

## **Complementarities, Competition, and Sustained Intra-Industry Heterogeneity in Profits**

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## **Complementarities, Competition, and Sustained Intra-Industry Heterogeneity in Profits**

A central question in the field of strategic management is what explains sustained intra-industry heterogeneity in profits. Recent work proposes that the mere complexity of a firm's strategy may be sufficient to generate profit heterogeneity. Complementarities between the activities that a firm engages in may make a firm's decision problem computationally complex and raise a significant barrier to imitation. We propose, however, that competition may moderate the impact of complementarities on intra-industry heterogeneity in profits. To explore this proposition, we develop a model of endogenous competition in complex environments building off a Cournot model of competition in an undifferentiated, oligopolistic market. Analyzing our model, we find that under certain conditions competition mediates the importance of complementarities and may even suppress profit heterogeneity all together.

Keywords: dynamic capabilities, complementarity, complexity, computational model

## **Complementarities, Competition, and Sustained Intra-Industry Heterogeneity in Profits**

A central question in the field of strategic management is what explains sustained intra-industry heterogeneity in profits. Researchers in an industrial organization tradition propose that firms are able to protect valuable strategic positions within product markets (and thus sustain intra-industry profit heterogeneity) by utilizing barriers to switching positions, such as large sunk costs, and by making credible commitments to retaliate against potential imitators (Porter, 1980; Ghemawat, 1991). Resource-Based theorists have looked within firms and proposed that valuable firm-level resources and capabilities may be difficult to imitate and thus sustain profit differentials within an industry (Lippman & Rumelt, 1982; Barney, 1991). This is particularly likely when resources embody socially complex processes, tacit knowledge and when there is ambiguity about causal mechanisms, competitors will have difficulty imitating those resources and capabilities.

Recent work extending these traditions argues that the mere complexity of a firm's strategy may be sufficient to generate intra-industry heterogeneity in profits (Rivkin, 2000). Complementarities among a firm's resources and activities may make a firm's decision problem (i.e, optimal choice of resources and activities) computationally intractable. Individual resources or activities may be easily imitated, but competitors have difficulty understanding and thus imitating the entire system. Furthermore, small imperfections in imitation of the entire system will generally lead to substantially inferior performance outcomes for the imitator. A growing empirical literature on complementarities supports this argument; several studies have found that the complex interaction of firm activities and resources serves to deter imitation (Ichniowski et al., 1997; Cockburn & Henderson, 1996; Milgrom & Roberts, 1995).

An important implication of the literatures on complementarity and complexity is that the greater the interaction among resource and activity decisions (i.e., the greater the complementarity in resource and activity sets) the greater the likelihood of heterogeneity in profits. However, we propose that the mere inimitability of complex strategies does not necessarily lead to profit heterogeneity. Competitors adopting divergent activity sets may still have a large effect on the profitability of their rivals. Even performance differences in productivity and quality may not translate directly into performance differences in profits.

Modeling efforts focused on complexity have not explicitly considered the role of competition in translating between the quality of an activity set and a firm's profits. While competition is implicit in this literature, modeling efforts have not recognized the endogenous nature of competition. Rather, the rugged performance landscapes evoked in this literature have assumed that the competitive actions of firms have no impact on the landscape itself or at the very least have not provided a clear model of how competition influences the landscape.

We propose that competition may moderate the impact of complementarities on intra-industry heterogeneity in profits. To fully comprehend the import of complementarity on the intra-industry heterogeneity of profits, we need an explicit treatment of the competitive game firms are playing. To explore this proposition, we develop a model of complex environments where competition is endogenized. Building on previous work by Levinthal (1997) and Rivkin (2000), we adopt a generic representation of complementarities where each of  $N$  strategic choices interacts with  $K$  other strategic choices. As  $N$  and  $K$  rise, such environments have been found to generate rugged performance landscapes characterized by multiple local optima that may make the firm decision problem intractable. We advance these models by embedding them in a Cournot model of competition in an undifferentiated, oligopolistic market.

Analyzing our model, we find that under certain conditions competition mediates the importance of complementarities and may even suppress profit heterogeneity all together even in environments with high complementarities. We find that both the strategies firms pursue and the type of game they are playing influence the relative effect of complementarity and complexity. In particular, the more piecemeal imitation of strategies across firms within an industry, the less the effect of complementarity on profit heterogeneity. Our model allows us to explore the relative tradeoff between various mechanisms that may allow some firms to achieve advantageous positions. We draw a number of specific recommendations for firms competing in markets with high complementarities.

## Model

To begin our modeling exercise, we consider an undifferentiated, oligopolistic market under Cournot competition. We assume price is set by the market and that firms choose their level of output. While this is obviously a rather simplistic competitive environment, it provides a nice starting point for our analysis and allows us to generate some interesting results.

To operationalize our model of Cournot competition, we first assume a simple linear market demand function.

$$Q = \alpha - p \quad \text{or alternatively, } p(Q) = \alpha - Q \quad (1)$$

where  $Q$  is total industry output,  $p$  is price, and  $\alpha$  is a demand parameter. The profit function for any firm,  $i$ , can be given by revenues (price times sales) minus costs.

$$\pi_i = p(Q) q_i - c_i(q_i) \quad (2)$$

where  $\pi_i$  are the profits for firm  $i$ ,  $q_i$  is the sales 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 costs.

Thus, the decision problem that each firm faces is to choose output so as to maximize profits.

$$\max_{q_i} \pi_i = (\alpha - \sum q_i) q_i - c_i q_i - c_f \tag{4}$$

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

$$q_i^* = [(\alpha + \sum c_i) / (n + 1)] - c_i \tag{5}$$

where  $n$  is the number of competitors and  $\sum c_i$  is the sum of marginal costs across all firms (see proof in Appendix).

To this point, our model is a standard Cournot competitive environment with marginal costs varying across firms in an industry. In such a world, we can show that the advantages of being a low cost producer vary both with the size of one's cost advantage and the number of firms in the market. Since our model assumes an undifferentiated market, the only advantage a firm may have is in terms of cost. In Figure 1, we consider the profit differentials between a low cost producer and the average profitability of the rest of the industry. We find that as the low cost producer's marginal cost goes down as a percentage of the industry average, the profit differential increases but at a decreasing rate. Furthermore, we find that as the number of competitors increase, this relationship is dampened.

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 Insert Figure1 about here  
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This simple exercise helps illustrates the importance of explicitly considering the competitive environment when exploring the impact of complementarities and complexity on

firm heterogeneity. Differences in performance (such as that captured by marginal cost) and difference in profits do not map one-to-one. There may be important factors that mediate the effect of complementarity and complexity on firm profitability.

In a traditional Cournot analysis, the firm-specific marginal costs considered above are assumed to be stable and exogenous. We diverge from orthodoxy and assume that firms actively try to lower their marginal costs. In particular, we assume that marginal cost is determined by the mix of tasks or activities that the firm engages. This is consistent with practical experience. Manufacturing firms do not choose their marginal cost directly. Rather, marginal cost arises out of the myriad of activities and resource decisions firms make in the production process. Firms adopt new practices and experiment with existing operations in an attempt to lower costs.

Following on Rivkin (2000) and Levinthal (1997), we assume that firms can engage in a finite set of activities or deploy a finite set of resources. (To limit confusion, we refer to them as resource profiles from here on out though, for our purposes, we are agnostic to the use of resource profiles or activity sets.) For simplicity, we represent these resource profiles as a vector of  $N$  binary resource decisions,  $\mathbf{x}_i$ . For example, a firm who 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 a resource profile as follows:  $\mathbf{x}_i = [10110]$  assuming only these 5 resource decisions.

