Does Interdependency Affect Industry Profitability?
An Empirical Test

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Abstract

Recent research asserts that interdependency among a firm's activities-- when the efficacy of how a firm conducts one or more productive activities depends on how the firm conducts other activities -- is fundamental to our understanding of business competition. In particular, researchers have argued that the potential for interdependencies among productive activities affects the distribution of firm profits within an industry (Lenox, Rockart, & Lewin 2006). However, despite extensive theoretical modeling efforts, almost no empirical work has been reported that tests for an effect of interdependency on profitability. In this paper, we present what we believe is the first large, cross-industry empirical analysis of the effect of interdependencies on the distribution of profits. 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. We find evidence consistent with previous theoretical work: average profitability peaks at moderate levels of interdependency; the dispersion of profits among firms within industries increases with interdependency; and industries with greater interdependencies have a more positively skewed performance distribution. The overall explanatory power of interdependencies is found to be similar to that of patent protection and industry growth rates.

(Keywords: Interdependencies, NK Model, Industry profitability)

1. INTRODUCTION

Recent research proposes that the potential for interdependencies among productive activities affects the distribution of firm profits within an industry (Lenox, Rockart, & Lewin 2006). Interdependencies exist when the value of one or more activities depends on how a firm conducts other activities (Levinthal 1997).[1,2] The higher the potential number of interdependencies the more difficult it is for firms to identify profit-maximizing sets of activities, reducing firm efficiency and driving down firm and industry profits. Similarly, the higher the potential number of interdependencies, the greater will be the variety in firm performance created as firms search for profitable combinations of activities (Levinthal 1997) and the less able firms will be to eliminate this variety (Rivkin 2000). The resulting sustained variance may lead to industries dominated by a few highly profitable firms (Demsetz 1973). Given these competing effects, recent theoretical models have attempted to clarify the relationship between interdependency and profitability. In particular, Lenox, Rockart, and Lewin (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 present what we believe is the first large, cross-industry empirical analysis of the effect of interdependencies on the distribution of industry profits. Despite extensive theoretical modeling efforts (Lenox, Rockart and Lewin 2007; Lenox, Rockart and Lewin 2006, Rivkin 2001, Rivkin 2000), little empirical work has been conducted to test for the effect of interdependencies on the magnitude of firm profitability or variation in firm profitability. The empirical work that has been done involves extensive individual case studies (Siggelkow 2001, 2002; Ichniowski et al., 1997; Milgrom & Roberts, 1995) 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

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).

been the difficulty in measuring interdependency systematically across a wide number of industries. 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 collected as part of the Carnegie Mellon University Survey of R&D Managers as proxy measures of interdependency (Cohen, Nelson and Walsh 2002). We test for the predicted relationships between interdependencies and both the mean and dispersion of firm performance within industries. 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.

2. 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) and interdependencies in productive activities are increasingly seen as an important driver of heterogeneity in firm performance. In particular, interdependencies increase the difficulty of discovering and imitating profitable combinations of activities. Levinthal (1997) demonstrates 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) demonstrates that even when interdependencies are small, interdependencies cause 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, Rockart, and Lewin (2006) continued this line of research 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* (PIA) – 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 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 Kaufmann NK model (Kaufmann, 1993), this underlying structure has been the basis for much of the modeling work on interdependencies and firm strategy.

Lenox, Rockart, and Lewin (2006) note that the traditional NK model fails to capture the inter-firm 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 (H1). In the model of Lenox, Rockart, and Lewin (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 any competitor is able to determine the most efficient way of operating and do so quite rapidly. 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 that are founded under different conditions (Stinchcombe 1965) or explore opportunities in a different order are less likely to converge on the same activity sets (Levinthal 1997). As a result, firms are like to be heterogeneous in their activities within an industry leading to increased variance in performance across 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 a small group of lower performing firms (if any). 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 determined by their own initial random differences rather than the potential of those activity sets. Thus, at higher levels of interdependency, the distribution of firms is more likely to reflect the normal distribution of activity sets (Weinberger 1991) with some bias toward he right hand side of the normal distribution (i.e., toward the better activity sets). As a result, we should expect not only the reduction in average performance that helps reduce industry profits, but also a shift from leftward to rightward skew in firm profit distributions.

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

To be clear, the arguments in Lenox, Rockart, and Lewin (2006) are not alternatives to the classic industrial organization economics structure-conduct-performance paradigm (Bain 1956). Rather, each of the arguments explicitly treats interdependency as an exogenous characteristic of the industry production function that influences the distribution of abilities with which firms compete and thus influences both industry structure and firm performance.

