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Interdependency, Competition, and the Distribution of Firm and Industry Profits

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Coordination of interdependencies among firms' productive activities has been advanced as a promising explanation for sustained heterogeneity in capabilities among firms. In this paper, we extend this line of research to determine the industry structures and patterns of expected firm profits for the case when difficulty optimizing interdependent activities does, in fact, generate and sustain capability heterogeneity among firms. We combine a widely used agent-based model where firms search to discover sets of activities that complement one another (reducing overall costs or raising product quality) with traditional economic models of competition among profit-maximizing firms. The agent-based model produces a distribution of performance (interpreted as variable cost or product quality) among firms and the competition models determine resulting industry outcomes including patterns of entry, exit, and profits. The integration of economic models of competition among firms with an agent-based model of search for improvement by firms reveals a rich relationship between interdependencies in production functions and industry structure, firm profits, and industry average profitability.

Key words: dynamic capabilities; interdependencies; computational model; search
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1. Introduction

A critical question in the field of strategy is: Why aren't the profits that accrue to favorable configurations of firm resources and activities competed away? Recently, interdependencies among the practices that comprise a firm's production function have been advanced as a promising explanation for sustained heterogeneity among firms (Levinthal 1997, Rivkin 2000). In this paper, we build on and extend this research by determining the patterns of firm and industry profits that would emerge given different degrees of interdependencies in industry production functions. In doing so, we explore fundamental issues that arise at the intersection of search, firm practices, and competition.

Interest in interdependencies among firm activities has been growing in the strategy literature in recent years (Porter 1996, Levinthal 1997, Rivkin 2000, Siggelkow 2002). Levinthal (1997) demonstrated that interdependencies among a firm's activities "provide an important source of diversity" among firms. Levinthal explored a general form of interdependencies where "the value of a particular feature of the organization depends on a variety of other features [of that organization]" (Levinthal 1997, p. 936). Central to Levinthal's argument is that firms seek out better sets of practices by evaluating and adjusting their practices over time. Levinthal showed that even when all firms are initially similar and engaged in similar search strategies for improvement, minor differences in the order of adjustment in the presence of interdependencies among multiple activities lead to the emergence of substantial differences in practices.

Milgrom and Roberts (1990) highlighted a specific kind of interdependencies among a firm's activities: interdependencies where sets of activities are complementary.[1] Two activities are complementary when the marginal value of engaging in each one is increased by engaging in the other. The potential for complementarity among a firm's activities may lead individual firms to adopt a host of specific practices in concert and result in "distinctly separated clusters of firm characteristics" (Milgrom and Roberts 1990, p. 527). Milgrom and Roberts (1995) proposed that the potential for such complementarities may in part explain the emergence of highly profitable industry leaders. Citing the success of Lincoln Electric in the arc-welding business, they observed that Lincoln Electric had adopted "a system of mutually enhancing

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[1] Milgrom and Roberts (1990) expanded the definition of complementarity from the "traditional sense of a relation between *pairs of inputs*" to "a relation among *groups of activities*" (p. 514). They operationalized complementarity with supermodularity thus restricting their model to groups of activities in which *all* possible pairs of activities are complementary (see Milgrom and Roberts 1990, p. 517).

elements, and that one cannot simply pick out a single element, graft it onto a different system without the complementary features, and expect positive results" (Milgrom and Roberts 1995, p. 204).

Rivkin (2000) advanced this line of analysis by showing that differences in firm practices will not only emerge but *persist*. Rivkin argued that while isolated practices may be easily imitated, competitors will have difficulty understanding and thus imitating an entire system of mutually enhancing practices (especially if some are tacit) without some error. When interdependencies are great, even small errors in imitation can lead to large differences in performance on dimensions such as cost or quality. Rivkin's argument is consistent with the empirical literature on complementarities that has found that the complex interaction of firm activities and resources serves to limit effective imitation (Milgrom and Roberts 1995, Cockburn and Henderson 1996, Ichniowski et al. 1997, Bresnahan et al. 2002). To the extent that interdependencies limit imitation, firms that discover and adopt sets of highly complementary practices will likely outperform rivals.

In this paper, we explore how interdependencies in activity sets will affect industry average profits and industry variance in profits both within and across industries. We focus on an industry's *potential for interdependency among activities* (PIA). The link between an industry's PIA and the distribution of an industry's profits remains largely unexplored. All else being equal, the greater the interdependencies in the production function, the greater the potential for productive activities to be complementary. One might conclude that industries where activity sets are highly interdependent and the resulting potential for complementarity is high would develop into highly profitable industries dominated by a handful of efficient firms that expanded faster than worse-performing rivals (Demsetz 1973). However, previous scholarship has not formally modeled the broader industry and competitive environment in which firms interact as they adjust their activities in pursuit of more complementary sets of activities. Thus, we do not have a clear picture of the link from PIA to firm and industry profits.

There is reason to question the existence of a simple and direct relationship between the potential for interdependency among firms' activities within an industry and the distribution of industry profits. Greater variance among firms in high-PIA industries should boost industry profits, as Demsetz (1973) has argued. However, the difficulty firms have in discovering highly complementary sets of activities in high-PIA industries will likely lower average quality or raise average costs, and thus reduce profits. In addition, changes in the distribution of costs and quality among competitors may raise or lower the number of viable competitors, and these changes in industry participation further complicate the relationship between the potential for interdependency among activities and industry profits.

To predict how industry PIA influences the distribution of industry profits, it is necessary to explicitly map firms' individual costs or quality to profits as an endogenous outcome of competition. This has not been done in previous models. We combine two models to accomplish it here. We start with the widely applied NK model of interdependency, where each of N activities interacts with K other activities, to determine the distribution of firms' activities and resulting cost or quality of firms within an industry. Given this distribution, we then extend prior research by explicitly modeling competition among firms in an industry. Mapping the cost or quality distribution from the NK model to competitive outcomes reveals new dimensions of the effects of interdependent activities on industry structure and enriches our understanding of the relationship between an industry's potential for interdependency among activities and average firm profits in that industry. This mapping also enriches our understanding of the range of behavior we can expect from traditional and widely used models of competition.

Analyzing our model, we find that the relationship between industry PIA and profits does not conform to a simple or direct relationship. Industry PIA both raises and lowers expected industry profits and shifts the relationship between productivity, heterogeneity, and industry profits in clear but unexpected ways. Most notably, we observe that expected industry average profits first rise with industry PIA as expected (Demsetz 1973), but then peak and later fall for industries with higher levels of PIA. We find that expected profits are highest in industries with intermediate PIA because very efficient or high-quality sets of practices are found by some but not all firms. Profits are lower in low- and high-PIA industries because very easy learning leads to great competitive intensity, and very difficult learning leads to low efficiency and low quality. Importantly, we also find that moderate levels of imitation in the search process actually improve rather than degrade expected industry profits.

2. The Model

The overall model advanced in this paper has two main components: (1) a model of interdependencies among a firm's resources and practices that determines firm performance in terms of cost or quality, and (2) a model of competition among firms that maps this distribution of firm cost or quality to firm and industry profits. For the model of interdependencies, we adopt a general representation of interdependencies among activities that allows for interactions consistent with Kauffman's (1993) NK model, which has been introduced into the strategic management field by Levinthal (1997) and Rivkin (2000). For the model of competition, we consider two alternative models widely used in economic theory and strategic management research. The first model of competition addresses an undifferentiated market where industry price depends on demand conditions and total industry output. The second model of competition addresses an industry where competitors are differentiated in quality, and thus each firm's sales depend on demand conditions as well as the quality and price offered by that firm and every other competitor. In both competition models, consumers are assumed to make choices among firms that maximize their own utility and firms that act to maximize their profits. The competition models provide a mechanism to determine how the relative cost or quality of firms within an industry (determined by the NK model) affects firm and industry profitability. Two competitive models are used to provide a richer sense for how the analysis can be applied to different settings.

2.1. The Competitive Models

2.1.1. Undifferentiated Competition. In undifferentiated competition there are two common ways to think about noncollusive firm decision making. One is the pricing behavior that leads to Bertrand-Nash equilibrium. There firms fail to recognize how competitors will react to their decisions, and thus undercut each other on price until no firm produces a profit or only the lowest-cost player remains. Because adopting this assumption about firm behavior would limit us to the study of oligopolies where firms had identical costs and no profits or monopolies, we investigate the most common alternative model, Cournot competition. The Cournot model assumes that firms recognize their interdependence and choose output quantities that maximize their profits given the expected output of their rivals. This model generally leads to oligopoly, but also produces monopoly as a special case when fixed costs are particularly high or one firm has a substantial variable cost advantage over all rivals.