To represent interactions between resource choices, we assume that the marginal contribution of each resource to marginal cost is a function of not only that resource decision but  $K$  other resource decisions as well. If  $K$  equals one, marginal cost is a linear combination of each of the individual resource decisions.

$$c_i = \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_N x_N \quad (6)$$

However, for  $K$  greater than one, the coefficients,  $\beta$ , associated with each resource depend on the constellation of  $K$  resources. This representation allows for interactions consistent with Kaufman's model of complexity that has been utilized by Levinthal (1997) and Rivkin (2000) in the strategic management field.

Our specification allows us to consider complementarity in a more generalizable sense than employed by Milgrom & Roberts (1995) and operationalized using supermodularity. Technically, our specification allows us to consider resource combinations that are both complements and substitutes. In some instances, the value of an individual practice will increase in the absence of another practice. Furthermore, our specification allows us to extend beyond simple pair-wise combinations of resources to consider the cumulative value of deploying a large mix of resources.

In this more generalizable world, as the number of potential input factors increase ( $N$ ) and the degree of interaction ( $K$ ) increase, we expect more complex performance landscapes (Rivkin, 2000). In other words, there will be an increasing number of local optima from which slight changes in resource profiles will raise costs. For even moderate  $N$  and  $K$ , the decision problem becomes analytically intractable and computational prohibitive. Thus, it is unreasonable to assume that firms achieve the optimal configuration of resources to minimize cost. We must really on heuristic models of firm decision making in such an environment. In the section that follows we describe how we model this decision making process.

## **Analysis**

Due to the analytical intractability of the  $NK$  portion of the model, we use computational methods to explore its implications. We begin by randomly parameterizing the marginal cost

equation coefficients,  $\beta$ 's (i.e., we generate a unique performance landscape). We then initialize firm resource sets ( $\mathbf{x}_i$ ) either randomly or by assigning all firms to identical resource profiles. Next, we calculate marginal cost, total cost, quantities produced, prices, and profits for each firm according to our Cournot model described above.

We then model variation and selection of resource profiles for each firm in the population. With some probability ( $\theta$ ), a firm considers altering an individual resource decision of the firm.<sup>1</sup> The firm accepts a change according to one of two updating heuristics. In the first, the firm will accept any change that improves firm profitability given the current state of the world. We refer to this as an innovation strategy. In the second, the firm will accept any change that is congruent with the resource decision of the best performing firm in the population. We refer to this as the imitation strategy. After each firm decides whether to alter their resource profile, we then recalculate marginal cost, total cost, quantities produced, prices, and profits for each firm.

The set of possible updating heuristics that we could consider is infinite. We choose these two stylized rules because they represent a nice dichotomy between internally focused improvement efforts (innovation) and outward focused search for best practices (imitation). To capture the possibility of mixed strategies, we assign each firm a parameter ( $\gamma$ ) bounded between zero and one that captures the relative likelihood that a firm pursues an innovation strategy. A firm with  $\gamma$  equal to zero will rely purely on internal innovation. A firm with  $\gamma$  equal to one will rely purely on imitation. For example, a firm with  $\gamma$  equal to  $\frac{1}{2}$  will evenly split its use of

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

innovation and imitation. In future work, we plan to explore an expanded set of decision heuristics.

For our analysis, we consider five canonical cases created by varying two model settings. First, we vary the initial distribution of resource profiles such that either 1) all firms initially have identical resource profiles or 2) all firms are randomly assigned a (possibly unique) resource profile. Second, we consider three classes of strategies pursued by the firms in the population: 1) all firms pursue internal innovation only, 2) all firms pursue imitation only, and 3) firms pursue various mixed strategies. The combination of these cases yields six unique categories. We do not include results from the canonical case where all firms begin with identical resource profiles and pursue a pure imitation strategy simply because there is no variance in such a world. All firms remain identical and unchanged throughout the entire experiment since all they do is copy from identical firms.

For each canonical case, we randomly assign the number of firms in the industry and our parameters  $N$ ,  $K$ , and  $\theta$ . We then iterate through 100 time periods in this world. We then reset the computational experiment and repeat 10,000 times.<sup>2</sup> Table 1 presents summary statistics of the parameters from our computational experiments. Looking at the statistics, we feel confident that our samples are comparable. The means and standard deviates for firms,  $N$ ,  $K$ , and  $\theta$  are nearly identical.  $\gamma$  varies depending on the canonical case. For example, in the pure innovation cases (case 1 and 4), the mean is zero and there is no variance. In the mixed cases, the mean is 0.51 and  $\gamma$  takes on values between 0 and 1.

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<sup>2</sup> We experimented with other time lengths and found that for nearly all (>99%) of runs had stabilized by 100 time periods. With 10,000 experiments for each canonical case, we are well within the range of the central limit theorem. Analysis found that summary statistics based on 1000 experiments were identical to those from 10,000 experiments.

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Insert Table 1 about here  
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Figure 2 provides data on a single computational experiment of the first canonical case, i.e., random starting positions and pure innovation strategy. The top part of the figure displays the evolution of profits for each of the four firms in the industry. The bottom part of the figure displays the evolution of marginal costs. At the initial time period, we observe variance in profits and marginal costs across the four firms as a result of randomly seeding initial resource profiles. The lower a firm's marginal cost, the higher the firm's profit. Over time, firms experiment with other resource configurations in an attempt to drive down costs. While none of the firms sees increases in their marginal costs (due to the nature of the decision rule), a firm's profitability may go up or down depending on its marginal costs relative to others. This is best highlighted by the solid-line firm who despite decreases in marginal costs sees its competitive advantage erode as others catch up and surpass them.

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Insert Figure 2 about here  
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There are number of interesting things to observe about this fairly typical run. First of all, the industry stabilizes in a relatively short period of time, i.e., future improvements in marginal cost are unlikely. This is a result of the complexity of the decision making environment. Recall that as  $N$  and  $K$  increase there will be multiple local optima. The pure innovation strategy evoked here is decidedly incremental in nature and akin to what is often referred to as a hill-climbing strategy. Firms search the region close to where they are currently

positioned for cost saving resource allocation changes. Once on a local optima (a local hill), a firm is unable to move (climb upwards) to other parts of the cost performance landscape that are more favorable but removed from the current position.

Interestingly, what matters for future profitability is not the relative cost advantage a firm has at the inception of the industry as much as the future prospects of closely-related resource profiles. In other words, it is not how high you land on a hill to start off with, but how high is the hill. In Figure 2, there is almost no correlation between initial starting position and future profitability. In fact, across our entire sample the correlation between a firm's relative profitability in period one and relative profitability in period one-hundred is only 6.7%.

To systematically explore across all our computational experiments, we calculated the average industry profitability across time for each canonical case (Figure 3). In each case, we find that average industry profitability increases over time but at a decreasing rate. This is due to the cost saving improvements firms are making over time. A natural outcome of our Cournot model of competition is that average profits increase as average industry marginal costs go down. More interesting is the relative difference in stable average industry profits. When all firms pursue a pure innovation strategy and there is variance in initial resource profiles due to random assignment (Canonical Case 1), average industry profits are statistically significantly higher than those industries represented by our other canonical cases. Interestingly, industries populated with firms pursuing a pure innovation strategy but in which there was no variance in initial resource positions (Canonical Case 4), performed the worst in the long-run.

The complementarities and the resulting complexity in the model create an interesting interaction between initial heterogeneity and long-run industry profitability. When all firms within an industry tend to pursue an imitation strategy, they quickly converge to a common

resource profile and thus stop locating cost saving innovations (Canonical Case 2). Firms pursuing a pure innovation strategy, on the other hand, have the flexibility to generate and adopt internal innovations and push the production function frontier even though they fail to learn from the innovations of others. Hence, we find that average industry profits are higher for industries populated by firms investing in internal innovation in Canonical Case 1.