3. DATA AND MEASURES

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 conducted by researchers at Carnegie Mellon University (CMU) with support from the Alfred P. Sloan Foundation (Cohen, Nelson and Walsh 2002). We sample all firms with records available in Compustat for the period from 1988 to 1996. The time period was established to bracket the time period reflected in the CMU survey which was conducted in early 1994 and asked respondents to reflect on conditions during the period 1991-1993. This produced a list of 174,669 observations for 15,781 publicly-traded firms across all industry sectors. Using the historical Standard Industrial Classification (SIC) code data reported in Compustat, we appended this to the data in the Carnegie survey using four-digit SIC codes. Limiting ourselves to records from manufacturing sectors represented in the Carnegie survey reduces the dataset to 22,229 observations for 3,088 firms from 104 industries over the entire period. After removing those observations where advertising or R&D expenditures were more than five times the total reported book value of assets and dropping observations where the estimated Q values were greater than three standard deviations above the mean value or were negative, the resulting dataset included 10,463 observations for 2,146 firms in 104 industries.[3]

3.1 Interdependency Measure

The challenge in conducting empirical research on interdependencies is finding good measures of interdependency. At their foundation, interdependency arguments rely on the mathematics of combination rather than on the specific items being combined. For example, Levinthal (1997) provides an abstract discussion of 'attributes' of 'organizational forms' leaving unstated what sorts of attributes might be relevant. Similarly, Rivkin (2000) begins with an abstract concept of the number of 'elements' or 'decisions' within a strategy.

One of the challenges for measuring interdependencies is their potential to appear at three different organizational levels. At the highest level are interdependencies in organizational form and strategic decisions. Siggelkow (2001, 2002), for example, documents key 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

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[3] 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 towards 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 re-estimated our empirical models on a less-restrictive sample and found consistent results.

Southwest airlines and several other companies. One level down, we see the potential for interdependencies within firms' broadly defined production technology. Ichniowski et al. (1997) show evidence of interactions among compensation and other policies within steel finishing lines. Milgrom and Roberts (1990, 1995) provide examples of similar interactions at Lincoln Electric and among a set of increasingly common modern manufacturing practices. Finally, substantial interdependencies may exist at the product or process level (Zander and Kogut 1991; Tyre 1991). For example, Henderson and Clark (1990) refer to the interdependencies inherent in the product architecture.

In practice, interdependencies are likely to exist at all three levels. As a result, any measure of observed interdependencies at one level is a potentially noisy estimate of the overall interdependency of the industry. More challenging is the idea that measures of interdependency at any one level may present a lower bound on the effective interdependency. This will occur if high interdependency at any level is a sufficient to lead to higher variance in firm performance. If so, when measuring interdependency, we can be certain that we find high interdependency when it is observed but will be uncertain whether we have found high or low interdependency when our measure at one level indicates low interdependency. Complicating matters further, many interdependencies go unexploited and thus unobserved. So while the potential for interdependencies may be high, the realized interdependencies may be low. These arguments suggest that observed interdependencies will likely under-represent interdependency.

Recognizing both the difficulty of any measurement scheme and the need for cross-industry measures, we measure the potential for interdependency in activities through a survey. Specifically, we create our measure of the potential for interdependency in activities, *Interdependency*, using items from the Carnegie Mellon University Survey of R&D Managers and Directors developed by Cohen, Nelson, and Walsh (2002). The Carnegie survey 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. Of 3,240 labs surveyed, 1,478 R&D unit managers responded for an unadjusted response rate of 46% (see Cohen, Nelson, and Walsh 2002 for more survey details).

To measure the potential for interdependency in activities, we use responses to an item from the survey which elicits 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). We think all of these measures of complexity correspond closely to manifestations of interdependency. However, when it comes to using 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 stronger: The lead dictionary definition of complexity refers to things "composed of many interconnected parts" (Dictionary.com, 2007). This definition of complexity as 'many interconnected parts' maps directly to the mathematical relationship hypothesized and epresented in the NK model with N parts with K interconnections.

Specifically, the survey items we use to measure Interdependency ask: “During the last three years, for what percent of your product innovations were each of the following effective in protecting your firm’s competitive advantage from those innovations?” The respondents were given eight possible sources of protection: 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 was then asked again with the word “product,” in both the question and list of items, replaced by the word “process”.Responses to the two questions were given on a scale of 1 to 5 signifying: below 10%; 10-40%; 41-60%, 61-90%; and over 90%. We convert the scale to the central tendency of the categorical bounds, i.e., 5%, 25%, 50%, 75%, and 95% respectively. 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 4-digit SIC code.[4] Since the survey was conducted once in 1994, our measure derived from the survey is time invariant.

The comparative survey question used to construct our 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, trademarks); the control of scare 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 reducing 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. These results are consistent with the central premise of the interdependency literature that interdependencies may serve as an important underlying driver of differences in firm profitability both within and between industries.

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

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

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).

3.2 Profitability Measures

To capture the distribution of firm profitability we use Tobin's q, i.e., the ratio market valuation of the firm to the value of assets. To the extent that a firm's market valuation is based on the expected discounted future cash-flows to the firm, it provides an appropriately scaled measure of firm and industry profitability. Compared to pure accounting measures of profitability, Tobin's q has the advantage of reflecting market expectations of future growth and profitability and thus better reflects 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 identities which may lead to idiosyncratic annual fluctuations in firm and industry profitability.

Following Chung and Pruitt (1994) and DaDalt et.al. (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. We do not adopt the more complicated measure of q proposed by Lindenberg & 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 three moments of q at the industry level, we create three variables (*MeanQ*, *VarQ*, and *SkewQ*) that represent the first (mean), second (variance), and third (skew) moments respectively of q for all firms within the same 4-digit SIC industry for each year in our panel.[5] All data for these calculations is taken from the Compustat dataset.

