Entry, Exit, and the Endogenous Market Structure in Technologically Turbulent Industries*

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Abstract

Empirical studies have found high correlation between entry and exit across industries, indicating that industries differ substantially in their degree of firm turnover. I propose a computational model of dynamic oligopoly with entry and exit in a turbulent technological environment. I examine how industry-specific factors give rise to across industries differences in turnover. An analysis of the endogenous relationships between firm turnover, industry concentration, and the performance variables shows: 1) the rate of turnover and industry concentration are positively related; 2) industry concentration and market price are positively related; 3) no general relationship exists between industry concentration and price-cost margin. (JEL: L10)

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1 Introduction

The traditional empirical literature in industrial organization consists of many cross-sectional studies that focus on the relationship between the market structure and performance across industries [Caves (2007)]. Due to the problem of data availability, these studies were restricted to cross-sectional approaches using structural measures and performance measures that were constructed from data at a point in time.[1] Some improvements were made by researchers through their attempts to construct panel data base and address the stability of such relationships over time [Domowitz, Hubbard, and Petersen (1986)]. Nevertheless, without a good understanding of the linkage between the dynamics of firm turnovers and the endogenous market structure, these studies offered only a partial understanding of the organization of industries at best. Recognizing this gap, more recent studies such as Dunne, Roberts, and Samuelson (1988) utilized the Census of Manufactures data for U.S. manufacturing over the period 1962-1982 to provide a more complete picture of industry dynamics. In particular, with respect to the regularities involving firm entry and exit, they conclude:

> "... we find substantial and persistent differences in entry and exit rates across industries. Entry and exit rates at a point in time are also highly correlated across industries so that industries with higher than average entry rates tend to also have higher than average exit rates. Together these suggest that industry-specific factors play an important role in determining entry and exit patterns."

Baldwin (1995) is another attempt at exploring the internal dynamics of industries on a broad cross-sectional basis using the panel data from the Canadian manufacturing sector that track the movements of firms over time. The main contributions of these recent efforts have been to shed light on the significant role that firm turnovers play in the evolutionary dynamics of industries and to establish a rich set of empirical regularities involving firm turnovers and market structure over time and across industries.[2]

The theoretical literature developed somewhat separately from the empirical literature. The earliest group of models involved static oligopoly models with fixed number of firms or with free entry. While these were adequate for providing a simple game-theoretic foundation for the conventional cross-sectional studies of structure and performance, they lacked the ability to directly explore the dynamics of firm entry and exit and their impact on the evolution of industries. A small group of more recent models focused on the shakeout phenomenon in infant industries, trying to support the emergence of such phenomenon as an equilibrium of a dynamic game in which optimizing firms make entry and exit decisions with perfect foresight [Jovanovic and MacDonald (1994), Klepper and Graddy (1990)].[3] Another recent class of models involve computing Markov Perfect Equilibrium (MPE) of dynamic oligopoly games that entail entry and exit by firms [Pakes and McGuire (1994), Ericson and Pakes (1995)]. The MPE models are potentially capable of addressing the class of dynamic issues that are of interest in this paper, while maintaining the standard assumption of perfect rationality and perfect foresight on the part of firms' decision making. The problem is, however, that these models suffer from the curse of dimensionality and are often unable to compute the equilibrium for industries that contain

[1] For comprehensive reviews of this early literature, see Weiss (1974) and Scherer (1980).

[2] See Caves (1998) for an excellent survey of this literature.

[3] For empirical evidences on the "shakeout" phenomenon, see Gort and Klepper (1982), Klepper and Simons (1997, 2000a, 2000b) and Klepper (2002). For a computational exploration, see Chang (2009).

more than a few firms. If one is interested in generating outputs that can match real industry data, this is a serious drawback.