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Insert Figure 3 about here

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However, as discussed above, in complex environments characterized by multiple optima there is a tendency to get “stuck” on a local optimal failing to recognize more radical innovations that may allow for substantial increases in performance. The innovation strategy is very good at incremental innovation, finding new cost-saving resource configurations in the general vicinity of a firm’s current resource profile. To the extent all the firms start with similar resource profiles, however, there is a tendency to make the same incremental innovations, i.e., to rush up the same hills. Variety in resource positions at the outset increases the likelihood that some firms will be in regions of the performance landscape that are particularly fruitful. Stated another way, they are on technical trajectories that lead to substantial future cost savings. The lower the initial variety in the sample, though, the fewer trajectories being searched and the lower the likelihood that substantial cost savings will be found. Imitation of others may help firms break free of these constraints. The periodic imitation of other’s resource decisions allows a firm to “jump” to other parts of the performance landscape. Consequently, even when all firms start in

the same position, average industry profitability is higher when firms are pursuing a mix of innovation and imitation strategies (Canonical Case 5).<sup>3</sup>

While average industry profitability is driven primarily by the likelihood that all firms find innovative cost saving resource configurations, variance in profits is driven by the ability of some firms to find cost saving innovations when others have not. Figure 4 presents the average variance in industry profitability across time for each canonical case. In the cases with random assignment to initial resource profiles (Cases 1-3), we find that average variance is greatest at the outset and declines over time. This is not surprising since over time firms will come to resemble one another as they either independently discover cost-saving innovations or imitate other's innovations (if not their entire resource profile). In the cases where all firms have the same initial resource profile (Cases 4-5), we find that variance quickly increases from zero and then begins to decrease over time. This reflects the timing of discovery of innovative opportunities. Early adopters of cost saving resource configurations see substantial increases in profits relative to competitors, increasing industry heterogeneity. Over time, other firms discover favorable resource configurations and variance in profit declines.

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Insert Figure 4 about here  
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In the long-run, we observe some interesting differences in variance in profits between our canonical cases. Perhaps not surprisingly, we find that long-run variance in profit decreases as more firms within an industry pursue an imitation strategy. In the extreme when all firms start from similar resource configurations and pursue a pure imitation strategy, we observe no

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<sup>3</sup> Recall, if all firms pursued a pure imitation strategy there would never be any changes in resource positions.

variance. Importantly, however, we find this result despite the presence of complementarities between firm resource decisions. While we do not deny prior findings that advantageous positions are hard to imitate (Rivkin, 2000), our results suggest that these positions are hard for everyone to find. At the very least, firms may exchange best practices and adopt similar if not identical average-performing resource positions.

Turning to the pure innovation cases, we find higher long-run variance than in the case of imitation. This is due to the ability of firms to pursue their own incremental innovations independent of the actions of others allowing firms to travel down divergent trajectories as the search for cost savings. Interestingly, we find only a slight difference between the random start condition and the identical start condition (Cases 1 & 4, respectively). Once again, we have little evidence that advantageous positions at the start of an industry are strongly correlated with eventual success. Even when all firms have identical resource profiles at time 0, they still generate substantial heterogeneity in profits by time 100. This suggests that there are numerous saddle-points on the performance landscape where seemingly profit-equivalent decisions can have drastic long-run performance implications.

The initial premise put forth in this paper is that the role complementarities play in intra-industry heterogeneity in profits is mediated by the competitive environment. We have shown that in complex environments where complementarities are present, variance in profit is tied to the resource updating strategies of firms within the industry. To explore how these results may change in the presence of varying levels of complementarity, we split our sample into four quartiles based on an industry complexity score equal to  $K + (1 - K/N)$ . This score captures the main effect of our interaction parameter  $K$  on complementarity but adds an additional element to

reflect that  $K$  is bounded by  $N$ . For example, an industry with  $K = 2$  and  $N = 4$  will have a slightly higher complexity score than one with  $K = 2$  and  $N = 2$ .

Figure 5 presents the average industry profitability over time for each quartile. We find that when complementarities are weak (the first quartile), average long-run profits are high. In such a world, the decision problem is relatively simple. Most firms either through imitation or individual innovation are able to eventually discover low cost resource positions. As illustrated in the second and third quartile, as complementarity between resources increases, average profitability decreases. This is consistent with Rivkin (2000) whose model suggested that greater complexity stymies imitation and decreases the ability of firms to find advantageous positions.

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Insert Figure 5 about here  
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Interestingly, however, average industry profits increases in quartile four. Further probing reveals that there is tension between the ability to drive average industry costs down and the ability to protect above-average profits from competition. As complementarity increases, it becomes more difficult for firms to find low cost resource configurations. However, as complementarity increases, it becomes more difficult for firms to imitate or discover valuable resource positions. Recall from Figure 1, the greater a firm's cost advantage relative to the rest of the industry, the larger its profits. We propose that average industry profits go up in quartile four due to the success of a few innovative firms whose profits are predicated on the fact that

others could not copy. The industry average increases because there is a floor on profits at zero. Specifically, firms who are not competitive due to high marginal costs, choose not to produce.<sup>4</sup>

If this in fact the case, we would expect to see high heterogeneity in profits when complementarities are greatest. Figure 6 presents the average variance in profits over time for each quartile. In the first quartile, consistent with our finding with respect to average profits, variance is low due to the relatively simple decision problem facing firms. For higher level of complementarity, we find higher variance in profits throughout the history of the industry. While there is no significant differences between the 2<sup>nd</sup>, 3<sup>rd</sup>, and 4<sup>th</sup> quartiles, they all are statistically different than the 1<sup>st</sup> quartile.

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Insert Figure 6 about here  
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To explore how these varying levels of complementarity interact with the competitive environment, we regress long-run variance in profits on our various model parameters using an ordinary least-squares (OLS) specification (see Table 2).<sup>5</sup> We include dummies for each Canonical Case as control. We suppress the constant to prevent collinearity with one of these dummies. We capture the underlying mix of competitive strategies among firms in the industry, by taking the industry average of  $\gamma$ . An industry-average  $\gamma$  of zero indicates that all firms are pursuing a pure innovation strategy and an industry-average  $\gamma$  of one indicates that all firms are

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<sup>4</sup> We can interpret this as exiting the industry. In many runs, we find firms who choose not to produce. While we do not explicitly model the exit process, it is natural to interpret these firms who have zero production and zero profits as exiting the industry.

<sup>5</sup> Using regression in this situation is an admission that we cannot derive the specific function form of the relationship between our parameters and firm profitability. This is why we ran computation experiments earlier rather than derive an analytical solution to our model. The regression can be viewed as a way to capture the linear tendencies of our parameter values as they relate to profits. To be clear, this is not an empirical test of our model. Rather it is a vehicle for us to explore the implications of our model.

pursuing a pure imitation strategy. Not surprisingly, we find that as the industry members pursue more of an imitation strategy, heterogeneity in profits is suppressed.

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Insert Table 2 about here  
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Consistent with Figure 6, we find that the greater the complementarity in resource decisions as captured by  $K$ , the greater the variance in profits. We do not find that  $N$ , the number of resource decisions, or the number of firms, has a significant impact on variance. In Model 2, we substitute  $K$  and  $N$  with our measure of complementarity:  $K + (1 - K/N)$ . Our results are identical to our specification splitting out  $K$  and  $N$  though we are more confident in the coefficient on our complementarity score. We do find in both Models 1 and 2 that the greater our parameter of consideration,  $\theta$ , the lower intra-industry heterogeneity in profits. This seems consistent with the idea that if firms are quickly updating their resource profiles (high  $\theta$ ), there will be an increased likelihood in convergence in profiles.