To operationalize our model of competition, we first assume that demand is a linear function of price:

$$Q = \alpha_1 - (1/\beta)p \quad \text{or alternatively,} \qquad p(Q) = \alpha - \beta Q, \tag{1}$$

where Q is total industry output, p is price, and α and β are the intercept and slope, respectively, of the inverse demand function. The profit function for any firm i is

$$\pi_i = p(Q)q_i - c_i(q_i), \tag{2}$$

where π_i is the profit for firm i, q_i is the sales quantity for firm i, and $c_i(q_i)$ is the cost of producing q_i. For simplicity, we assume a linear cost function,

$$c_i(q_i) = c_i q_i + c_f, \tag{3}$$

where c_i is firm-specific marginal cost and c_f represents fixed industry-specific costs.

Each firm chooses output to maximize profits:

$$\max_q \pi_i = \left(\alpha - \beta \sum q_i\right) q_i - c_i q_i - c_f. \tag{4}$$

Given this decision problem, a rational oligopolist will set quantity such that

$$q_i^* = \left(\alpha + \sum c_i\right)/\beta(n+1) - c_i/\beta, \tag{5}$$

where n is the number of competitors and $\sum c_i$ is the sum of marginal costs across all firms (see the proof in supplemental Appendix A; all appendices are available at http://mansci.pubs.informs.org/ecompanion.html). Thus, firms with lower variable costs will have higher output and greater profits.

In this undifferentiated competition model, the advantages of being a low-cost producer vary both with the magnitude of one's cost advantage and with the number of firms in the market. Ultimately, average industry profitability is a function of both average industry marginal costs and the distribution of these marginal costs across firms within the industry. For example, if marginal costs are distributed uniformly amongst firms, average industry profits will increase at an increasing rate as dispersion between firms' marginal cost positions increases. This highlights the importance of an explicit treatment of the competitive environment when exploring the effects of an industry's potential for interdependency in activities on profit heterogeneity. The relationship between a firm's profits and its efficiency depends on the number of competitors and the distribution of efficiency among those competitors, which also changes with the industry's potential for interdependency in activities.

2.1.2. Competition with Quality Differentiation. To model quality differentiation, we assume that firms search for combinations of activities that enhance product quality rather than search for combinations of activities that reduce costs. Firms profit from higher quality because customers value quality. Specifically, we apply a random utility model so that the utility a consumer j derives from firm i is

$$U_{i,j} = \kappa + x_i - p_i + \varepsilon_{i,j}, \tag{6}$$

where κ is the value any consumer derives from a basic reference good, x_i is a firm-specific outcome of the NK model representing the amount by which the quality of the good from firm i exceeds the quality of this basic good, p_i is the price charged by firm i, and $\varepsilon_{i,j}$ captures randomly distributed consumer preferences for specific goods.[2]

The random utility model implies that customers have firm-specific preferences that are randomly distributed in the population of consumers, not that consumers choose randomly. When consumers choose among all goods (including a none-of-the-above option) to maximize their own utility and the randomly distributed preferences fall in a double-negative exponential distribution, demand for each firm i (q_i) follows the multinomial logit (MNL) equation widely used in economics (McFadden 1974):

$$q_i = \frac{e^{\rho U_i}}{\sum_{n=1,N} e^{\rho U_n} + \phi}, \tag{7}$$

where ϕ captures the utility of the none-of-the-above option (saving the expense for future periods or buying a different kind of good) and ρ determines the strength of the randomly distributed preferences. Larger values of ϕ, lower quality, and higher prices for the goods will all shrink the overall demand realized by firms in the industry as consumers choose to spend their money on other goods. Low values of ρ indicate a larger effect of outside preferences on utility, and thus tend to equalize share across competitors. High values of ρ indicate smaller outside preferences so that market share differences among firms are more responsive to differences in the firms' prices and quality.

To determine the firms' profit-maximizing prices, we start with the profit function for any firm i:

$$\pi_i = p_i q_i(x_i, p_i) - c_i(q_i), \tag{8}$$

where π_i is the profit for firm i, q_i is the sales quantity for firm i, and $c_i(q_i)$ is the cost of producing q_i. For simplicity, we assume a linear cost function as we did with our Cournot model (see Equation (3)) except that all firms have the same marginal cost ($c_i = c_m$). Given the distribution of quality levels, each firm chooses the price that maximizes profits:

$$\max_p \pi_i = p_i q_i(x_i, p_i) - c_m q_i(x_i, p_i) - c_f. \tag{9}$$

A rational firm will set price such that

$$\tilde{p}_i^* = \frac{1}{\rho}(1-q_i)^{-1} + c_m. \tag{10}$$

(See the proof in supplemental Appendix B.) Because firm demand (q_i) is a function of price, Equation (10) is not a complete analytic solution to the optimal pricing decision. Unfortunately, the multinomial logit demand function makes a complete closed solution for the optimal price intractable. However, embedded in an iterative model subroutine, Equation (10) quickly converges to provide the optimal pricing decision.

Firms' outputs and profits in this model depend on their own quality and the quality of their rivals. If all firms produced products of the same quality, then all firms would choose the same price and split the market evenly. In markets where firms differ in quality, firms with higher-quality goods enjoy higher demand and charge higher prices. Average industry profitability will fall with the number of players in the industry as each firm gains a smaller share and prices more aggressively (Equations (7) and (10)), and rise with quality variance as some firms are able to command a greater share at a greater price premium. Industry profits will also rise with average industry quality as the industry is able to take more demand from customers' outside do-nothing option.

2.2. NK Model of Interdependencies

To the extent that standard competitive models consider cost or quality differences among firms, they tend to treat such differences as stable and exogenous. We augment these competitive models of competition by assuming that firms adopt new practices and experiment with existing operations in an attempt to either lower marginal costs or improve quality (Lippman and Rumelt 1982). In particular, we assume that this process affects cost or quality by altering the mix of tasks or activities that the firm engages. This improvement process is consistent with practical experience. Manufacturing firms do not choose their marginal cost or product quality directly. Rather, marginal cost and product quality result from how the firms conduct activities in the production process and the extent to which they capture complementarities among interdependent activities.

To capture differences in PIA among industries and to translate realized interdependency between firm activities into marginal costs and quality, we employ the assumptions, machinery, and imagery of the widely applied NK model of interdependencies (Kauffman 1993). The NK model as applied in management research is effectively a complex production function. The production function is based not only on aggregate supplies of capital and labor, but also on a firm's specific mix of activities, practices, and resources.[3] The N in the NK model refers to the number of potential activities that a firm may adopt or

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[2] The randomly distributed component of consumer preferences in random utility models has been used by psychologists to capture inconsistencies in individual preferences over time, and by economists to account for unobservable differences in tastes among individuals (Anderson et al. 1992).

[3] For the sake of simplicity, we refer to activities, practices, and resources simply as activities and the possible combinations of activities, practices, and resources as "activity sets."

employ. The K in the NK model refers to the number of activities that interact with each of these N activities. When K is high, there are many combinations of activities that could complement one another in the sense that together these activities would produce a distinctly higher quality or lower cost than would be achieved from slight variations in those activity sets.

As an illustration, consider that among the many things a manufacturing firm needs to decide are whether it is going to use just-in-time logistics, piece-rate payments, sampling techniques to control quality, work teams, and stock options as incentives. In some manufacturing industries, the cost of using a just-in-time system may depend on several but not all of these other activities. For example, in a study of steel-finishing lines, researchers found evidence that firms adopting incentive pay, teams, flexible job assignment, employment security, and training had substantially higher productivity than would be expected from the sum of the individual activities (Ichniowski et al. 1997).

To operationalize the NK model, we represent each firm's activity set as a vector of N binary activity decisions, $\mathbf{s}_i$. For example, a firm that adopts just-in-time supply logistics forgoes piece-rate payments, uses quality sampling, encourages integrated work teams, and refuses to offer stock options may have an activity set as follows: $\mathbf{s}_i = [10110]$. To represent interactions between activity choices, each activity decision is assigned one of 2^{K+1} potential costs or quality values corresponding to the two possible values for that activity decision and the $K-1$ related practices with which it interacts. For example, if each activity decision interacts with two other decisions, there are eight (2^{2+1}) potential combinations of activities, and each one is assigned a unique cost or quality coefficient randomly drawn from a uniform $U(0,1)$ distribution. A coefficient is then assigned to each activity decision from the resulting N by 2^{K+1} coefficient array based on the overall activity set, and the mean of these assigned coefficients becomes the firm's overall marginal cost or quality.