What is needed, then, is a dynamic model of industry competition that is capable of generating the various empirical regularities on firm turnovers and market structure over time and across industries, while also having a sufficiently wide scope to be able to identify the causes of the inter-industry differences in the extent of these regularities. This paper is motivated by these challenges. The model I propose is a computational one that permits a comprehensive study of the internal dynamics of industries with heterogeneous firms. The model features entry and exit by firms, continual innovations in production technologies, and market competition based on heterogeneous cost positions of firms resulting from divergent technology choices. The critical feature of the model is the turbulent nature of the technological environment within which these actions take place. Using this model, I am able to track the development of an industry from the moment of its birth to full maturity, even though the main focus is on the long-run behavior of firms in the mature industry that has attained a steady state throughout the course of repeated entries and exits of firms.[4] The model generates persistent series of entries and exits even when an industry has attained a steady state. Such movements of firms are induced by the external shocks applied to the technological environment within which firms carry out their production. A sudden and unexpected change in technological environment induces exits by unfortunate incumbents, who are then replaced by new entrants who find the new environment hospitable given their initial endowment of production technologies. With this model I investigate the within-industry time-series properties of the turnover variables, as well as the underlying causes of the cross-industry differences in the long-run average behavior of the relevant endogenous variables including the rate of firm turnovers, market concentration, and industry price-cost margin. The latter investigation allows me to explain the cross-sectional turnover-structure-performance relationship as an endogenous outcome of the competitive industry dynamics.

To briefly summarize the findings of this study, the time series results on firm entry and exit and the endogenous performance variables show: 1) the contemporary rates of entry and exit are positively correlated; and 2) the rates of entry and exit are positively correlated with market price, but negatively correlated with the industry price-cost margin (PCM). Hence, the period with a higher rate of turnover is likely to have a higher market price but a lower industry PCM. The cross-sectional properties are inferred from the steady-state outputs of the endogenous variables for when the relevant parameters that capture industry-specific factors have different values. These parameters consist of those that capture the exogenously specified structure of the industry (fixed cost and market size) and those that capture the firms' potential to adapt to changing technological environment (rate of change in technological environment and firms' propensity to innovate). I find that each parameter has the same qualitative impact on the rates of firm entry and exit, industry concentration, and market price, but *not* on the industry PCM. As such, an industry with a high entry rate is also likely to have a high exit rate (and thus be categorized as a high turnover industry); and a high turnover industry is likely to have a high concentration and have a high market price. No such general conclusion is possible in terms of the relationship between the industry concentration and the industry PCM.

The contribution of this study is twofold. First, it offers a comprehensive model of industry evolution which has the potential to integrate the divergent research agenda from the existing literature. Of particular importance is the model's capacity to combine, in a unifying framework,

[4] A similar model was used in Chang (2009), but with the focus exclusively on the study of the intial shakeout phase of the industries. The technological environment was also assumed to be stable, contrary to the current model which assumes persistent technology shocks.

the insights from the cross-sectional studies of turnover-structure-performance relationships and the time-series studies of firm turnovers. By using the computational model to generate and track the relevant firm-level and industry-level outputs over time, I am able to engage in detailed comparative dynamics analyses and identify relationships between industry-specific factors and the long-run industry behavior.

Second, it shows that many stylized empirical facts on industrial dynamics can be replicated using a computational model that specifies a set of rather simple decision rules for the firms.[5] The standard neoclassical firms with perfect rationality and perfect foresight are replaced with myopic firms who are motivated mainly by static profits based on limited information about the competitive environment.[6] These firms, however, are adaptive in that they engage in technological innovations which allow them to learn about new ways to improve their production efficiency and the consequent profits. I view this departure from the usual assumption of dynamic optimization as being worthwhile, as it allows me to devote a substantial amount of available computational resource to tracking and analyzing the movements of those variables that capture the state of the market and the adaptive behavior of the firms in the industry. This should be contrasted to the MPE models which must devote substantial amounts of computing resources to solving individual firm's dynamic optimization problem in a recursive manner. By giving up the perfect foresight assumption, I am then able to re-allocate the computing resources thus released to tracking and describing the movements of firms in and out of the market in realistic details. The validity of the model is then shown by its ability to replicate the well-known regularities in the empirical literature.

The next section describes the model in detail. This is followed by a discussion in Section 3 of how the computational experiments are designed and executed. Section 4 describes the results from a representative replication using the baseline parameter values. Section 5 reports the time series properties of the turnover variables within industries. How the industry-specific factors affect the steady state properties of the endogenous variables is discussed in Section 6. The implications of the steady-state properties on the endogenous relationships between turnover, structure, and performance are discussed in Section 7. Section 8 provides the concluding remarks.