3.3 Controls

Of course, interdependency is not the only influence on firm and industry profitability. 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). We begin with the idea that the market value (M) of a firm (*i*) in time period (*t*) is a function of the tangible (Vp) and intangible (Vi) assets of the firm:

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

where δ is the relative shadow price of intangible versus tangible assets and *X* is a vector of firm and industry level effects that magnify the value of these assets (Griliches 1981; Hall, Jaffee and Trajtenberg 2005). We then use standard transformation and approximations to derive the following equation for estimation (Griliches 1981):

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

where $Q_{it} = M_{it} / Vp_{it}$ and ε_{it} is a disturbance term.[6] To be clear, our model specification assumes that industry characteristics have a multiplicative effect on the value of intangible assets (see Equation 1) and that this multiplicative effect is estimated as a linear sum of effects by taking the logs of both sides (see Equation 2).

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[5] For our empirical models, *MeanQ* is calculated as the mean of the log of *FirmQ* to be consistent with our theoretical specification (provided below). *VarQ* is calculated as the standard deviation of *FirmQ*, i.e., the square root of the variance of *FirmQ*.

[6] We assume that the observed range of intangible to tangible asset ratios is small enough that $\delta Vi_{it} / Vp_{it}$ is a reasonable proxy for $\log(1 + \delta Vi_{it} / Vp_{it})$.

To be consistent with our model, we first create a measure of the natural log of *FirmQ* which we refer to as *LogQ*. Following previous work on intangibles, we use R&D expenditures (*RD*) and advertising expenditures (*ADV*) as proxies for the stock of intangible assets (Vi) such that:

$$Vi_{it} = \beta_{RD} RD_{it} + \beta_{ADV} ADV_{it} \tag{2}$$

Dividing each by the tangible assets of the firm (Vp), we create two measures: *R&D Intensity* and *Advertising Intensity*.[7] 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* either at the industry-year level (for the panel) or the aggregate-industry level (for the cross-section).

As for the vector (X), we include two industry-level factors in addition to our measure of interdependency. *Industry Growth* (change in industry sales over the prior year sales) was calculated using the U.S. Census of Manufactures input-output tables at the 4-digit SIC level. Arguably, 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. *Patent Effectiveness* was constructed using data from the CMU Survey of R&D Managers and Directors. Previous work has found evidence that patent effectiveness has a significant positive effect on the relationship between R&D expenditures and Tobin's q (Cockburn & Griliches 1988; Ceccagnoli 2007). Simply stated: the more effective patents, the greater a firm's ability to appropriate the returns to R&D. We construct our *Patent Effectiveness* measure using the patent protection responses from the same product and process appropriability questions used to construct our *Interdependency* measure. As with *Interdependency*, we create an industry level score by converting each response to the central tendency of the categorical bounds and by averaging across all respondents in the same 4-digit SIC code. Finally, to

[7] Almost two thirds of the observations have unreported advertising. We report numbers assuming the unreported values are zero. Alternatively, dropping the values reduces the statistical significance of the estimates but has little effect on the coefficient estimates of the variables of interest.

control for potential sources of unobserved heterogeneity, we include year, industry, and firm effects where appropriate.[8]

4. ANALYSIS AND RESULTS

Table 1 includes information on our measures of interdependency and the first three moments of Q (mean, variance, and skew) for a subset of the 104 industries in our sample.

Insert Table 1 about here

Table 2 includes summary statistics and pair-wise correlations for each of our variables. The central tendency for *LogQ* is 0.39 which is equivalent to an average *FirmQ* of 1.48 in our sample. *R&D Intensity* and *Advertising Intensity* are 11% and 1% on average, respectively. These seem reasonable in light of the fact that our sample favors industries with identifiable R&D labs that were included in the CMU survey. *Industry Growth* is 7% on average with a maximum observed growth rate of 19%. *Patent Effectiveness* and *Interdependency* range from 5% to 95% (as constructed) and have means of 32% and 43%, respectively. We observe, as expected, significant positive correlations between *LogQ* and *Industry Growth*, *Patent Effectiveness*, and *Interdependency*. We observe a negative pairwise correlation between *Patent Effectiveness* and *Interdependency* (-0.16) which should help allay concerns that higher survey responses simply reflect success in protecting innovations.

Insert Table 2 about here

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[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.

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 866 industry-year observations of 104 industries.[9] We adopt an OLS specification with year and industry fixed effects.[10] 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 our independent variables of which we are confident of the estimates of *R&D Intensity*, *Advertising Intensity*, and *Industry Growth*.[11] Thus we find evidence, that industry average Tobin's q is increasing in intangible assets (*R&D Intensity*, *Advertising Intensity*), industry growth, and patent effectiveness.

Insert Table 3 about here

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*, *Advertising Intensity*, and *Industry Growth*. Our explained variance (adjusted R^2) modestly increases from 36% to 38% though that increase is relatively large when one considers that the other measured variables combined add only a small amount over the portion explained by the latent year and industry effects (~27%).