Echoing Ghemawat and Levinthal (2000), one of the desirable aspects of the NK specification is that it captures interdependencies in a more general sense than employed by Milgrom and Roberts (1990). Milgrom and Roberts examine interdependencies where all possible pairs of activities are complementary in the sense that more of each activity enhances the value of more of the other. This assumption allows for closed-form comparative static results using the concepts of lattice theory and supermodularity. In contrast, the NK specification "avoids imposing a specific structure on the linkages among choices" and "allows the richness of such linkages to vary across situations" (Ghemawat and Levinthal 2000, p. 17). The NK specification allows consideration of more general resource combinations that include both complements and substitutes. In some instances, for example, the value of an individual practice in an NK model will increase in the absence of another practice.

Interdependencies in activity sets captured by the NK model create a difficult optimization problem for firms. Imagine mapping all possible activity sets along a two-dimensional plane where the cost or quality corresponding to a particular activity set appears as the height of a three-dimensional surface or "landscape." The firm's objective in such a world is to find the highest "peak" in that landscape.[4] When there are no interdependencies among activities, the landscape is concave; there is a continuous slope up to a single globally optimal peak. A firm can find this peak by evaluating whether its efficiency or quality improves when it alters one of the activities independent of any other changes. However, as interdependencies increase, the landscape becomes a rugged surface with many peaks (local optima) and no rapid algorithmic solution can be devised to find the highest peak (Rivkin 2000).

The optimal activity set in an NK landscape can be found by exhaustive computational search *once the cost or quality coefficients are known*. In practice, this qualification about information is crucial. Firms must engage in costly and time-consuming data gathering and trial-and-error discovery to determine the nature of the interdependencies among activities that determine the cost coefficients. Not knowing these cost coefficients, firms are unable to quickly calculate a globally optimal decision and are forced to rely on experiments to evaluate how changes in activities will affect and be affected by other activities.

Because any given landscape must be learned by exploration, we specify a repeated evolutionary game where firms search for and implement changes in business activities as they receive feedback on cost or quality. In the first period, we assume that all firms within an industry choose an initial set of activities and observe their own cost or quality relative to competitors. In subsequent periods, firms search for activity sets that will improve their cost or quality and hopefully raise their profits. Improvements in cost or quality do not guarantee increases in profits, however, as improvements by competitors may offset any gains made by a firm.

Although numerous names and variants have been employed, previous research has considered two primary categories of search—innovation and imitation (Nelson and Winter 1982, Massini et al. 2005).

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[4] We will refer to the highest peak as being the most efficient point to sustain the imagery, although in fact firms are seeking the lowest marginal cost in the undifferentiated competitive model.

We consider the effects of interdependencies given both types of search strategies as well as hybrid strategies combining innovation and imitation. Search to improve or innovate new practices generally follows three key tenets: Firms search only a fraction of the enormous number of possible changes to their activity sets; firms concentrate search on "local" alternatives that attempt modifications to one or a few activities at a time because incremental modifications are likely to be the easiest to evaluate; and firms adopt changes when their analysis suggests that changes will improve cost or quality. Recognizing that there is an infinite number of variants possible on innovative search rules that follow these tenets, we adopt the basic innovative search model employed by Levinthal (1997), where firms consider only one change in an activity at a time and adopt any change that represents an improvement.[5] Imitation is conducted in a similar manner to innovation in that firms only evaluate a subset of all possible changes at any given time, but imitation differs in that firms adopt changes that will make them more like the best firm even if doing so lowers quality or raises costs.[6]

As a practical matter, imitation involves an element of independent (innovative) search (Westney 1987, Szulanski 2000). To test hybrid strategies, we assign each firm a parameter (γ) bounded between zero and one that captures the relative likelihood that a firm pursues an innovation or imitation logic in any given period when making changes to activities. A firm with γ equal to zero will rely purely on internal innovation. A firm with γ equal to one will rely purely on imitation. Search progresses over time as each firm in each period considers altering each individual activity with probability θ.[7] In the model, firms adjust their activity sets, then we recalculate marginal cost, quality, total cost, quantities produced, prices, and profits for each firm, and repeat.

To review, firms begin with randomly generated sets of activities. A firm first decides whether to update activities before the next period based on a logic of imitation (chosen with probability γ) or a logic of innovation that will be applied to all activity decisions for that period. Then, with probability θ, the firm considers changing its first activity using the chosen logic. If a firm considers changing the activity and is following an imitation logic, the firm will mimic the activity choice of the most profitable firm in the industry. If a firm considers changing the activity and is following an innovation logic, the firm will change its activity choice if and only if it will improve its profitability in the industry, given the current state of the world.[8] The firm continues through its set of activities in this manner so that it may consider changing no activities, a few activities, or potentially all activities. The same logic is applied to each activity considered, and the firm takes into account any changes made in the activity set so far.

We assume that firms will enter and exit the industry depending on the attractiveness of the industry and the attractiveness of their position within the industry. At any time t, we assume that there exists a pool of potential entrants to the industry. The likelihood that a potential entrant will attempt to enter in a given time period is determined in part by the attractiveness of the industry; thus,

$$P(\text{entry}) = \min(\lambda \bar{\pi}^{\tau}, 1), \tag{11}$$

where $\bar{\pi}$ is average industry profits and λ ($\lambda \geq 0$) and τ ($\tau \in 0, 1$) are parameters. If we set $\tau = 0$, then the likelihood of attempted entry is constant at λ and independent of average industry profitability. If we set $\tau = 1$, higher average industry profits attract more potential entrants. At high levels of average industry profits when $\tau = 1$, all potential entrants attempt to enter.

While a firm will attempt entry, it will not necessarily stay in the market. Upon attempting entry, a firm calculates its expected profits given its marginal cost (or product quality) and the marginal cost (or product quality) of all other competing firms. We assume firms enter (or remain in) the market if they expect to make positive profits by producing in the following period. Similarly, existing players within the industry will calculate expected profits given the distribution of marginal costs (or product quality) and will exit the market if their optimal decision is to not produce.[9]

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[5] Variants on this innovative search strategy have been employed by other researchers. Rivkin (2000) broadens the search and focuses changes by assuming that firms evaluate all alternative activity sets with up to M changes from the current activity set and select the very best one. Levinthal (1997) also considers the possibility of innovative "long-jumps," where a firm considers a single randomly drawn alternative where as many as all elements of the activity set may change. Rivkin and Siggelkow (2005) and others also consider the effects of organizational structures that divide search and evaluation into subsets of firms' activities.

[6] Imitation, like innovation, has been modeled in varying ways. For example, Rivkin (2000) allows firms to imitate on many dimensions at once, but with error.

[7] In each period, a firm has the potential to consider altering each of its resource decisions. Given the probability (θ) of considering one resource decision, the probability of considering all resource decisions is θ^N. Thus, for $\theta = 0.10$ and $N = 10$, the likelihood of considering altering at least one decision is 65% ($1-(1-\theta)^N$), and all decisions is 0.00000001%. We emphasize that *considering altering* a resource decision does not necessarily mean a firm *will alter* a decision.

[8] All else being equal, improvements in cost or quality will lead to increases in profits. Thus, the results are identical if firms choose activities that improve cost or quality rather than profits.

[9] We experimented with profit hurdle rates greater than zero and found that they have no effect on the results presented in this

3. Analysis and Results

Due to the analytical intractability of our model, we rely on computational methods for analyzing the model. For each of our competitive models, we simulated 55,000 test cases created by varying the updating heuristics firms use and the potential for interdependency of the industry. Heuristics were equally represented, ranging from industries where all firms only innovate ($\gamma = 0$) to industries where all firms only imitate one another ($\gamma = 1$).[10] For each test case, we assigned the rate of change (θ), the parameters N and K (which determine the potential for interdependency of the industry), demand parameters (α, β, and ρ),[11] and entry parameters (λ, τ).[12] We generate an industry production function (i.e., a cost or quality landscape) by randomly drawing marginal cost equation coefficients from a uniform distribution ranging from zero to one.[13] Finally, we randomly initialized firms' activity sets ($\mathbf{s}_i$) such that each activity decision was equally likely to assume a value of zero or one.

