rapidly or only very slowly, but first movers can generate profits when experiential learning is rapid enough for early entrants to develop a lead over later entrants, but not so rapid that later entrants would quickly match the first mover's efficiency. Schoemaker (1990) reached a similar conclusion based on a more probabilistic argument that is the most similar to the one we explore here: he asserted that profits peak when decision problems are hard enough that boundedly rational managers will choose different heuristic solutions, but easy enough that a few of those solutions will work well. Unlike the Lenox *et al*., 2006 model tested here, these arguments do not provide predictions

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for the higher-order moments of the profit distributions within industries.

Clearly, our analysis depends on the validity of our proxy measures for interdependency. We believe that the natural language meaning of the term complexity, the comparison with other protection measures, and the respondent agreement on the survey items all support the notion that the survey responses from firm managers on the complexity of their products and processes offer a reasonable reflection of interdependency.

While we adopt industry, firm, and year effects, we make no claims to have completely controlled for unobserved heterogeneity across firms and industries. We are hard-pressed, however, to come up with an alternative interpretation of our interdependency measure that has the same range of effects on the distribution of profits and does not capture the essence of interdependencies.

It is worth noting that our coefficient estimates on the skew of industry Tobin's q suggest that skew may decrease at high levels of interdependency. This result may be a byproduct of our sample. Lenox *et al.* (2006) found that heterogeneity in profits at high levels of interdependency was driven by a few industries with highly skewed profit distributions. In particular, they found that at the highest levels of interdependency, roughly only 25 percent of industries demonstrated high skew. In other words, only a handful of industries in high-interdependency environments are dominated by very successful firms relative to others in the industry, while most industries are more equitable. Observing skew in performance at higher levels of interdependency is thus particularly sensitive to the exclusion of a few industries from the dataset.

It is possible that firms have some control over the level of interdependencies in an industry. Firms may choose which activities to conduct and which will be conducted by upstream, downstream, and complementary industries (Jacobides, 2008). Firms may define industry boundaries (i.e., select activities to perform within the firm) to minimize ongoing coordination costs (Novak and Wernerfelt, 2007) and transaction costs (Williamson, 1979). For example, Novak and Wernerfelt divide the parts of an automobile into 36 'megaparts' such as airbags and steering columns. Automobile companies such as GM and Toyota could produce all these megaparts internally, but instead divide them among various suppliers. The division of megaparts among specialist subindustries appears to be limited by managers' desire to retain parts that are highly interdependent under the control of one firm: wherever a change in one part *regularly* requires offsetting changes in another part, those two parts are usually made by the same firm. Moving some activities (automobile megaparts) into supplier subindustries reduces the number of ways that competitors such as GM and Toyota may differ. Some interdependent parts do get split among competitors, leaving the more tightly defined industry in which GM and Toyota compete with fewer internal decisions and interdependencies.

In this light, our findings speak to the effect of the level of interdependency that currently exists within an industry after this process of division occurs. It also means that our findings speak not only to how managers might choose to select among industries, but potentially to factors that may influence managers' decisions about defining industry boundaries. Managers would choose to draw boundaries that include enough interdependency to allow some firms to find particularly good combinations of activities (i.e., create the potential for variation in performance that raises average industry profits), but not so much interdependency that firms struggle to manage the range of activities.

This study provides the first broad empirical test of the theoretical findings from an NK model. We by no means present this as the definitive empirical treatment of the relationship between interdependency and profitability, but we are very encouraged by these findings. The CMS appears to have provided robust proxy measures of interdependency, and the findings of our analyses are consistent with theoretical predictions concerning interdependency. Given the explosion of theoretical modeling work on interdependency without accompanying large-scale empirical support, we hope that this work will serve to inspire further empirical investigations.

CONCLUSIONS

In this study, we have taken a first step in constructing a novel measure of interdependencies that we have used to conduct a large-sample empirical study relating interdependencies to the distribution of profits within and across industries. Our novel

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measure of interdependency allows us to explore its effect on the distribution of firm profits across a wide variety of industries. Overall, the results are consistent with the effects of interdependency on the first three moments of industry profitability predicted in previous theoretical work. Specifically, we present evidence that moderate levels of our measure of interdependency are most strongly correlated with greater average profitability, while higher levels of interdependency are associated with greater variability and skew in firm performance.

The study of interdependencies among firms' activities builds on the long tradition in evolutionary economics of exploring how challenges to identifying profitable sets of productive activities can lead to intra-industry heterogeneity and provide a nuanced understanding of how competition evolves over time. Interdependencies are important because they influence the extent and nature of heterogeneity that arises among profit-seeking firms (Levinthal, 1997), the nature of decisions that will be made by firms with varying internal structures (Rivkin and Siggelkow, 2003), the amount of heterogeneity that will persist when imitation of more successful firms may not rapidly drive out heterogeneity (Rivkin, 2000), how profit distributions are likely to differ among industries (Lenox *et al*., 2006) and how industries will develop over time (Lenox *et al*., 2007). The findings in this paper support further attention to interdependencies, showing that their effects are not only identifiable in practice, but similar in magnitude to factors that have received considerably more attention.

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