In Model 3, we include an interaction term between complementarity and industry-average  $\gamma$ . We find a significant, negative coefficient suggesting that the impact of complementarity on variance in profits is lower the greater the use of an imitation strategy among industry members. We present the coefficients to the fifth decimal place to highlight the difference in the two coefficients and to generate a comparison of the effect of complementarity on variance in profits under different industry strategy mixes (see Figure 7). We find that while the variance in profits does increase with greater complementarity, the slope of this relationship is lower the more firms pursue an imitation strategy. In the extreme, when all firms pursue a

pure imitation strategy, complementarity has almost no effect of intra-industry heterogeneity in profits.

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Insert Figure 7 about here  
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To this point, we have looked at the drivers of the variance in industry profits without exploring what individual features may drive one firm to be more profitable than others within an industry. In particular, are there individual strategies,  $\gamma$ , that allow firms to achieve advantageous competitive positions? It is difficult to say in any meaningful way what is the best mixed strategy based on  $\gamma$ . We do believe, however, that there will be a concave relationship between our strategy parameter,  $\gamma$ , and long-run firm profitability. When firms favor imitation too frequently, the industry may converge on a given realm of the performance landscape and the subsequent loss of variety will stifle innovation. Firms pursuing a pure innovation strategy, while very good at incremental innovations, are likely to exhaust cost-saving innovations within a given realm of the performance landscape. A mixed strategy marked by periodic imitation of other's resource decisions allows a firm to "jump" to other parts of the performance landscape while still searching locally. This is consistent with the notion that firms periodically need to explore for new knowledge and ideas if they are going to continue to innovate (March, 1990).

To explore this proposition, we regress our model parameters on long-run *individual* firm profits once again controlling for the Canonical Case (see Table 3). We find not surprising that the more firms in an industry (i.e., the lower industry concentration), the more likely a firm is profitable. Furthermore, we find that as  $N$  and  $K$  increase, long-run profits decrease: in more complex environments, it is more difficult to find low cost positions. As a robustness check, we

run the model using our measure of complementarity and find consistent results (Model 5). We do not find a significant coefficient for  $\theta$  in either Models 4 or 5.

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Insert Table 3 about here  
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To capture the concave relationship between updating strategy and profits, we include both  $\gamma$  and  $\gamma^2$ . We find a positive coefficient on  $\gamma$  and a negative coefficient on  $\gamma^2$  consistent with our intuition. In Figure 8, we graph the relationship between  $\gamma$  and its marginal contribution to profits. We find that a strategy which favors imitation approximately 75% of the time and internal innovation 25% of the time fairs best. This is interesting since previously we found that greater imitation stifles both average industry profits and variance in profits. This is reflected in the coefficients for our case types. We find that the coefficients for those industries where firms are pursuing a pure innovation strategy (Cases 1 and 4) are higher than those industries who firms are pursuing either a mixed or pure imitation strategy (Cases 2, 3, and 5).

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Insert Figure 8 about here  
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To explore this further, we create two variables. *Start type* is a dummy variable equal to one when firms were randomly assigned resource profiles at time zero. *Strategy type* varies from zero to one depending on the industry mix of strategies. Once again, a zero score represents an industry where all firms are pursuing a pure innovation strategy. In Model 3, we find that firms are more profitable in industries where there is initial variety in resource profiles. This is consistent with our interpretation of Figure 3. We also find that the more a firm's competitors

pursue in imitation strategy, the lower a firm's profitability. We included the squared term of strategy type to reflect potential decreasing returns. Figure 9 presents the estimated relationship between industry strategy mix and its marginal contribution to individual firm profits.

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Insert Figure 9 about here  
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This suggests an interesting tension between a firm's individual desired strategy and the desired strategy of the industry as a collective. Firms on average are better off if they and their competitors pursue a variety of different approaches and invest in internal innovation. At the same time, individual firms benefit from imitating the innovations of competitors. A market failure of sorts may result where firms all favor imitation at the expense of innovation, reducing the requisite variety in resource positions, causing stagnation and a reduction in both profitability and variance in profits.

Interestingly, complementarities may help mitigate this destructive tendency. In Model 4 of Table 3, we interact our measure of complementarity with  $\gamma$  and  $\gamma^2$ . Figure 10 presents the relationship between  $g$  and profits for various levels of complementarity. The greater the degree of complementarity between resources, the greater the extent to which an optimal strategy entails investing in internal innovation. In other words, the maximum point on any given curve shifts to the left. The steepness of the curves also increases as complementarities increase. This suggests that the penalty for adopting a non-optimal strategy is greater in the presence of complementarities.

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Insert Figure 10 about here  
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## **Discussion**

Consistent with previous work, we find that as complementarities in resource profiles increase, firms have greater difficulty finding favorable positions resulting in lower industry average profits. However, at high levels of complexity, average profits rise as those firms who are able to find favorable resource configurations are protected from imitation and their competitors are forced from the market. As a result, all else being equal, intra-industry heterogeneity in profits is greater with greater complementarity.

However, we find that the magnitude of this effect is mediated by the nature of competition within the industry. In particular, variance in industry profits is greatest in the long-run when there is initially variety in the resource positions within the population and firms individually invest in internal innovation. Thus, the effect of complementarity is suppressed in environments lacking requisite variety in the initial population and where firms favor an imitation strategy.

Interestingly, firms individually are best served pursuing a mixed strategy favoring imitation more frequently than innovation. This creates a potential dilemma in that firms wish that others within the industry will adopt divergent positions and pursuing internal innovation while they imitate what their competitors learn. Complementarities may mitigate this problem however due to the increased value of internal innovation due to the greater difficulty of others to imitate valuable innovations.

Our approach has a number of advantages. We create a simple, tunable model of competition and complementarity. Our approach builds on recent efforts using agent-based modeling (Levinthal, 1997; Rivkin, 2000) by explicitly endogenizing competition. This allows us to analysis a complexity model in a truly competitive setting. We adopt a simple model of Cournot competition for illustration, though we suspect that more complicated models will only highlight the need for an explicit consideration of the competitive game firms are playing when consider the relative importance of complementarity.

To the extent our model is concerned with an attribute of performance (marginal cost in this case), the implications of the model should hold whether we are discussing quality, durability, or some other performance attribute. This may not be the case in markets where differentiation is possible based on differences in consumer preferences across the population. An interest extension would be to explore the relationship between heterogeneity in profits and complementarity in a spatial differentiation model of competition. Such an extension is beyond the scope of this paper, however.

There are a number of interesting extensions to explore based on the model presented. In particular, the model allows for a natural exploration of industry dynamics. In future work, we plan to explore relative differences in industry concentration, growth, entry rates, and exit rates based on the model developed in this paper. To the extent that the model generates industry dynamics consistent with stylized facts, the greater confidence we would have that the model captures the realities of competition. Such an endeavor is left to future work.

## Conclusion

In this paper, we explore the implications of complementarity and competition on sustained intra-industry heterogeneity in profits. We develop a model of resource allocation in complex environments embedded in a Cournot model of competition in an undifferentiated, oligopolistic market. Due to the analytical intractability of our model, we run a series of computational experiments based on a wide range parameter values. Using a sample of over two-million observations from these computational experiments, we present a series of findings that help tease out the conditions under which we expect to observe variance in profits within an industry.