During the course of our computational experiments, firms compete on cost or quality and search for more productive combinations of activities. We generate the variation and selection of activity sets for each firm in the population according to its updating heuristic. We calculate the marginal cost, quality, total cost, quantities produced, prices, and profits for each firm according to one of our two competitive models. Finally, firms enter and exit the industry according to the specification described above. For each test environment, this process is repeated for 100 time periods.[14]

One of the interesting features of NK environments is that the greater the PIA, the better the best possible low-cost (or high-quality) configurations of activities (Kauffman 1989). In other words, the best position achievable (the global optima) improves as the number of interactions (K) among activities rises. This is explainable from a purely statistical standpoint. A greater number of interdependencies increases the number of random draws selected for each activity, and more draws will generate more extreme minimum and maximum values. Simply put, more interactions produce more unique configurations, and thus raise the likelihood of a highly efficient global optimum.

One could make a compelling argument that this trait of NK models has a nice analogy to actual experience: the greater the potential for complementarities, the greater the possibility of low-cost or high-quality configurations of activities, thus improving the best cost or quality achievable in an industry. We decided, however, to eliminate this feature of the NK specification by expressing individual firm marginal cost or quality as a percentage of the global optimal.[15] In doing so, we standardize each of our test environments such that the lowest cost or highest quality attainable is the same in each test environment. Standardizing helps create a level field between test environments and simplifies inference from our results. In the final analysis, this decision has a conservative effect on our results by dampening the general patterns presented.

Below, we first consider the results for undifferentiated competition and then consider the results for competition with quality differentiation.

3.1. Complementary Potential and Industry Average Profits in an Undifferentiated Market

Analyzing the undifferentiated competitive model, we find a curvilinear relationship between the potential

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paper. While higher hurdle rates decrease the likelihood of entry and increase the likelihood of exit, they do not affect the general relationships between average industry profits and PIA presented here. The discussion section considers how more sophisticated rules for entry and exit might affect the main results presented in this paper.

[10] We ran 5,000 computational experiments for γs between 0 and 1 in increments of 0.1. With 5,000 experiments for each case, we felt confident that the summary statistics had converged. Analysis found that summary statistics based on 1,000 experiments were identical to those from 5,000 experiments.

[11] For the Cournot model, we assume that $\alpha = 1$ and $\beta = 1$. Assuming $\alpha = 1$ is simply a scaling of the overall demand curve and does not, therefore, limit generalizability of the results. If one substitutes the individual production quantity function (Equation (5)) into the profit function (Equation (4)), it is clear that the slope of the demand curve β directly raises or lowers the output and gross margin for firms, but does not change the relative output or relative gross margins among firms. By scaling gross margins up or down, however, more elastic demand will increase the disparity in profits among firms when there are positive fixed costs. This result will be revisited later in the paper as it becomes relevant to reported results.

For the differentiation model, we assume that $\alpha = 1$, $\beta = 0.1$, and $\rho = 2$.

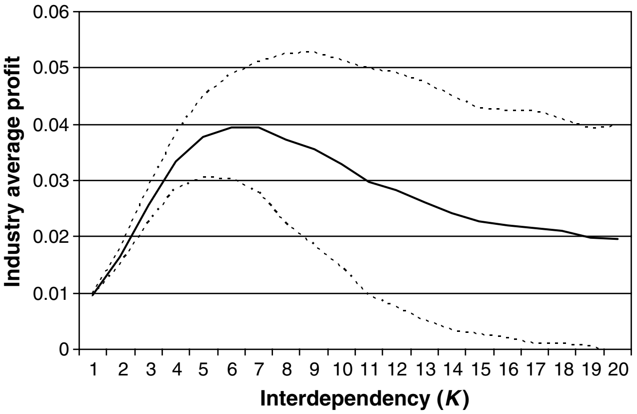
[12] For the results presented, we assume a pool of 20 potential entrants. Assuming a likelihood of attempted entry of 50%, the probability that all 20 firms would attempt to enter simultaneously is 0.000001. We experimented with larger and smaller pools and found that they did not substantively affect the results reported.

[13] It is important to note that the comparison we are noting is among industries with different levels of potential for interdependency. Casual conversation sometimes suggests that innovative firms or technologies "create" new complementarities. We treat such innovations as occurring within the model whenever three or more activities interact ($K > 2$) and a firm changes one of these activities so that it is now more valuable to do two other activities in a given way than it was before.

[14] We experimented with other time lengths with no differences in the results. Nearly all runs (>99%) stabilize within 100 periods.

[15] In the case of our Cournot competitive model, we express marginal cost as one, less the percent of the global optimum attained, plus a constant so that higher values indicate lower cost. A constant is included to assure that the best achievable marginal cost is greater than zero. Varying this constant has no bearing on our results.

Figure 1 **The Effect of Interdependency on Industry Average Profits (Cournot)**



Notes. The solid line in this graph presents the industry average profits associated with a given level of interdependency (K). The top and bottom dotted lines present the average profits of the best firm in the industry and the rest of the firms in the industry, respectively. These results are those found at the end of 100 iterations across a range of search strategies ($0 \leq \gamma \leq 1$). By 100 iterations, firms almost uniformly (>99%) have reached a stable equilibrium where they are unable to improve their cost or quality by altering one of their activity decisions (i.e., a local optima). To increase comparability, we graphed the results from simulations with firms making decisions about 20 critical business practices ($N = 20$), where the practices range from completely independent ($K = 1$) to completely interdependent ($K = N$). Sensitivity analysis found that the general patterns presented persist at various parameter values.

for interdependency of an industry (manipulated by changing K) and expected industry average profits (see the solid line in Figure 1).[16] At higher levels of PIA, we observe increasing variance in industry profits, yet declining average profits (see the dotted lines in Figure 1). This rise and fall of average profits and the increase in variance in profits is robust to the number of potential firms within the industry, the search strategies pursued (γ), the number of activities under consideration (N), and the likelihood of updating activities (θ).

What causes the nonmonotonic relationship between PIA and industry average firm profits? This curvilinear relationship results in part from the trade-off between (1) the greater difficulty firms have in finding superior low-cost positions (see Graph A of Figure 2), and (2) the greater variance in marginal costs among players within the industry (see Graph B of Figure 2) as industry PIA increases. With respect to the former, if industry profits were driven primarily by average firm efficiency, then industry profits would be monotonically decreasing with PIA. As PIA increases, average firm costs rise because the increase in the sheer number of local optima makes it less likely that firms will find globally optimal activity sets (Kauffman 1989), and because with increasing conflicts among the activities the local optima available for firms to find become less efficient (Weinberger 1991). With respect to the latter, if industry average profits were driven by variance in firm efficiency, as Demsetz (1973) hypothesized, industry average profits would be monotonically increasing with PIA. Variance in marginal costs increases naturally with PIA because there are a greater number of stable efficiency levels (local optima) upon which firms get stuck as the number of interactions increase (Rivkin 2000).

Examining the industry profit function provides insight into why the factors that raise industry average profits dominate at low levels of PIA, but not at high levels of PIA. If we assume firms' costs are distributed uniformly over a range $(\bar{c} - d, \bar{c} + d)$, we can determine an exact analytical equation relating average firm profits within the industry to average firm marginal cost ($\bar{c}$), the dispersion of cost (d), and the number of competitors (n):

$$E(\pi_i) = \frac{1}{\beta}\left(\frac{(\alpha - \bar{c})^2}{(1+n)^2} + \frac{d^2}{3n}\right) - c_f \tag{12}$$

(see supplemental Appendix C for the proof). We observe that industry profits rise with increased dispersion of cost (d) and with reductions in the number of competitors (n), but fall with rising average costs ($\bar{c}$).