2 The Model

The model entails a repeated oligopoly competition with firm entry and exit, where firms are subjected to externally generated turbulence in technological environment. Two aspects of the model distinguish it from other economic models of industry dynamics: 1) how technology is defined and 2) how turbulence in technological environment is modeled. The unique approach taken here allows me to model the process of innovation as that of adaptive search guided by a

[5] See Tesfatsion and Judd (2006) for comprehensive and up-to-date reviews of models that use similar approaches.

[6] As Kirzner (1973) states: "We see the market as made up, during any period of time, of the interacting decisions of consumers, entrepreneur-producers, and resource owners. Not all the decisions in a given period can be carried out, since many of them may erroneously anticipate and depend upon other decisions which are in fact not being made... [E]ven without changes in the basic data of the market (i.e., in consumer tastes, technological possibilities, and resource availabilities), the decisions made in one period of time generate systematic alterations in the corresponding decisions for the succeeding period. Taken over time, this series of systematic changes in the interconnected network of market decisions constitutes the market process. The market process, then, is set in motion by the results of the initial market-ignorance of the participants." [pp.9-10] The modelling of firms and industry evolution in this paper takes this view of "competition as a process" seriously and offers a way to explore such a process in an explicit and sytematic fashion.

hill-climbing algorithm. I start by describing the specific way in which production technology is modeled before moving on to other aspects of the market process.

2.1 Technology

Each period, firms engage in market competition by producing and selling a homogeneous good. The good is produced through a process that consists of N distinct tasks. Each task can be completed using one of several different methods. Even though all firms produce a homogeneous good, they may do so using different combinations of methods for the N component tasks. The method chosen by a firm for a given task is represented by a sequence of n bits (0 or 1) such that there are 2^n possible methods available for each task and thus $2^{N \cdot n}$ different variants of the production technology.

In period t, a firm i's *technology* is then fully characterized by a binary vector of $N \cdot n$ dimensions which captures the complete set of methods it uses to produce the good. Denote it by $\underline{z}_i^t \in \{0,1\}^{N \cdot n}$, where $\underline{z}_i^t \equiv (\underline{z}_i^t(1), ..., \underline{z}_i^t(N))$ and $\underline{z}_i^t(h)$ is firm i's chosen method in task $h \in \{1, ..., N\}$ in period t such that $\underline{z}_i^t(h) \equiv (z_i^t(h,1), ..., z_i^t(h,n)) \in \{0,1\}^n$. An example with $N = 24$ and $n = 4$ is given below:

task (h) :	#1	#2	#3	$\cdots\cdots$	#24
task methods ($\underline{z}_i^t(h)$):	1101	0010	1001	$\cdots\cdots$	1110

Note that there are $16(= 2^4)$ different methods (or bit configurations) for each task. What is shown above for a given task represents a particular method chosen out of the 16 available methods. Given that the production process is completely described by a vector of $96(= 24 \times 4)$ bits, there are then 2^{96} possible bit configurations (and, hence, 2^{96} possible technologies) for the overall production process.

In measuring the degree of heterogeneity between two technologies (i.e., method vectors), $\underline{z}_i$ and $\underline{z}_j$, we shall use "Hamming distance," which is defined as the number of positions for which the corresponding bits differ:

$$D(\underline{z}_i, \underline{z}_j) \equiv \sum_{h=1}^{N} \sum_{k=1}^{n} |z_i(h,k) - z_j(h,k)| \, . \tag{1}$$

In order to represent the technological environment that prevails in period t, I specify a unique methods vector, $\widehat{\underline{z}}^t \in \{0,1\}^{N \cdot n}$, which is defined as the *optimal* technology for the industry in t. How well a firm's chosen technology performs depends on how close it is to the prevailing optimal technology in the technology space. More specifically, the marginal cost of firm i realized in period t is a direct function of $D(\underline{z}_i^t, \widehat{\underline{z}}^t)$, the Hamming distance between the firm's chosen technology, $\underline{z}_i^t$, and the prevailing optimal technology, $\widehat{\underline{z}}^t$. The firms are uninformed about $\widehat{\underline{z}}^t$ *ex ante*, but engage in search to get as close to it as possible by observing its actual profit which depends on its marginal cost. The optimal technology is common for all firms. As such, once it is defined for a given industry, its technological environment is completely specified for all firms since the performance of any technology (which may be chosen by a firm) is well-defined as a function of its distance to this optimal technology.