Our model suggests that a thorough understanding of the industry competitive dynamics is necessary to identify the conditions under which complementarities may lead to intra-industry heterogeneity in profits. Consistent with the complementarities literature, we find that all things being equal the greater the interaction between resource positions, the greater profit differentials within an industry. However, we find that this relationship is dampened the greater the diffusion of imitation strategies among competitors. In the extreme, environments characterized by numerous, rich complementarities may not generate intra-industry heterogeneity in profits at all. In the end, competition mediates the impact complementarities have on profit differentials within an industry.

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## Appendix

This appendix gives the derivation of the optimal output decision for a firm given its marginal cost and the marginal cost of all other firms in our undifferentiated market model:

$$\text{Given the profit function ...} \quad \pi_i = p(Q) q_i - c_i(q_i) \quad (1)$$

$$\text{Substituting ...} \quad \pi_i = (\alpha - Q) q_i - c_i q_i - c_f \quad (2)$$

$$\text{Splitting Q ...} \quad \pi_i = \alpha q_i - (\sum_{j \neq i} q_j + q_i) q_i - c_i q_i - c_f \quad (3)$$

$$\text{Rearranging ...} \quad \pi_i = \alpha q_i - (\sum_{j \neq i} q_j) q_i - q_i^2 - c_i q_i - c_f \quad (4)$$

$$\text{Taking the first derivative ...} \quad \delta \pi_i / \delta q_i = \alpha - (\sum_{j \neq i} q_j) - 2q_i - c_i = 0 \quad (5)$$

$$\text{Rearranging ...} \quad \delta \pi_i / \delta q_i = \alpha - (\sum_{j \neq i} q_j + q_i) - q_i - c_i = 0 \quad (6)$$

$$\text{Replacing with Q ...} \quad \delta \pi_i / \delta q_i = \alpha - Q - q_i - c_i = 0 \quad (7)$$

$$\text{Solving for } q_i \text{ ...} \quad q_i = \alpha - Q - c_i \quad (8)$$

$$\text{Summing across all } i, \quad \sum q_i = n\alpha - nQ - \sum c_i \quad (9)$$

$$\text{Replacing with Q ...} \quad Q = n\alpha - nQ - \sum c_i \quad (10)$$

$$\text{Solving for Q ...} \quad Q = (n\alpha - \sum c_i) / (n+1) \quad (11)$$

$$\text{Subbing back into (8)...} \quad q_i = \alpha - [(n\alpha - \sum c_i) / (n+1)] - c_i \quad (12)$$

$$\text{Solving for } q_i \text{ ...} \quad q_i = [(\alpha + \sum c_i) / (n+1)] - c_i \quad (13)$$

**Table 1. Summary statistics for the parameters of the computational experiments**

				mean	std. dev.	min	max
Case 1	starting condition:	random	firms	6.99	2.50	1	10
	updating:	innovation only	N	11.18	5.79	2	20
	iterations:	10,000	K	7.26	4.62	1	20
	observations:	543,500	$\gamma$	0.00	0.00	0	0
			$\theta$	0.51	0.29	0	1
Case 2	starting condition:	random	firms	6.99	2.50	1	10
	updating:	imitation only	N	11.18	5.79	2	20
	iterations:	10,000	K	7.26	4.62	1	20
	observations:	543,500	$\gamma$	1.00	0.00	0	0
			$\theta$	0.51	0.29	0	1
Case 3	starting condition:	random	firms	7.02	2.45	1	10
	updating:	mixed strategies	N	10.70	5.83	2	20
	iterations:	10,000	K	7.06	4.69	1	20
	observations:	556,300	$\gamma$	0.50	0.29	0	0
			$\theta$	0.51	0.29	0	1
Case 4	starting condition:	identical	firms	6.99	2.44	1	10
	updating:	innovation only	N	10.68	5.50	2	20
	iterations:	10,000	K	7.12	4.45	1	20
	observations:	557,500	$\gamma$	0.00	0.00	0	0
			$\theta$	0.50	0.29	0	1
Case 5	starting condition:	identical	firms	6.99	2.50	1	10
	updating:	mixed strategies	N	11.18	5.79	2	20
	iterations:	10,000	K	7.26	4.62	1	20
	observations:	557,500	$\gamma$	0.00	0.00	0	0
			$\theta$	0.51	0.29	0	1

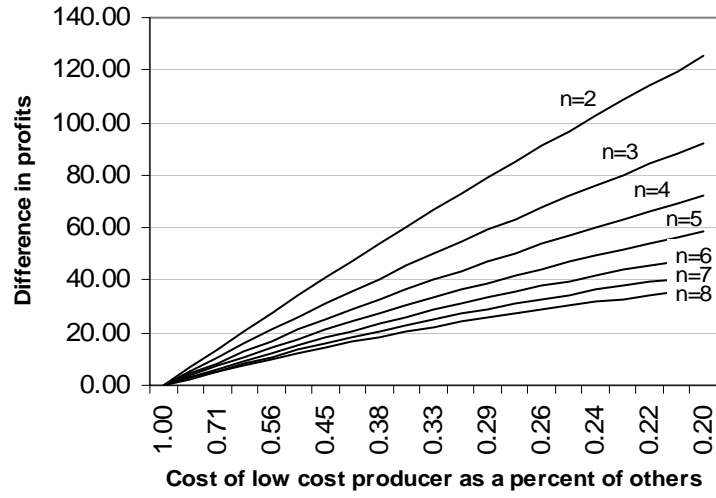
**Table 2. Variance in profits regressed on model parameters (OLS)**

	Model 1	Model 2	Model 3
industry-average $\gamma$	-0.041 (0.006)	-0.041 (0.006)	-0.033 (0.006)
K	0.001 (0.000)		
N	-0.000 (0.000)		
complementarity		0.001 (0.000)	0.00122 (0.000)
industry-average $\gamma$ X complementarity		0.001 (0.000)	-0.00106 (0.000)
firms	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
$\theta$	-0.021 (0.002)	-0.021 (0.002)	-0.021 (0.002)
case 1 dummy	0.069 (0.002)	0.068 (0.002)	0.065 (0.002)
case 2 dummy	0.054 (0.006)	0.053 (0.006)	0.050 (0.006)
case 3 dummy	0.046 (0.004)	0.045 (0.004)	0.042 (0.004)
case 4 dummy	0.055 (0.002)	0.054 (0.002)	0.051 (0.002)
case 5 dummy	0.038 (0.004)	0.037 (0.004)	0.034 (0.004)
Observations	4543	4543	4543
F-statistics	473	473	475
Adjusted R <sup>2</sup>	0.5100	0.5096	0.5109