In Models 3 and 4, we explore the nonlinear effect hypothesized in Hypothesis 1 by adding *Interdependency* squared to our list of variables in Model 2. In Model 3, we continue with an industry level analysis and estimate positive but not statistically significant coefficient estimates for the main and

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[9] A handful of industries have no observed firms at earlier periods of the panel. We speculate that this may reflect nascent industries that have no publicly traded firms.

[10] Industry fixed-effects are at the 2-digit SIC level. Given the time invariant nature of *Interdependency* and *Patent Effectiveness*, they are collinear with 4-digit SIC level dummies.

[11] Note that *R&D Intensity* and *Advertising Intensity* represent industry annual averages in the industry panel.

quadratic terms (*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 in Model 4 and re-estimate our specification in Model 3 for our firm-level panel increasing our sample to 10463 firm-year observations of 2146 firms in our 104 industries. We adopt *LogQ* as our dependent variable and use firm level measures of *R&D Intensity* and *Advertising Intensity*. To address unobserved heterogeneity at the firm level, we adopt a random effects GLS specification.[12] The estimation results for this specification are presented in Model 4. Consistent with Hypothesis 1, we find a significant, positive coefficient on *Interdependency* and a significant, negative coefficient on *Interdependency*^{2} supporting a concave relationship over the relevant range of *Interdependency* (see Figure 1).

Insert Figure 1 about here

As for the economic import of *Interdependency*, we estimate that the difference between a low interdependency industry (*Interdependency* = 0.05) and a mid-interdependency industry (*Interdependency* = 0.50) is approximately an average difference in firm Tobin's q of 0.53.[13]   For an average firm in our sample (*FirmQ* = 1.46), this represents a 36% increase in Tobin's q. As for the relative importance of interdependency, we find that the marginal effect of *Interdependency* on industry profitability is larger than both *Patent Effectiveness* and *Industry Growth* over most of the relevant range of each of these variables (see Figure 2).

Insert Figure 2 about here

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[12] We choose not to adopt a more restrictive firm fixed-effect specification since the firm fixed-effects will be collinear with our industry-level, time invariant measures, Interdependency and Patent Effectiveness.

[13] Referring to Figure 1, the difference between low (0.05) and mid (0.50) interdependency leads to a difference in *LogQ* of 0.423. Taking the exponent gives 0.53.

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 5, we adopt *VarQ* as our dependent variable and use our industry panel of industry-year observations of 104 industries.[14] As before, we adopt an OLS specification with year and industry fixed effects. Consistent with Hypothesis 2, we estimate a positive, significant coefficient on *Interdependency* suggesting that industry variance in profitability increases with interdependency. In addition, we estimate positive coefficients on *R&D Intensity*, *Advertising Intensity*, and *Industry Growth* and a negative coefficient on *Patent Effectiveness*. While we are only confident that the coefficient estimates are significantly different from zero in the case of *R&D Intensity*, it is interesting to note that the direction of the coefficients is consistent with intuition. Arguably, in growing industries there is more innovative ferment and experimentation leading to greater variance in performance. While in industries with strong patent effectiveness, non-innovating firms are driven from the market leading to an overall decrease in performance.

Insert Table 4 about here

As a robustness test, we re-estimate our specification in Model 5 adding the square of *Interdependency*. Observing the coefficient estimates on *Interdependency* and *Interdependency*^{2} (see Model 6), it appears that in combination they merely reflect a linear relationship over the range of relevance for our interdependency measure. This appears likely given the high correlation between *Interdependency* and *Interdependency*^{2} (0.97).

As an additional robustness test, we test for the expected effects of interdependencies on variance in firm profits using our full firm-level dataset and the multiplicative heteroskedasticity model (Harvey 1976; Greene 2003; Sorenson 2002). The multiplicative heteroskedasticity model looks like any standard

[14] In some years, industries have too few participants to be able to calculate the variance and skew reducing the sample from 866 to 733 industry-year observations.

estimation equation for the expected (mean) value of a dependent variable (Y_i), in this case *LogQ*, based on values of a vector of independent variables (X_i): $Y_i = \beta X_i + u_i$. However, the variance of the dependent variable around that expected value is explicitly modeled as dependent on other factors (z_i), in this case the level of interdependency as hypothesized and the other independent variables for completeness: $\sigma_i^2 = \sigma^2 \exp(z_i^{'}\alpha)$. In Model 7, we present the coefficient estimates for the variance portion of the model. Since the multiplicative heteroskedasticity model does not allow for a straightforward inclusion of firm effects, we continue to include industry fixed effects at the 2-digit SIC level. Consistent with Hypothesis 2, we find a significant positive coefficient on *Interdependency*.

One concern is that our measures of within industry variance in Tobin's q do not vary greatly over time. As such, we risk overstating the significance of our coefficient estimates in the panel. As a further robustness test, we collapse the industry panel into a cross-section taking the averages across time of all of our variables. While this is a relatively conservative test as it does not make use of the full variability in our data, we continue to find a significant, positive coefficient on *Interdependency* once again supporting our hypothesis that variance in industry profitability is increasing with industry interdependency (see Model 8).