I allow turbulence in the technological environment. Such turbulence is assumed to be caused by factors external to the industry in question. An obvious example is a technological innovation that originates from outside of the given industry. Consider, for instance, two different industries that are linked together in a supply chain. The firms in the upstream industry supply essential inputs to the firms in the downstream industry. When the upstream firms adopt new technological innovations that affect their production and delivery of the inputs to the downstream firms, the firms in the downstream industry may experience sudden changes in their bargaining positions and their production environment. Existing mechanisms for coordinating the flow of materials in the supply chain may no longer be as effective and the firms may have to reconfigure their activities and/or adopt certain equipment in order to remain viable in the downstream market. How smooth such an adjustment will be for a firm depends on what its prior mode of operation was and how the external shock has affected its competitive position relative to other firms in the market.[7]

How an externally generated innovation can lead to major re-configuration of firms' activities can be seen from the experience in the 1990s of the economy-wide revolution in information technology (IT). The rapid diffusion of IT is often said to have caused major changes in the way businesses conduct their daily routines. For instance, Bresnahan, Brynjolfsson, and Hitt (1999) found that the use of IT is correlated with a new workplace organization that includes broad job responsibilities for line workers, more decentralized decision making, and more self-managing teams. Bartel, Ichniowski, and Shaw (2007) claim that plants that adopted new IT-enhanced equipment also shifted their business strategies through more frequent product switching and greater product customization, while adopting human resource practices that support increased technical and problem-solving skills. That technology shocks can rearrange the cost positions of the firms and reverse their fortunes can be seen in Brynjolfsson, McAfee, Sorell, and Zhu (2008), in which they report that IT-intensive industries accounted for most of the increase in industry-level turbulence from 1987 to 2006, where turbulence is measured as the average size of rank changes of all firms in the industry from one period to next.

These findings then indicate: 1) external technology shocks tend to *redefine* firms' production environment; and 2) such environmental shifts affect the cost positions of the firms in the competitive marketplace by changing the effectiveness of the methods they use in various activities within the production process. These unexpected disruptions pose renewed challenges for the firms in their efforts to adapt and survive. It is precisely this kind of external shocks that I try to capture in this paper. My approach is to allow the optimal technology, $\underline{\hat{z}}^t$, to vary from one period to the next, where the frequency and the magnitude of its movement represent the degree of turbulence in the technological environment. The exact mechanism through which this is implemented will be described later in Section 2.4 which covers the dynamic structure of the model.

Finally, in any given period t, the optimal technology is unique. While the possibility of multiple optimal technologies is a potentially interesting issue, it is not explored here because in a turbulent environment, where the optimal technology is constantly changing, it is likely to be of negligible importance.[8]

[7] An externally generated innovation can also be viewed as a shock that affects the relative input prices for the firms. If firms, at any given point in time, are using heterogeneous production processes with varying mix of inputs, such a change in input prices will have diverse impact on the relative efficiencies of firms' production processes – some may benefit from the shock; some may not. Such an external shock will then require (with varying degrees of urgency) a series of adaptive moves by the affected firms for their survival.

[8] Chang (2009) offers an alternative approach by modeling the technological environment as being stable but with multiple locally optimal technologies. The main focus is on the industry dynamics during the initial shakeout phase, where one of the objectives was to investigate the impact of multiple optima on the shakeout dynamics. In the current paper, I am more interested in the turnover dynamics along the steady-state path in the presence of technological turbulence. As such, I abstract away from the possibility of multiple local optima.

2.2 Demand and Cost

In each period, there exists a finite number of firms that operate in the market. In this sub-section and the next, I define the static market equilibrium among such operating firms. The static market equilibrium defined here is then used to approximate the outcome of market competition in each period. In this sub-section and the next, I will temporarily abstract away from the time superscript for ease of exposition.

Let m be the number of firms operating in the market. The firms are Cournot oligopolists, who choose production quantities of a homogenous good. In defining the Cournot equilibrium in this setting, I assume that all m firms produce positive quantities in equilibrium.[9] The inverse market demand function is specified to be

$$P(Q) = a - \frac{Q}{s}, \tag{2}$$

where $Q = \sum_{j=1}^{m} q_j$ and s denotes the size of the market.[10]