At low levels of PIA, industries have low dispersion and the potential salutary effect of increasing dispersion is small. However, the impact of variance in marginal costs on industry concentration is large. As variance increases, more firms find it unprofitable to remain in the industry and exit (see Graph C of Figure 2). The initial boost to profits from decreasing the number of competitors is greater than the reduction in profits directly caused by rising average costs. For example, a reduction from nine firms to eight firms increases average firm profits by nearly 25%. Industry average marginal costs would need to be cut by more than half to provide the same rise in industry average profits as the reduction of a single competitor.[17]

Why does the average number of firms within an industry decline and then rise (see Graph C of Figure 2) with PIA?[18] At low levels of PIA, marginal costs

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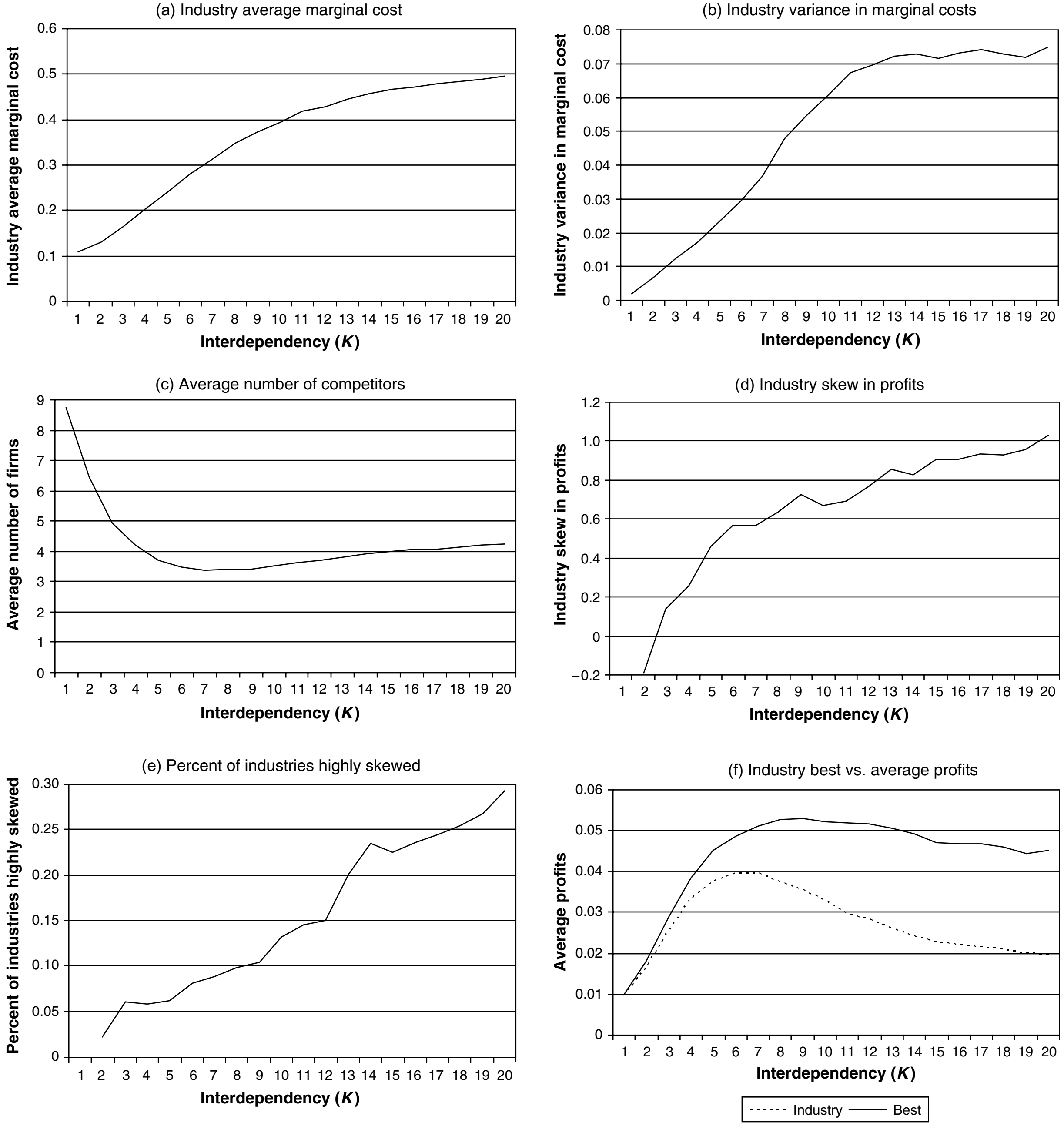
[16] We present industry average profits weighted by sales so as not to dilute industry average profits due to the presence of a number of marginal (i.e., high-cost, low-output) firms. Using unweighted industry average profits does not affect the general results presented. Industry average profits continue to decrease as PIA increases, although not at the same rate.

[17] Conditional on average firm marginal costs at low PIA being equal to 10% of the greatest willingness-to-pay ($\bar{c} = \alpha/10$). This is the case in the runs presented, and seems to be a reasonable assumption for a low-PIA/low-cost industry.

[18] This result persists when varying the entry parameters: the baseline level of entry (λ) and sensitivity to average industry profits (τ).

Figure 2 Drivers of Industry Average Profits (Cournot)



Notes. To increase comparability, we graphed the results from simulations with firms making decisions about 20 critical business practices ($N = 20$), where the practices range from completely independent ($K = 1$) to completely interdependent ($K = N$). Sensitivity analysis found that the general patterns presented persist at various parameter values.

are low and uniform across firms, leading to a large and evenly shared industry that supports more firms. At moderate levels of PIA, average marginal cost is higher, reducing industry demand; and firm marginal costs are more widely dispersed, so a few firms take a large share of that market, making it harder for rivals to compete. At high levels of PIA, average marginal costs are even greater, which reduces industry demand further, and the variance in marginal costs is even greater. This would imply an even smaller number of competitors. However, the number of competitors rises slightly. This seemingly contradictory pattern follows from the NK specification. As K increases, the number of local optima increases, and these optima become less varied and less efficient on average (Weinberger 1991). Thus, in high-PIA industries, diversity in costs is falling among the lower-performing firms, allowing more firms to compete.

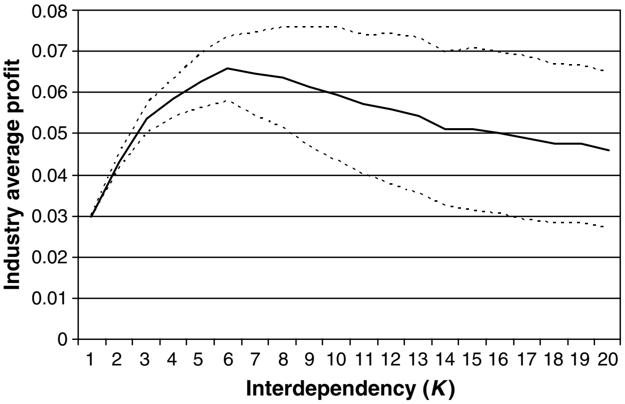
More firms compete in high-PIA environments, even though the higher profits in the mid-PIA environments attract more potential entrants.

We observe increasing variance with PIA because the reduction in cost dispersion among the lower-performing firms happens alongside an increase in disparity between the best firms and the rest (see Graph F of Figure 2). This results in an increase in the positive skew of marginal costs as PIA increases (see Graph D of Figure 2). For low levels of PIA, we observe little skew, which means that firms cluster around similar profits levels. For high-PIA industries, we expect a few high performers and a relatively large number of laggards. High levels of PIA produce industries where most firms cluster around low profit levels and a few firms occasionally achieve vastly superior profits.

For empirical research and normative conclusions, it is important to note that a strong skew is apparent in only a minority of the industry runs. Examining the percentage of runs in which the distribution of industry profits is highly positively skewed (skew > 1), we find that the percent of skewed runs is increasing with PIA, but high skew occurs in less than a third of the cases (see Graph E of Figure 2). As a result of this minority of runs, we observe that the variance in the number of competitors is increasing, on average, with PIA. However, the number of industries with a small set of high-performing firms is much greater for high-PIA environments than for mid-PIA environments.

Combining our results on average industry profits with the results on the variance and skew in industry profits, we observe a pattern where leading firms are an increasingly poor guide to likely profits in the industry. Industry average profitability decreases with PIA (after an initial rise), but the average profitability of the best firm in the industry stabilizes (see Graph F of Figure 2). The best firms' profits remain strong in the face of rising PIA despite worse marginal costs than those of the best firms in low-PIA industries. The best firms' profits stay high because the rest of the firms in the industry become even less efficient. This leads to highly concentrated, but inefficient, industries. It also means that the key drivers of individual firm profits are conditioned by the level of PIA. In low-PIA industries, individual firm profits are driven by the ability of all firms to find low-cost positions *absolutely*; while in high-PIA industries, individual firm profits are driven by the ability of the best firms to find better cost positions *relative* to those of rivals.