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 of 104 industries. Once again, we adopt an OLS specification with year and industry fixed effects. Consistent with our hypotheses, we estimate a positive, significant coefficient on *Interdependency* indicating that industry skew in profitability increases with interdependency.

Insert Table 5 about here

To test the non-linear relationship hypotheses in Hypothesis 3, we re-estimate 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. As a robustness test, we once again re-estimate our model limiting our sample to the cross-section as we did with our analysis of variance. As we see in Model 11, we continue to observe a positive, significant coefficient on *Interdependency* and a negative, significant coefficient *Interdependency*^{2}. Interestingly in both Models 10 and 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.

5. 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 lower on average in industries with low and high level of interdependency relative to mid-levels of interdependency (H1), 2) variance in Tobin's q across firms in an industry is increasing with the level of interdependency of the industry (H2), and 3) variance in Tobin's q across firms in an industry is increasing with the level of interdependency of the industry at a decreasing rate (H3). Our results were robust across a number of specifications including the inclusion of year, industry, and firm effects where appropriate. We estimated similar coefficients in both our panel sample and our pooled cross-sectional sample. We found similar results when testing a number of alternative specifications including some using different methods for constructing our measure of interdependency and using a more expansive sample.

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 enough 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 when firms enter at different times, 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 which 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. It is not clear, however, from any of these arguments what the expectations should be for the higher-order moments of the profit distributions within industries.

Clearly, our analysis depends on the validity of our proxy 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. Using the CMU survey responses allows us to create a common comparable measure across industries. The primary question of course is whether there is an alternative interpretation of our measure or some source of unobserved heterogeneity that may be collinear with interdependency and produce the same effects on the three moments of profitability. 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 measure that has the same range of effects and does not capture the essence of interdependencies as we have articulated them.

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, Rockart, and Lewin (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 find that at the highest levels of interdependency roughly only 25% 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 inclusiveness of the dataset. .

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 Carnegie survey appears to have provided a solid measure 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 feel that such an initial test is more than overdue. We hope that this work inspires further empirical analysis.

6. CONCLUSION

We assert that interdependency is fundamental to our understanding of business competition. Interdependencies are among a short list of largely exogenous industry features (e.g., scale-economies, sunk costs, demand characteristics) that likely influence industry profitability. Notably, interdependencies affect the dispersion of firm activity sets offering a new explanation of both inter and intra-industry profit variation. Interdependencies influence the extent and nature of heterogeneity that arises among smart and 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, Rockart and Lewin 2006) and how industries will develop over time (Lenox, Rockart and Lewin 2007). In this way, the study of interdependencies 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.

In this study, we have taken a first step in developing a large-scale empirical literature relating interdependencies to the distribution of profits within and across industries. We utilize a novel measure of interdependency that allows us to explore its effect on the distribution of firm profits across a wide variety of industries. Overall, we are encouraged that the results of our analysis 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. We look forward to future work in this domain.

REFERENCES

Bain, Joe S. 1956. *Barriers to New Competition*. Cambridge: Harvard University Press.

Baron, R. M. and D. A. Kenny (1986). "The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations." Journal of Personality and Social Psychology **51**(6): 1173-1182.

Ceccagnoli, Marco. 2007. “Appropriability, preemption, and firm performance.” (under review)

Chung, C.H., and S.W. Pruitt. 1994. A simple approximation of Tobin's q. *Financial Management* 23:70-74.

Cockburn, Iain, and Zvi Griliches. 1988. Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents. *The American Economic Review: Papers and Proceedings* 78 (2):419-423.

Cohen, Wesley M., Richard R. Nelson, and John P. Walsh. 2002. **Links and impacts: The influence of public research on industrial R&D**. *Management Science* 48 (1):1-23.

Dadalt, Peter J., Jeffrey R. Donaldson, and Jacqueline L. Garner. 2003. Will any q do? *The Journal of Financial Research* XXVI (4):535-551.

Demsetz, H. (1973). "Industry Structure, Market Rivalry, and Public Policy." The Journal of Law and Economics **16**: 1-9.

Dictionary,com (2007). http://dictionary.reference.com/search?q=complex.

Greene, William H. 2003. *Econometric Analysis*. Fifth Edition ed. New York: Macmillan Publishing Company.

Griliches, Zvi. 1981. Market value, R&D, and patents. *Economic Letters* 7:183-187.

Hall, Bronwyn H., Adam Jaffe, and Manuel Trajtenberg. 2005. Market value and patent citations. *The Rand Journal of Economics* 36 (1):16-39.

Harvey, A.C. 1976. Estimating Regression Models with Multiplicative Heteroscedasticity. *Econometrica* 44 (3):461-465.

Henderson, Rebecca, and Kim Clark. 1990. Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failures of Established Firms. *Administrative Science Quarterly* 35:9-30.

Ichniowski, C., K. Shaw and G. Prennushi (1997). "The effects of human resource management practices on productivity: A study of steel finishing lines." The American Economic Review **87**(3): 291-313.

Kauffman, S.A. 1993. *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford, U.K.: Oxford University Press.