Each operating firm has its production technology, $\underline{z}_i$, and faces the following total cost function:

$$C(q_i) = f_i + c_i \cdot q_i. \tag{3}$$

Hence, f_i is the fixed cost of production for firm i, while c_i is its marginal cost. As mentioned above, the firm's marginal cost depends on how different its technology, $\underline{z}_i$, is from the optimal technology, $\widehat{\underline{z}}$. Specifically, c_i is defined as follows:

$$c_i(\underline{z}_i, \widehat{\underline{z}}) = 100 \cdot \frac{D(\underline{z}_i, \widehat{\underline{z}})}{N \cdot n}. \tag{4}$$

c_i is, hence, an increasing function of the Hamming distance between the firm's chosen technology and the optimal technology for the industry. The marginal cost is at its minimum of zero when $\underline{z}_i = \widehat{\underline{z}}$, while it is at the maximum of 100 when all $N \cdot n$ bits in the two technologies are different from one another. Given the expression for c_i, the total cost can be re-written as:

$$C(q_i) = f_i + 100 \cdot \frac{D(\underline{z}_i, \widehat{\underline{z}})}{N \cdot n} \cdot q_i. \tag{5}$$

2.3 Cournot Equilibrium with Asymmetric Costs

Given the inverse market demand function and the firm cost function, firm i's profit is:

$$\pi_i(q_i, Q - q_i) = \left(a - \frac{1}{s} \sum_{j=1}^{m} q_j \right) \cdot q_i - f_i - c_i \cdot q_i \tag{6}$$

For simplicity, the firms are assumed to have identical fixed cost so that $f_1 = f_2 = ...f_m \equiv f$.

The first-order conditions for profit maximization are

$$a - \frac{1}{s} \left(\sum_{j=1}^{m} \overline{q}_j + \overline{q}_i \right) - c_i = 0 \tag{7}$$

[9] In actuality, there is no reason to suppose that in the presence of asymmetric costs all m firms will produce positive quantities in equilibrium. Some of these firms may become *inactive* by producing zero quantity. The algorithm used to distinguish among active and inactive firms based on their production costs will be addressed in a later section.

[10] This funtion can be inverted to $Q = s(a - P)$. For a given market price, doubling the market size then doubles the quantity demanded.

$\forall i \in \{1, ..., m\}$, where the output vector in Cournot equilibrium is $(\overline{q}_1, \overline{q}_2, ..., \overline{q}_m)$. Adding the first-order conditions for all firms yields

$$m \cdot a - \frac{m}{s}\sum_{j=1}^{m}\overline{q}_j - \frac{1}{s}\sum_{j=1}^{m}\overline{q}_j = \sum_{j=1}^{m} c_j \tag{8}$$

Dividing both sides by m and simplifying, we get

$$\sum_{j=1}^{m}\overline{q}_j = s\left[a\left(\frac{m}{m+1}\right) - \left(\frac{1}{m+1}\right)\sum_{j=1}^{m} c_j\right] \tag{9}$$

Hence, the equilibrium market output (and the equilibrium market price) depends only on the *sum* of the marginal costs and not on the *distribution* of c_is [Bergstrom and Varian (1985)]. Using the inverse demand function, one can then write the equilibrium market price as $\overline{P}$:

$$\overline{P} = \left(\frac{1}{m+1}\right)\left(a + \sum_{j=1}^{m} c_j\right). \tag{10}$$

Given the vector of marginal costs defined by the firms' chosen technologies and the optimal technology, $\overline{P}$ is then uniquely determined and is independent of the market size, s. Furthermore, from the first order condition for each firm one can express the Cournot equilibrium output rate as

$$\overline{q}_i = s\left[\left(\frac{1}{m+1}\right)\left(a + \sum_{j=1}^{m} c_j\right) - c_i\right] \tag{11}$$

$$= s\left[\overline{P} - c_i\right] \tag{12}$$

$\forall i \in \{1, ..., m\}$. A firm's equilibrium output rate depends on its own marginal cost and the equilibrium market price. The Cournot equilibrium firm profit is

$$\pi(\overline{q}_i) = \overline{P} \cdot \overline{q}_i - f - c_i \cdot \overline{q}_i \tag{13}$$

$$= \left(\overline{P} - c_i\right)\overline{q}_i - f$$

$$= \frac{1}{s}\left(\overline{q}_i\right)^2 - f \tag{14}$$

Note that $\overline{q}_i$ is a function of c_i and $\sum_{j=1}^{m} c_j$, while c_k is a function of $\underline{z}_k$ and $\widehat{z}$ for all k. It is then straightforward that the equilibrium firm profit is fully determined, once the vectors of methods for all firms are known. Further note that $c_i \leq c_k$ implies $\overline{q}_i \geq \overline{q}_k$ and, hence, $\pi(\overline{q}_i) \geq \pi(\overline{q}_k) \forall i, k \in \{1, ..., m\}$.