Figure 3 **The Effect of Interdependency on Industry Average Profits (Differentiation)**



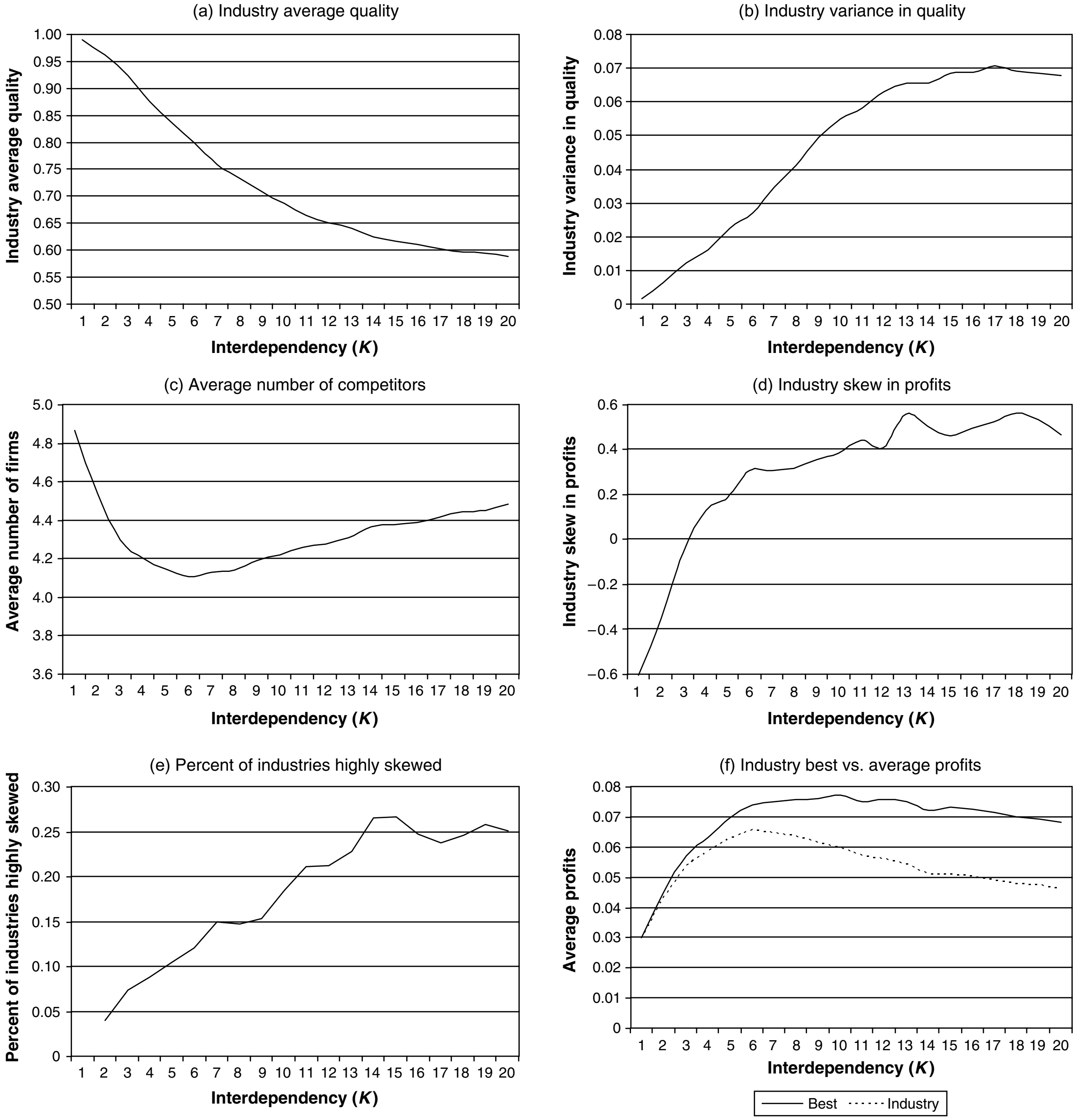
Notes. The solid line in this graph presents the industry average profits associated with a given level of interdependency (K). The top and bottom dotted lines present the average profits of the best firm in the industry and the rest of the firms in the industry, respectively. These results are those found at the end of 100 iterations across a range of search strategies ($0 \leq \gamma \leq 1$). By 100 iterations, firms almost uniformly ($>$99%) have reached a stable equilibrium where they are unable to improve their cost or quality by altering one of their activity decisions (i.e., a local optima). To increase comparability, we graphed the results from simulations with firms making decisions about 20 critical business practices ($N = 20$), where the practices range from completely independent ($K = 1$) to completely interdependent ($K = N$). Sensitivity analysis found that the general patterns presented persist at various parameter values.

3.2. Complementary Potential and Industry Average Profits in a Differentiated Market

Analyzing the quality differentiation model of competition, we find a similar curvilinear relationship between the potential for interdependency of an industry and expected industry average profits (see the solid line in Figure 3). Once again, at higher levels of PIA, we observe increasing variance in industry profits, but declining average profits (see the dotted lines in Figure 3). As before, industry average profits first rise as the number of competitors fall and the dispersion of quality increases, then decline as industry average quality falls and more firms compete (see Graphs A, B, and C of Figure 4).

As before, these results are amplified by entry and exit: The average number of firms within an industry declines with PIA and then rises (see Graph C of Figure 4). Once again, industries with low potential for complementarities are less attractive, but allow for the largest number of viable competitors. Industries with moderate PIA are the most attractive, but the least accommodating to firms. Industries with high PIA offer the tempting possibility of highly desirable above-average profits (see Graphs D and F of Figure 4). However, industries where these privileged positions are achieved by anyone are few (see Graph E of Figure 4) and, on average, firms are not able to discover high-quality combinations of practices (see Graph F of Figure 4). As a result, we see more entry, but few firms doing well, in high-PIA environments.

Figure 4 Drivers of Industry Average Profits (Differentiation)



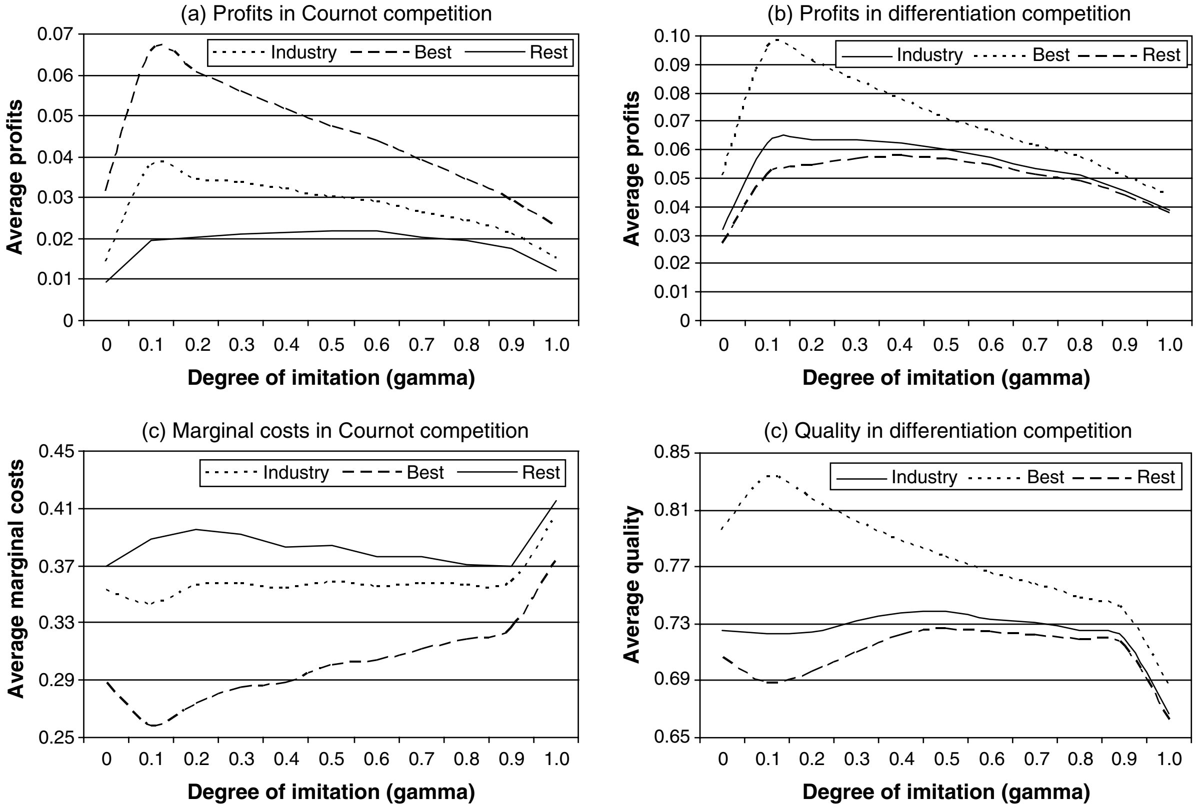
Notes. To increase comparability, we graphed the results from simulations with firms making decisions about 20 critical business practices ($N = 20$), where the practices range from completely independent ($K = 1$) to completely interdependent ($K = N$). Sensitivity analysis found that the general patterns presented persist at various parameter values.