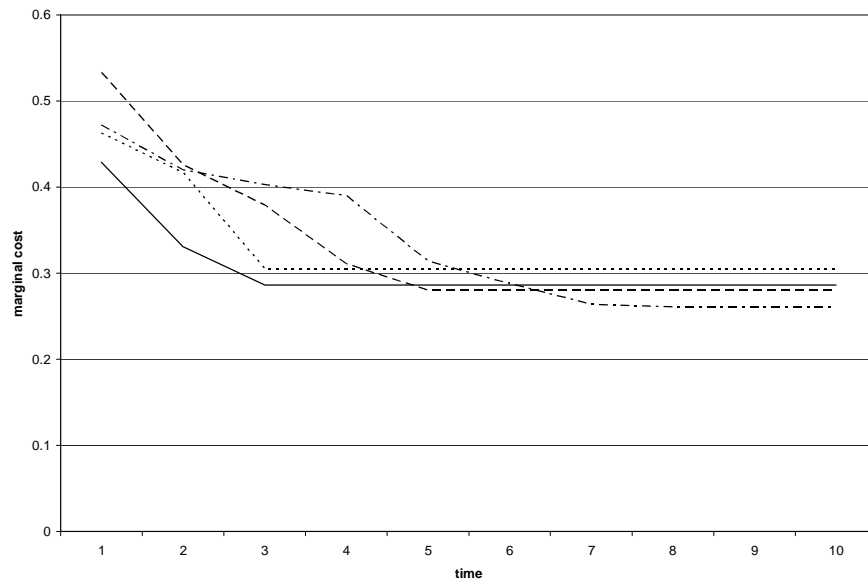
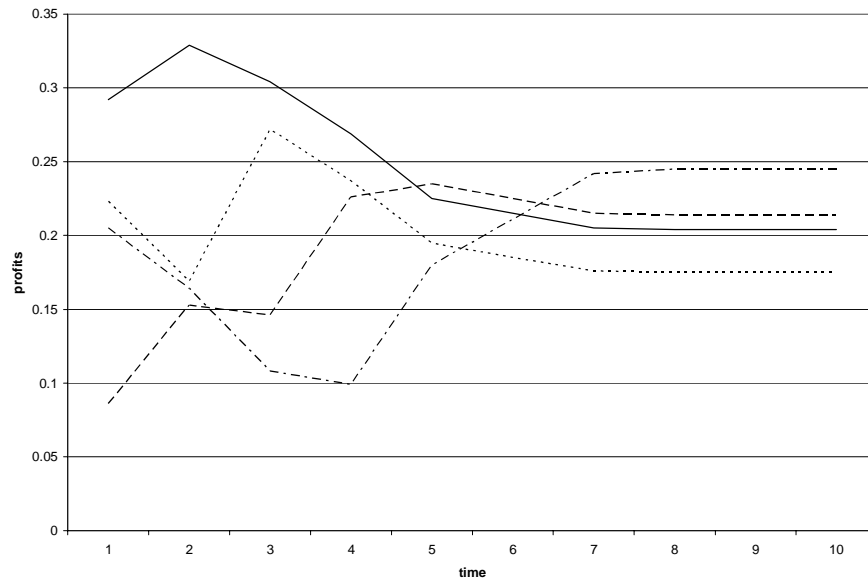
**Table 3. Firm profitability regressed on model parameters (OLS)**

	Model 1	Model 2	Model 3	Model 4
$\gamma$	0.039 (0.012)	0.039 (0.012)	0.039 (0.012)	0.020 (0.014)
$\gamma^2$	-0.026 (0.011)	-0.026 (0.011)	-0.026 (0.011)	-0.008 (0.001)
K	-0.001 (0.000)			
N	-0.000 (0.000)			
complementarity		-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)
$\gamma$ X complementarity				0.003 (0.001)
$\gamma^2$ X complementarity				-0.002 (0.001)
firms	-0.038 (0.000)	-0.038 (0.000)	-0.038 (0.000)	-0.038 (0.000)
$\theta$	-0.002 (0.001)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)
case 1 dummy	0.428 (0.002)	0.427 (0.002)		
case 2 dummy	0.412 (0.004)	0.412 (0.004)		
case 3 dummy	0.415 (0.003)	0.415 (0.003)		
case 4 dummy	0.424 (0.002)	0.423 (0.002)		
case 5 dummy	0.413 (0.003)	0.413 (0.003)		
start type			0.003 (0.001)	0.003 (0.001)
strategy type			-0.030 (0.009)	-0.030 (0.009)
strategy type <sup>2</sup>			0.016 (0.009)	0.016 (0.009)
Observations	27583	27583	27583	27583
F-statistic	10473	11521	4067	3254
Adjusted R <sup>2</sup>	0.8068	0.8068	0.5412	0.5412

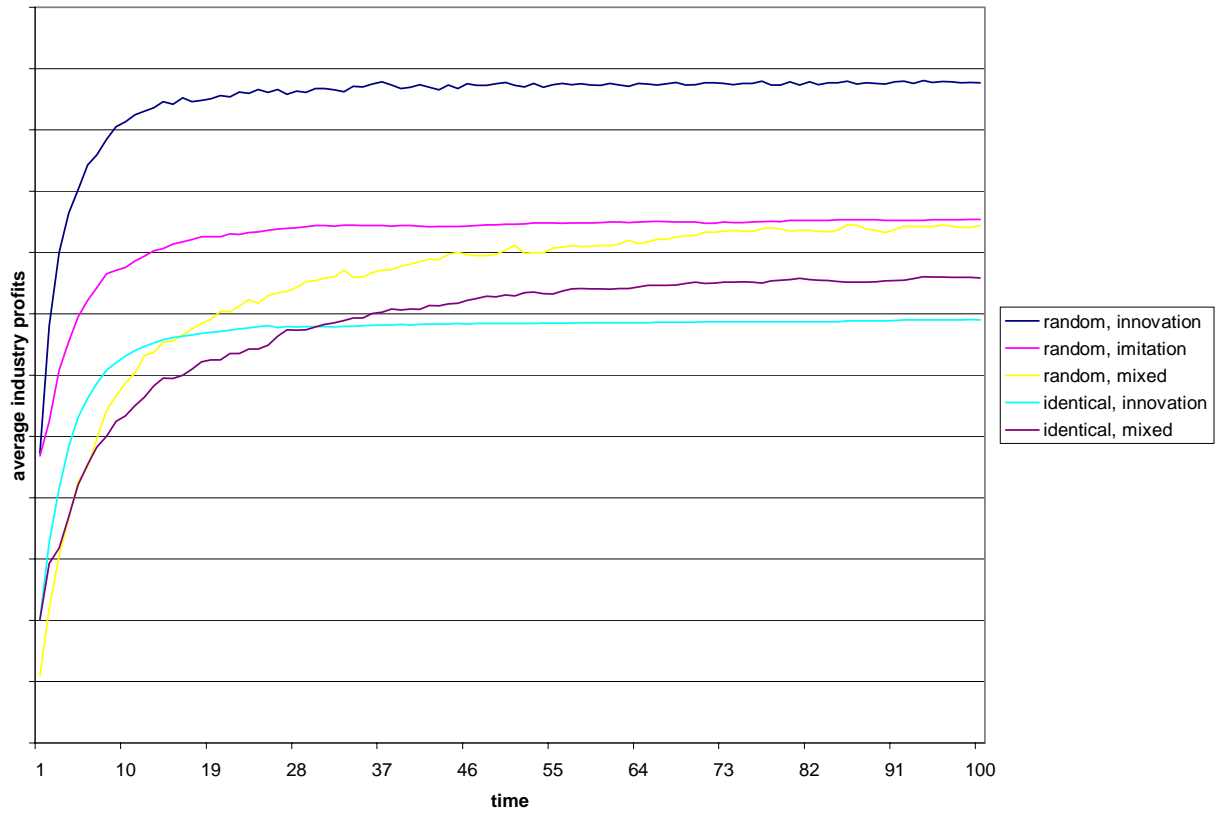
**Figure 1. Relationship between low cost production and profits**