Kruskal, William H., and W. Allen Wallis. 1952. Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association* 47 (260):583-621.

Lenox, M., S. Rockart and A. Y. Lewin (2006). "Interdependency, Competition, and the Distribution of Firm and Industry Profits." Management Science **52**(5): 757-772.

Lenox, Michael, Scott Rockart, and Arie Y. Lewin. 2007. Interdependency, Competition, and Industry Dynamics. *Management Science* 53 (4):599-615.

Levinthal, Daniel A. 1997. Adaptation on Rugged Landscapes. *Management Science* 43 (7):934-950.

Lieberman, M. B. (1987). "The Learning Curve, Diffusion, and Competitive Strategy." SMJ **8**: 441-452.

Lindenbergh, Eric B., and Stephen A. Ross. 1981. Tobin's q Ratio and Industrial Organization. *The Journal of Business* 54 (1):1-32.

Lloyd, Seth. 2001. Measures of complexity: A non-exhaustive list. *IEEE Control Systems Magazine*, August, 7,8.

Milgrom, P. and J. Roberts (1990). "The Economics of Modern Manufacturing: Technology, Strategy and Organization." American Economic Review **83**(3): 511-529.

Milgrom, P. and J. Roberts (1995). "Complementarities and fit: Strategy, structure, and organizational change in manufacturing." Journal of Accounting and Economics **19**: 179-208.

Montgomery, C. A. and B. Wernerfelt (1988). "Diversification, Ricardian Rents, and Tobin's q." Rand Journal of Economics **19**: 623-632.

Porter, Michael. 1996. What is Strategy? *Harvard Business Review* (November-December):61-78.

Rivkin, J. (2000). "Imitation of Complex Strategies." Management Science **46**(6): 824-844.

Rivkin, J. (2001). "Reproducing Knowledge: Replication without Imitation at Moderate Complexity." Organization Science **12**(3): 274-293.

Rivkin, Jan, and Nicolai Siggelkow. 2003. Balancing search and stability: Interdependencies among elements of organizational design. *Management Science* 49 (3):290-311.

Schoemaker, P. J. H. (1990). "Strategy, Complexity, and Economic Rent." Management Science **36**(10): 1178-1192.

Siggelkow, N. (2001). "Change in the presence of fit: The rise, the fall, and the renaissance of Liz Claiborne." Academy of Management Journal **44**(4): 838-857.

Siggelkow, N. (2002). "Evolution toward fit." Administrative Science Quarterly **47**(1): 125-159.

Sorensen, Jesper. 2002. The Strength of Corporate Culture and the Reliability of Firm Performance. *Administrative Science Quarterly* 47:70-91.

Stinchcombe, Arthur L. 1965. Social structure and organizations. In *Handbook of Organizations*, edited by J. G. March. Chicago: Rand McNally & Company.

Tyre, Marcie, and Eric Von Hippel. 1997. The situated nature of adaptive learning in organizations. *Organization Science* 8 (1):71-83.

Weinberger, Edward D. 1991. Local properties of Kauffman's N-k model: A tunably rugged energy landscape. *Physical Review A* 44 (10):6399-6413.

Zander, U., and B. Kogut. 1995. Knowledge and the speed of the transfer and imitaiton of organizational capabilities: An empirical test. *Organization Science* 6 (1):76-92.

Table 1: Summary of Interdependency and the Moments of Tobin's q by Industry[a]

SIC4	Description	Inter-dependency	MeanQb	VarQ	SkewQ
3679	Electronic Components, NEC	0.66	1.17	1.78	3.79
3663	Radio and Television Communications Equipment	0.56	1.25	1.70	3.10
3845	Electromedical and Electrotherapeutic Apparatus	0.53	2.06	2.52	2.38
2891	Adhesives and Sealants	0.53	1.87	2.50	3.15
3674	Semiconductors and Related Devices	0.51	1.41	1.39	2.49
2835	In Vitro and In Vivo Diagnostic Substances	0.48	2.71	3.14	1.76
3728	Aircraft Parts and Auxiliary Equipment, NEC	0.48	1.20	1.27	1.71
3577	Computer Peripheral Equipment, NEC	0.47	1.48	2.42	2.83
3572	Computer Storage Devices	0.47	1.23	1.35	2.36
3812	Search, Detection, Navigation, Guidance Instruments	0.46	0.78	0.88	3.83
2821	Plastics Material and Synthetic Resins	0.45	1.18	1.17	3.89
3721	Aircraft	0.45	1.04	0.75	2.53
3841	Surgical and Medical Instruments and Apparatus	0.45	2.41	2.49	1.91
3714	Motor Vehicle Parts and Accessories	0.45	1.18	1.28	3.48
3861	Photographic Equipment and Supplies	0.44	1.12	1.22	2.78
3661	Telephone and Telegraph Apparatus	0.44	1.56	2.12	2.59
2836	Biological Products, Except Diagnostic Substances	0.43	3.25	2.88	1.74
2834	Pharmaceutical Preparations	0.43	3.02	2.91	1.88
3842	Orthopedic, Prosthetic, and Surgical Appliances	0.42	1.78	2.32	2.53
2851	Paints, Varnishes, Lacquers, Enamels	0.42	1.36	0.46	0.64
3829	Measuring and Controlling Devices, NEC	0.41	1.29	1.77	3.21
2844	Perfumes, Cosmetics, and Other Toilet Preparations	0.40	1.46	1.83	2.34
3559	Special Industry Machinery, NEC	0.40	1.19	1.55	4.41
3621	Motors and Generators	0.38	1.29	2.27	3.27
3724	Aircraft Engines and Engine Parts	0.38	0.87	0.36	2.02
2621	Paper Mills	0.37	1.06	0.47	1.55
3312	Steel Works, Blast Furnaces, and Rolling Mills	0.36	0.72	0.32	0.39
3825	Instruments for Measuring and Testing of Electricity	0.33	1.08	1.66	4.60
2911	Petroleum Refining	0.33	0.99	0.20	0.63
3585	Air-Conditioning and Warm Air Heating Equipment	0.30	1.11	1.47	3.84
3613	Switchgear and Switchboard Apparatus	0.24	1.18	0.52	0.58