3.3. The Effect of Imitative Search

One may hypothesize that imitative search should remove the potential for skew in industry profits as firms mimic those who have discovered superior configurations of practices. Interestingly, however, we find that imitative search actually *exacerbates* this pattern, at least at low levels of imitation. In Figure 5, we graph the average profits of the lowest-cost or highest-quality firm across industries for varying levels of imitative search (γ) in our Cournot and differentiation competitive environments (Graphs A and B). At low levels of imitation, the average profitability of the lowest-cost or highest-quality firm is dramatically better, while the rest of the industry competitors see their profits improve by considerably less.

Why do low levels of imitation improve the best profits achieved in an industry? In high-PIA industries, the landscape is populated with many relatively poor but steep local peaks. As stated earlier, small differences in firms' activity sets can make big differences in costs or quality, so imitation does little to reduce variance between imitator and imitated (Rivkin 2000). However, imitation can help firms avoid getting caught on these local peaks by enabling

Figure 5 **The Effect of Imitation on Industry Average Profits**



Notes. "Best" represents the average profits of the best firm within an industry. "Rest" represents the average profits of the rest of the industry minus the best firm. "Industry" represents the industry average profits. To increase comparability, we graphed the results from simulations with firms making decisions about 20 critical business practices ($N = 20$), where the practices range from completely independent ($K = 1$) to completely interdependent ($K = N$). Sensitivity analysis found that the general patterns presented persist at various parameter values.

them to search greater parts of the landscape. When firm search is limited, most will land in the relatively dense center of the distribution, which covers only a small range of the potential landscape heights. With some imitation, however, we see that average performance improves, which means that firms are in a tail of the distribution (specifically, the tail at higher landscape positions). This makes sense because imitation is less likely to get firms away from peaks that have "wider bases," and higher peaks have wider bases (Levinthal 1997). In the tail of a distribution, however, the density of the distribution is at its lowest, which means that the same probability density covers a greater range of performance.[19] Because the same probability density covers a wider range of landscape heights in the tail, firms will likely be more spread out.

Effectively, imitation serves as an excuse for firms to try practices that will raise current costs or lower quality, but might open the firm up to new and more productive combinations. The wider resulting search increases the odds that all firms discover better combinations of activities. However, the differences among the better configurations are greater than the differences among all configurations, so the differences among firms rise even as firms improve in cost and quality.

Eventually, as imitation increases, it lowers the expected gap in profits. At high levels of imitation, imitation suppresses industry profits because (1) it decreases variance in cost or quality as firms are able to replicate the cost or quality of their rivals, and (2) it decreases the best efficiency or quality levels discovered by limiting the range of search for good configurations of activities. While the first effect is to be expected, the latter effect may in fact be the more detrimental to average industry profits and is more likely to reduce social welfare. We find, in fact, that the best marginal costs and quality realized are worse at high levels of imitation, lending support to this argument.

4. Discussion

In summary, we find that average industry profits and heterogeneity in profits within industries do not

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[19] Weinberger (1991) proves that the potential peaks are normally distributed, thus clearly giving us thin tails.

simply rise with the industry's potential for interdependency in activities. Intermediate levels of PIA produce the highest-expected average industry profits because here the potential for preferable sets of business practices combines with a lower likelihood that *all* firms will be able to discover these desirable sets of practices. This leads to a small and efficient set of profitable competitors. This beneficial combination of high efficiency and low competition is not evident at low or high levels of PIA. Low-PIA industries suffer from intense competition because potential demand is large and cost or quality differences among firms are small. High-PIA industries have fewer competitors, but profits are restrained because firms are less efficient on average and similar in their level of inefficiency. These results are consistent with Schoemaker's proposition that the potential for economic rents is highest when the complexity of the underlying production decision problem is neither so simple that imitation is rampant nor so "hopelessly complex" that firms struggle to find good resource configurations (Schoemaker 1990, p. 1184).

We further find that in high-PIA industries the potential exists for an individual firm to discover a highly efficient configuration of business practices relative to rivals and to realize profits well above the industry average. Thus, the average profits in high-PIA industries are bolstered by the occasional highly successful firm. As Rivkin (2000) showed, imitative search does not necessarily suppress this possibility. In fact, our results highlight the potential benefit of low levels of imitation because it leads to wider search, raising the likelihood that a firm will find a highly efficient configuration. While the existence of this kind of skewed profit distribution is striking when observed, it remains a relatively infrequent outcome even in high-PIA industries. Rivkin (2001) highlights the gap between a firm's ability to replicate its own successful set of activities and its rivals' ability to imitate that set of activities. If expanding to take advantage of their success is particularly difficult, profit in high potential for interdependency industries would be even lower.

While we recognize the difficulties in measuring the potential for interdependency among activities of industries, our results do provide a path for empirical testing. One route is through "as-if" testing. We should see some industries (those with low PIA) with low average profits where firms have similar cost or quality, profits, and practices. We should see other industries (those with intermediate levels of PIA) with high average profits, in which firms have considerable differences in cost or quality, profits, and practices. Finally, we should see industries (those with high levels of PIA) with low average industry profits where most firms have minimal differences in cost or quality and profits despite wide variety in practices. Paradoxically, it is within these otherwise unattractive industries that we are most likely to observe an outstanding firm that is both high performing and highly profitable.

These patterns have important implications for the industrial organization literature and antitrust considerations. In our model, we do not observe industries with high average profits and low variance in activities, cost, and quality. If high industry average profits were associated with low variance in practices and efficiency, this would strongly suggest that profit was driven by other factors, such as barriers to entry. On the other hand, if we see high industry average profits coupled with high variance in practices and efficiency, this suggests that some firms have simply figured out efficient ways of operating. Thus, the existence of high industry average profits is not necessarily an indicator of undesirable market power. When average profits are high, differences in practices among firms may signal that success is based on inherent complementarities between interdependent activities and consequent efficiency advantages, and is not based on the exercise of monopoly power.

Another route for empirical testing is more direct and detailed. Armed with a theory for the relationship between interdependency potential and the distribution of profits among and within industries, it is natural to move beyond looking for patterns (as-if testing) and to test the theory against (and controlling for) alternative theories. These results provide a theoretical justification for a positive main effect of PIA and a negative squared effect of PIA on industry profit. The major hurdle facing such empirical studies is the development of an industry-level measure of interdependency potential. We believe that the development of such a systematic measure, while laborious, is feasible. Notably, Siggelkow (2001, 2002) describes a systematic process of archival and interview research for mapping interdependencies among core and elaborating activities within firms. Repeated for one or more firms across several industries, the relative density of such systematically collected maps could serve as an ordinal measure of PIA among industries.

Comparing the density of these maps among industries will only be possible if managers and/or researchers are able to identify more interactions when interactions are stronger or more numerous. However, it will not be necessary that managers or researchers fully understand the nature of these interactions nor—critically in light of the search processes posited—that they are able to determine the best way of combining practices. With a large sample, cruder means of collecting similar information, such as through surveys, might suffice for the purpose of mapping potential complementarities onto the distribution of profits.

Models always involve a large number of simplifying assumptions. We could introduce any number of additional factors to our model, such as adjustment costs or learning errors or different forms of innovation and imitation strategies (Lewin and Massini 2003). While such changes will surely shift the numerical results, we do not expect them to interact with PIA in a way that would alter the overall pattern of results presented. For example, both adjustment costs and learning errors will simply reinforce the advantage of privileged firms relative to their rivals in high-PIA industries, while simultaneously making it more difficult for any firm to find highly efficient configurations of business practices.