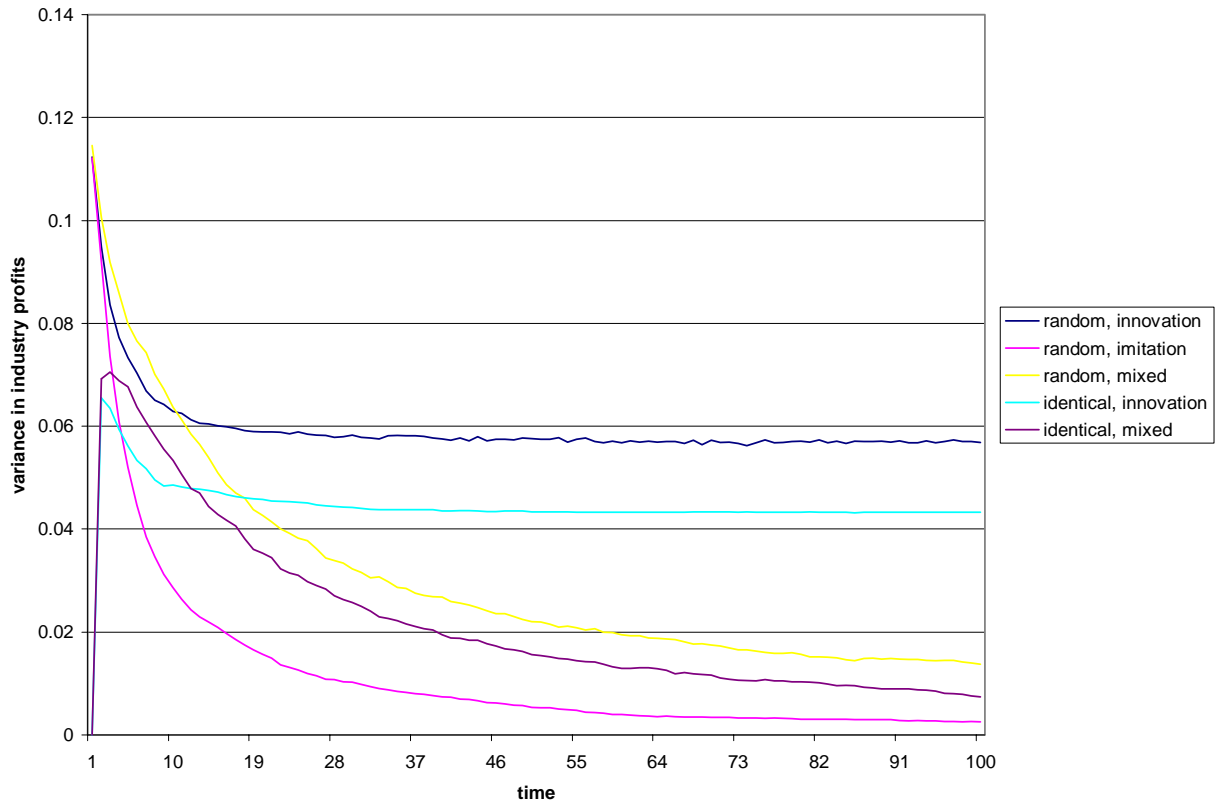
**Figure 2. An example computational experiment**  
(case= random/pure innovation, firms = 4, N = 15, K = 11)



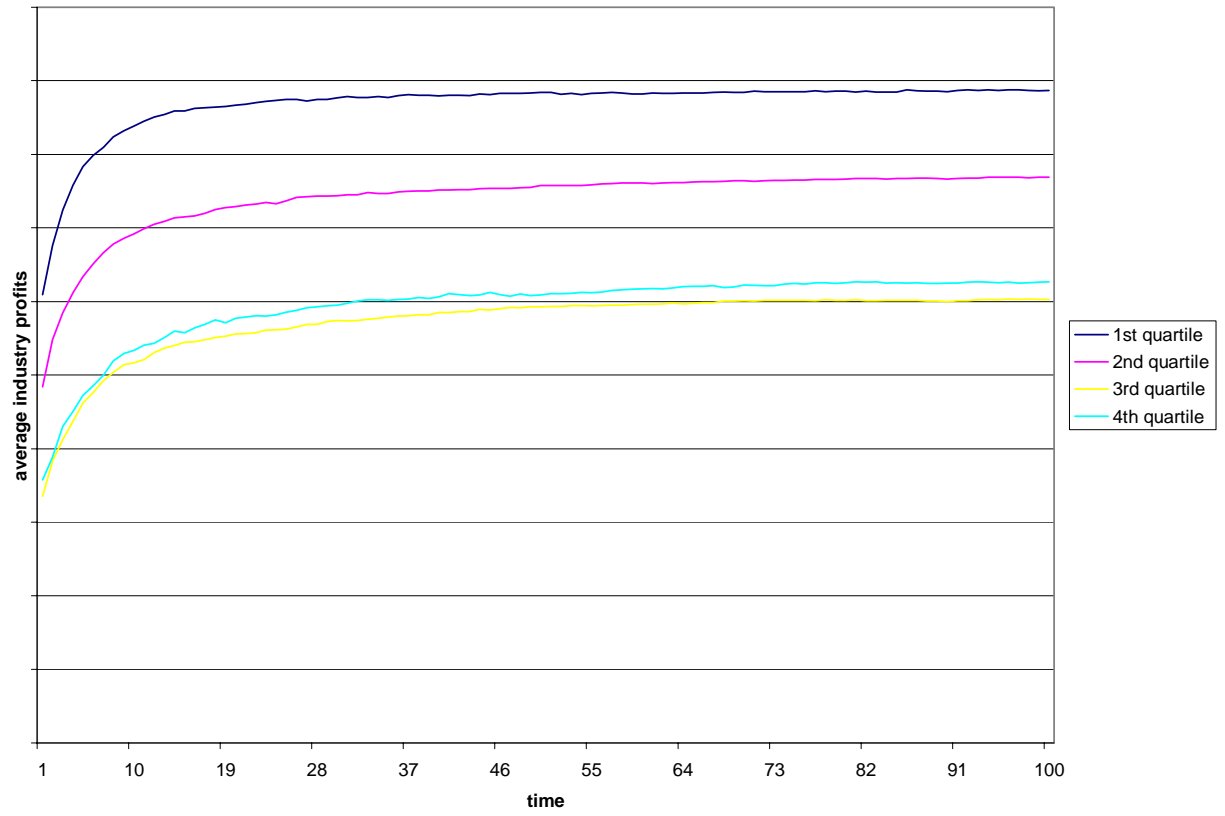
**Figure 3. Average industry profits over time for each canonical case**



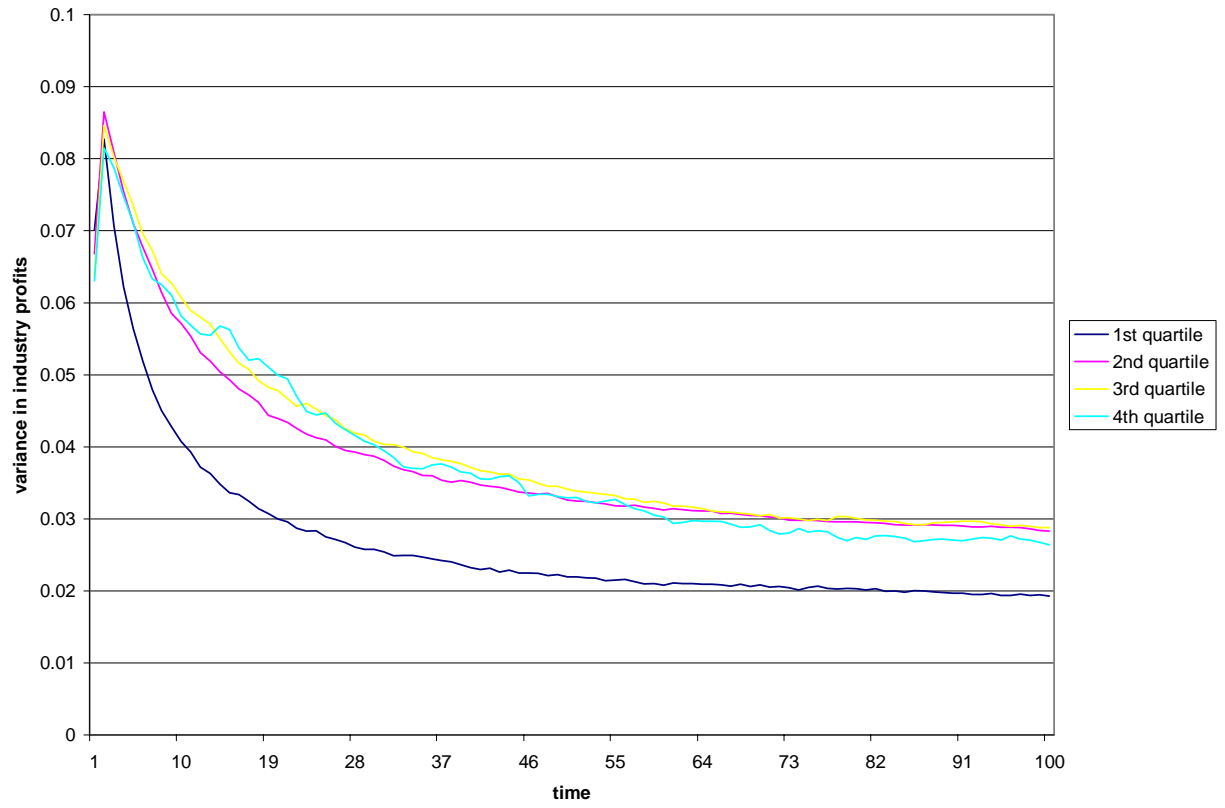
**Figure 4. Variance in industry profits over time for each canonical case**