[a] Table includes all industries with 10 or more respondents to the CMU product complexity question.
[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.

Table 2: Descriptive Statistics and Pairwise Correlations

	1	2	3	4	5	6	7	8	9
1. LogQ	1.00								
2. MeanQ	0.57 *	1.00							
3. VarQ	0.42 *	0.75 *	1.00						
4. SkewQ	0.03 *	0.06 *	0.38 *	1.00					
5. R&D Intensity	0.34 *	0.28 *	0.24 *	0.12 *	1.00				
6. Advertising Intensity	-0.01	-0.02	0.01	0.00	-0.04 *	1.00			
7. Industry Growth	0.23 *	0.41 *	0.29 *	0.19 *	0.22 *	-0.09 *	1.00		
8. Patent Effectiveness	0.25 *	0.45 *	0.28 *	-0.01	0.17 *	0.02	0.24 *	1.00	
9. Interdependency	0.10 *	0.18 *	0.20 *	0.30 *	0.10 *	-0.06 *	0.27 *	-0.16 *	1.00
	1	2	3	4	5	6	7	8	9
Observations	10463	10463	10330 [a]	10330 [a]	10463	10463	10463	10463	10463
Mean	0.39	0.39	1.67	1.69	0.11	0.01	0.07	0.32	0.43
Standard Deviation	0.79	0.45	1.01	1.04	0.18	0.05	0.03	0.13	0.10
Minimum	-4.82	-1.30	0.01	-1.24	0.00	0.00	-0.02	0.05	0.05
Maximum	2.82	1.73	6.85	5.27	3.84	2.13	0.19	0.95	0.95

* $p < 0.05$

[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
Dependent Variable	MeanQ	MeanQ	MeanQ	LogQ
Specification	OLS	OLS	OLS	RE-GLS
Sample	Industry Panel	Industry Panel	Industry Panel	Firm Panel
R&D Intensity [a]	2.516 ***	2.315 ***	2.357 ***	0.702 ***
	(0.278)	(0.277)	(0.274)	(0.054)
Advertising Intensity [a]	1.916 ***	1.826 ***	1.830 ***	0.293 +
	(0.522)	(0.493)	(0.493)	(0.175)
Industry Growth	1.559 **	1.382 ***	1.295 **	2.300 ***
	(0.501)	(0.473)	(0.469)	(0.375)
Patent Effectiveness	0.070	0.154	0.143	0.707 ***
	(0.117)	(0.122)	(0.120)	(0.098)
Interdependency		0.392 ***	0.141	1.471 ***
		(0.100)	(0.267)	(0.399)
Interdependency^2			0.318	-1.248 **
			(0.342)	(0.470)
Year Effects	x	x	x	x
Industry Effects [b]	x	x	x	
Firm Effects [c]				x
Constant	-0.096	-0.237 *	-0.188 *	-0.372 ***
	(0.114)	(0.121)	(0.127)	(0.093)
Observations	866	866	866	10463
Industries	104	104	104	104
Firms				2146
Adj R-Square	0.369	0.383	0.383	
F Stat or χ^2 Stat	25.50 ***	26.23 ***	25.41 ***	1195.54 ***

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two tailed tests of hypotheses)
Robust standard errors in parentheses

[a] *R&D Intensity* and *Advertising Intensity* represent industry annual averages in the industry panel and firm annual intensities in the firm panel.
[b] SIC2 level (SIC4 level dummies are collinear with *Interdependency* and *Patent Effectiveness*)
[c] Modeled as random effects due to time invariant nature of *Interdependency*