For our analysis, we assume that managers struggle to find optimal configurations of activities that lower cost or raise quality, yet are able to calculate the optimal price and output. We believe that these behavioral assumptions are not inconsistent or contradictory. In both cases, we assume that managers can optimize over a well-defined concave function. In the case of cost and quality, managers face a highly nonlinear decision problem that violates concavity (at least in the presence of high interdependency). As argued earlier, even experimentation is unlikely to guarantee optimal configurations in a reasonable time period. In the case of price and output, managers face a far simpler decision problem for which the calculation of the optimal is feasible. If we assume that firms' managers have some sense of the industry demand and the average industry marginal cost/quality, then the calculation of optimal pricing and output is straightforward. If managers do not know average industry marginal cost or quality with certainty, our results will generally hold in expectation. Even a systematic bias in managers' estimates will not affect our results as long as the extent of bias is not correlated with a firm's own productivity. We do not expect substantively different results even if we relax our behavioral assumption that managers explicitly calculate the optimal price or quantity. Firms are likely to receive much faster feedback about the viability of pricing and output decisions than about the viability of individual activity decisions, and thus are likely to quickly adjust price and output to near-optimal levels.

The results we report for the undifferentiated competition model assume a specific demand slope ($\beta = 1$). As shown in Equation (12), a more or less strongly sloped demand curve would lower or raise average firm profits, but do so by affecting all profit components that change with PIA (number of firms, average cost, and dispersion of cost) equally. Absent any reason to expect a systematic relationship between industry PIA and demand elasticity, therefore, different assumptions about price sensitivity will affect the scale but not the shape of the reported profit results.

There are other potential variants on the competitive model that could be explored. The most dramatic might be to link activities to differentiation in kind as well as differentiation in quality. Activities that only created differences in kind would likely encourage firms to "spread out" in a way that softens competition and raises profits for all levels of PIA without shifting the results of the models presented (Schmalansee 1978). If we consider that some activities might play a dual role—affecting both differentiation in kind and differentiation in costs or quality—we might find that differentiation in kind is a positive by-product of a search for quality that softens competition and increases profits, particularly at higher levels of PIA. We may also encounter "dancing landscapes" (Kauffman 1995), where improvement by each competitor not only reduces the absolute profitability of all possible sets of practices, and stretches or compresses the profit differences among sets of practices (as they do in the undifferentiated and quality differentiation models presented here), but also changes the sign of the profit differences among sets of practices. Capturing differentiation in kind would require an explicit model of the distribution of tastes, as they are linked to activities and an explicit modeling of customers (and not just firms) as agents making individual choices. Capturing this effect in an empirical study would require controls for cross-price elasticity among firms within the industry.

There is a wide range of alternative assumptions that might be employed to model entry and exit. We modeled entry and exit with a relatively simple rule, where firms enter or exit based on their expected profits in the following period. On the opposite extreme, firms might enter or exit based on a much more sophisticated rule, where they estimate and discount expected profits over time. We believe it is unlikely that such a rule would change the reported results. The higher realized firm profits at intermediate levels of PIA will invite entry only up to the point that they are balanced by higher risk. Unlike low-PIA industries where firms are certain (or nearly certain) of improving rapidly toward the best possible set of activities, and unlike high-PIA industries where firms reaching any local optima can expect to be competitive with the bulk of rivals, medium-PIA industries present firms with a very real potential for competing for a long period without becoming competitive.

Entry and exit are important to understanding market dynamics and equilibrium outcomes for several reasons. First, entry and exit change the number of competitors, and thus affect the market power of firms. Any model exploring variables that change the number of viable competitors will thus benefit from considering entry and exit. Second, entry and exit may change the nature of competitors (Mitchell 1994). Models that explore situations where a firm's history influences its future (e.g., through accumulations of learning, tendency toward local search, founding conditions, or through irreversible investments in assets or reputations) almost certainly benefit from understanding when history-laden incumbents will be replaced by entrants either less constrained by history or simply quite dissimilar to incumbents. We believe that exploring the differences between entrants and exiting incumbents will be a fertile future ground for the use of NK models embedded in competitive structures.

In a similar vein, we believe that how firms search for more efficient sets of business practices is a crucial uncertainty to explore. For this reason, we examined results where firms engage in a range of mixes of innovative and imitative search. The overall result that average industry profits are highest for intermediate levels of PIA proves robust from one extreme of pure innovation to the opposite extreme of pure imitation. Interestingly, the results show that imitation does not deserve its reputation as solely a destroyer of variance. Some imitation at high levels of PIA does little to allow firms to close gaps in their efficiency, but leads to wider exploration and thus a concomitantly wider range of efficiency.

5. Conclusions

Interdependencies among resources and practices have increasingly played a central role in explanations of how organizations discover more efficient business practices; why differences in efficiency, once established, continue to persist across firms; and why differences in efficiency among firms develop into differences in average profits across industries. We present a model in this paper that brings those three traditions together to develop a more complete understanding of how differences in potential production interdependency within industries affects the distribution of profits that we expect to find within and among industries.

This examination reveals that potential interdependency among activities has several mechanisms for influencing industry cost or quality. The potential for interdependency affects the distribution of potential efficiency and quality levels attainable, the difficulty of finding better cost or quality levels, and whether imitation narrows or expands overall search. As a result of this interplay of factors, profits and heterogeneity in profits do not rise or fall uniformly depending on PIA in industries where firms differ in cost or quality. Instead, for these kinds of industries we expect a sweet spot where industries with intermediate levels of PIA enjoy the greatest expected efficiency and profits, while high-PIA industries hold out the possibility that a firm finds a highly efficient set of business practices that allows the firm to stand out relative to competitors and generate significant economic rents.

These results are important for understanding not only the role of PIA in generating profit heterogeneity, but for our larger understanding of the sources of competitive advantage. Our results provide guidance for identifying likely industries where competitive advantage accrues to a chosen few firms that have valuable, rare, nonsubstitutable, and hard-to-imitate resources and capabilities that allow for favorable market positions relative to rivals. In this way, interdependencies provide an explanation not only for what sustains profit heterogeneity within and across industries, but why it emerges in the first place in some industries more than in others. By recognizing that industries can vary in terms of potential interdependency due to technology and other structural factors, we also see the beginning of a reconnection of firm-level and industry-level analyses. To the extent that the potential for interdependency is driven by structural elements of an industry, industry structure can be used to explain differences in firms' resources, capabilities, and profits.

Our coupling of a model of interdependency among firm activities with standard models of competition is useful in addressing a number of fundamental questions concerning industry structure and evolution. There has been a great deal of interest among economists in how firm heterogeneity may affect the structural evolution of industries. Jovanovic (1982) proposed a formal model where competing firms are heterogeneous at founding. In this model, each firm is uncertain about its own type, which is revealed over time. Klepper (1996) introduced a model where firm growth is the result of investments based on their beliefs about their type, and these investments then change their type over time. Pakes and Ericson (1998) explore the empirical implications of more passive learning models such as Jovanovic's and more active learning models such as Klepper's. The integrated model in this paper is similarly directed toward understanding how firm heterogeneity arises and how that affects industry structure and firm profits. Our model differs from earlier models by providing a rich structure to the learning environment faced by firms and by introducing the mediating role of industry potential for interdependency.

Our approach of marrying a model of interdependency among firm activities with an explicit model of competition may prove fruitful for a number of research domains. For example, researchers studying the effects of search routines on organizational adaptation may find that the dual consideration of interdependency and competition provides additional insight into managerial incentives to search, into strategic considerations when choosing search methods, as well as insights into the survival chances of firms that engage in change efforts. Those studying processes of creative destruction may gain new insights by seeing how the interaction of complexity and competitive intensity within industry environments affects whether or not incumbents should or can change without destroying themselves in the process. Those who are concerned with public policy may find that a model such as ours provides insights into how mergers and firm failures affect not only competitive intensity but also how it affects search and average industry productivity or quality. Perhaps most promising, those studying industry dynamics may find that a more explicit treatment of interdependency provides new insights into the structural evolution of industries.

An online supplement to this paper is available on the *Management Science* website (http://mansci.pubs.informs.org/ecompanion.html).

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