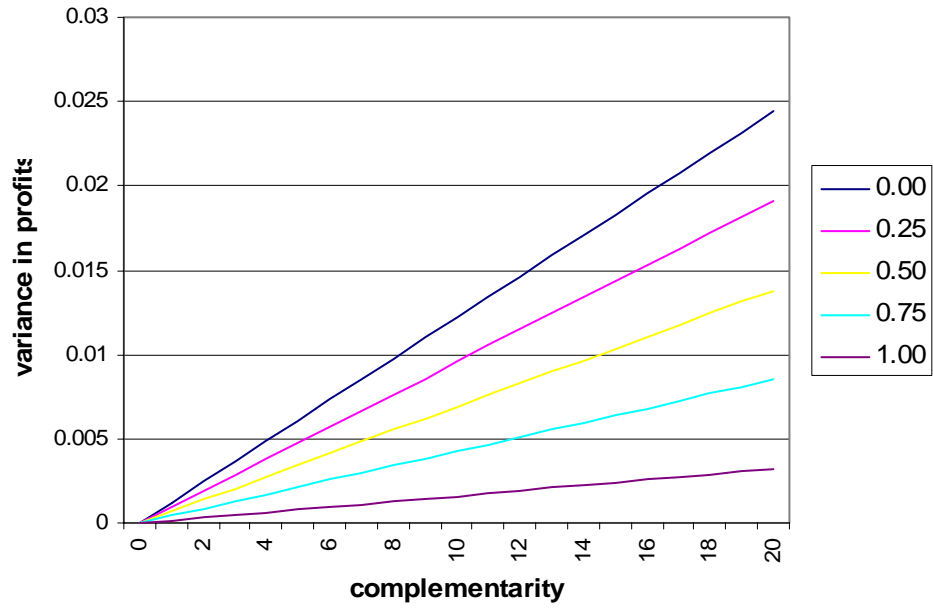
**Figure 5. Average industry profits over time based on degree of complementarity**



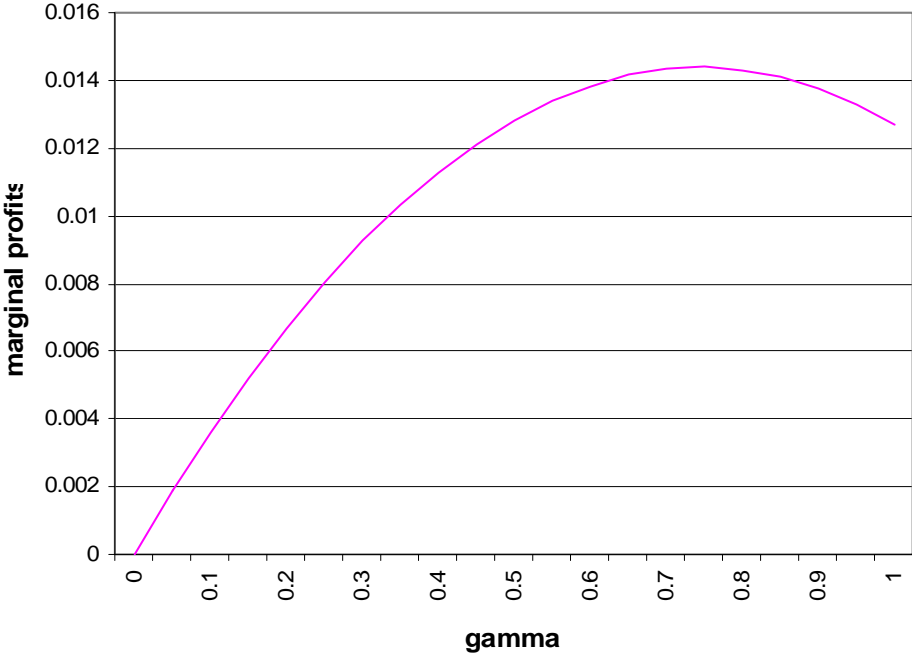
**Figure 6. Variance in industry profits over time based on degree of complementarity**



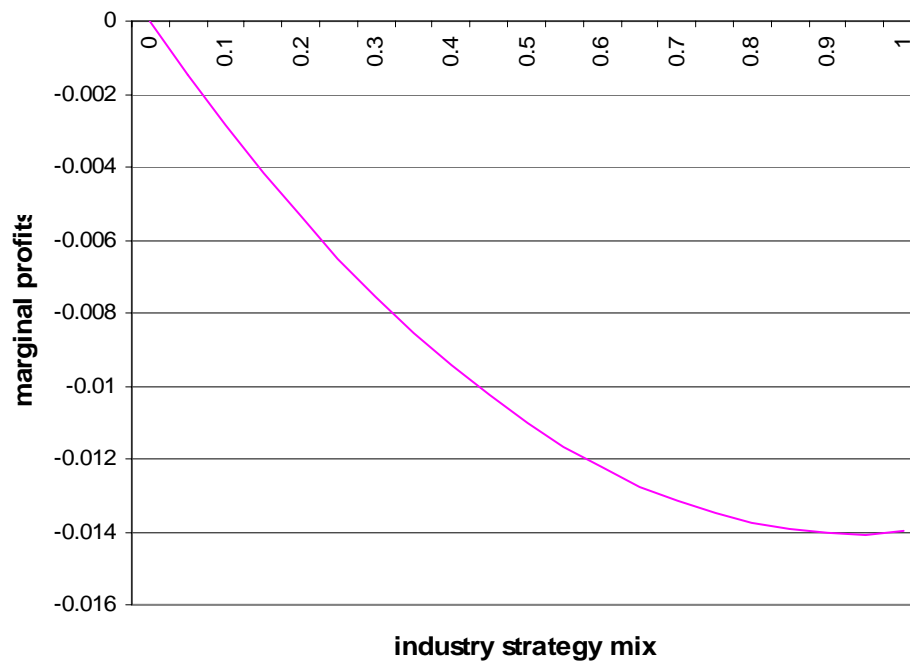
**Figure 7. Relationship between complementarity and variance in profits  
(mediated by industry strategy mix)**



**Figure 8. Relationship between updating strategy,  $\gamma$ , and long-run firm profits**



**Figure 9. Relationship between industry strategy mix and long-run firm profits**



**Figure 10. Relationship between updating strategy,  $\gamma$ , and long-run firm profits (mediated by complementarities)**