Table 4: Interdependency and the Variance of Tobin's q

Model	5	6	7	8
Dependent Variable	VarQ	VarQ	LogQ	VarQ
Specification	OLS	OLS	MH[c]	OLS
Sample	Industry Panel	Industry Panel	Firm Panel	Industry Cross[d]
R&D Intensity [a]	6.962 ***	6.965 ***	1.009 ***	7.198 ***
	(0.907)	(0.915)	(0.097)	(1.582)
Advertising Intensity [a]	1.456	1.457	0.262	2.851
	(1.142)	(1.152)	(0.243)	(2.436)
Industry Growth	1.104	1.098	-0.043	6.163 *
	(1.578)	(1.530)	(0.674)	(2.598)
Patent Effectiveness	-0.243	-0.244	-0.276 *	0.081
	(0.329)	(0.327)	(0.138)	(0.571)
Interdependency	0.637 *	0.618	0.548 **	0.879 +
	(0.289)	(0.960)	(0.212)	(0.510)
Interdependency^2		0.024		
		(1.135)		
Year Effects	x	x	x	
Industry Effects [b]	x	x	x	
Constant	0.234	0.237	-1.027 ***	0.517
	(0.339)	(0.361)	(0.111)	(0.690)
Observations	733	733	10463	104
Industries	104	104	104	104
Firms			2146	
Adj R-Square	0.242	0.241	0.249	0.309
F Stat or χ^2 Stat	9.04 ***	8.73 ***	3233.69 ***	10.20 ***

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two tailed tests of hypotheses)
Robust standard errors in parentheses

[a] *R&D Intensity* and *Advertising Intensity* represent industry annual averages in the industry panel and firm annual intensities in the firm panel.
[b] SIC2 level (SIC4 level dummies are collinear with *Interdependency* and *Patent Effectiveness*)
[c] First stage coefficient estimates for the multiplicative heteroskedasticity model were as follows: R&D Intensity, 1.419 (0.074); Advertising Intensity, -0.903 (0.170); Industry Growth, 1.798 (0.243); Patent Effectiveness, 0.606 (0.065); Interdependency 0.442 (0.257) and 0.041 (0.314).
[d] For the industry cross-section, all variables represented their averages across time.

Table 5: Interdependency and the Skew of Tobin's q

Model	9		10		11	
Dependent Variable	SkewQ		SkewQ		SkewQ	
Specification	OLS		OLS		OLS	
Sample	Industry Panel		Industry Panel		Industry Cross[c]	
R&D Intensity [a]	5.014	***	4.359	***	4.650	+
	(0.792)		(0.781)		(2.772)	
Advertising Intensity [a]	3.976	**	3.717	***	-2.660	
	(1.265)		(1.142)		(3.213)	
Industry Growth	1.600		2.961	+	0.992	
	(1.594)		(1.609)		(3.810)	
Patent Effectiveness	0.330		0.531	+	0.878	
	(0.290)		(0.280)		(0.893)	
Interdependency	1.563	***	5.820	***	5.623	*
	(0.303)		(0.669)		(2.558)	
Interdependency^2			-5.326	***	-7.141	*
			(0.792)		(2.785)	
Year Effects	x		x			
Industry Effects [b]	x		x			
Constant	-1.146	***	-2.014	***	0.517	
	(0.210)		(0.310)		(0.600)	
Observations	733		733		104	
Industries	104		104		104	
Adj R-Square	0.294		0.321		0.183	
F Stat or χ^2 Stat	11.49	***	12.51	***	2.53	***

+ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ (two tailed tests of hypotheses)
Robust standard errors in parentheses

[a] *R&D Intensity* and *Advertising Intensity* represent industry annual averages.
[b] SIC2 level (SIC4 level dummies are collinear with *Interdependency* and *Patent Effectiveness*)
[c] For the industry cross-section, all variables represented their averages across time.

Figure 1: Marginal Effect of Interdependency on Tobin's q

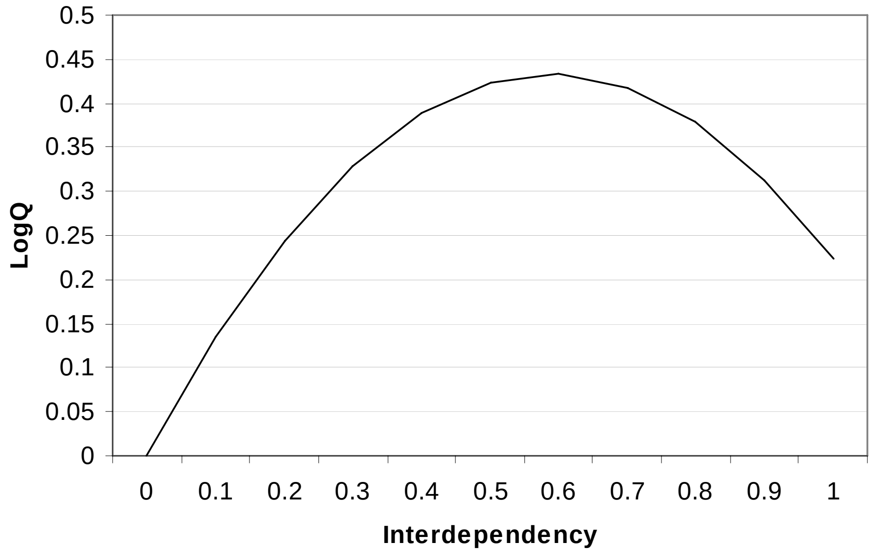

Figure 2: Relative Marginal Effect of Interdependency on Tobin's q