It is useful to consider what implications this static model of Cournot oligopoly has on the long-run free-entry equilibrium when firms have homogeneous marginal costs. Assuming $c_i = \overline{c}\ \forall i \in \{1, ..., m\}$, it is straightforward to show that $\pi(m) = s\left(\frac{a-\overline{c}}{m+1}\right)^2 - f$. The long-run equilibrium number of firms, m^*, consistent with free entry, is defined as (the integer part of) m that satisfies $\pi(m) = 0$ such that

$$m^* = (a - \overline{c})\sqrt{\frac{s}{f}} - 1. \tag{15}$$

Notice that m^* is positively related to the market size (s) and negatively related to the fixed cost (f). The static model with symmetric marginal costs then predicts that an industry with a larger (smaller) market size and/or a smaller (larger) fixed cost will be able to sustain a greater (fewer) number of firms under free entry. We will revisit this issue later as the model is extended to a fully dynamic version which allows for heterogeneous firm costs that evolve over time.

2.4 Dynamic Structure of the Model

Central to the model is the view that the firms engage in search for the optimal technology over time, but with limited foresight. What makes this "perennial" search non-trivial is the stochastic nature of the production environment – that is, the technology which was optimal in one period is not necessarily optimal in the next period. This is captured by allowing the optimal technology, $\widehat{\underline{z}}^t$, to vary from one period to the next in a systematic manner. The mechanism that guides the shift dynamic of the optimal technology is described below.

Consider a binary vector, $\underline{x} \in \{0,1\}^{N\cdot n}$. Define $\delta(\underline{x}, l) \subset \{0,1\}^{N\cdot n}$ as the set of points that are exactly Hamming distance l from $\underline{x}$. The set of points that are *within* Hamming distance l of $\underline{x}$ is then defined as

$$\Delta(\underline{x}, l) \equiv \bigcup_{i=0}^{l} \delta(\underline{x}, i). \tag{16}$$

Given this definition, the shift dynamic of the optimal technology is driven by the following mechanism:

$$\widehat{\underline{z}}^t = \begin{cases} \widehat{\underline{z}}' & \text{with probability } \gamma \\ \widehat{\underline{z}}^{t-1} & \text{with probability } 1-\gamma \end{cases}$$

where $\widehat{\underline{z}}' \in \Delta(\widehat{\underline{z}}^{t-1}, g)$ and γ and g are constant over all t.[11] Hence, with probability γ the optimal technology shifts to a new one that is within g Hamming distance from the current technology, while with probability $1-\gamma$ it remains unchanged at $\widehat{\underline{z}}^{t-1}$. The volatility of the technological environment is then captured jointly by γ and g, where γ is the frequency and g is the maximum magnitude of changes in technological environment. In this paper, I focus on the impact of γ, which I will refer to as "the rate of change in technological environment," while holding fixed the maximum magnitude of the change (g) at the baseline value.

The change in technological environment is assumed to take place in the beginning of each period. However, firms have no way of perceiving such changes until they engage in production which takes place only after the entry decisions and the innovation decisions have been made. Indeed, each period of the horizon consists of four stages in the way firms make decisions. Figure 1 shows the sequence of these decision stages. The main feature is that the entry decisions in stage 1 and the innovation decisions in stage 2 are made on the basis of technological conditions realized in the previous period, $\widehat{\underline{z}}^{t-1}$, while the output decisions in stage 3 and the exit decisions in stage 4 are made in the context of the current environment, $\widehat{\underline{z}}^t$, realized through production and market competition. The intuition is that the acts of entry and innovation represent commitments which must be made on the basis of incomplete information, while the output decisions (as approximated by the Cournot equilibrium output rates) are based on the *realized* production environment which surrounds the market competition in stage 3. There are then two distinct limitations on firms' rationality in this model. One, firms are short-sighted and make their decisions on the basis of the projected performance in the current period only. Two,

[11] In the computational implementation of this mechanism, I assume that $\widehat{\underline{z}}'$ is chosen on the basis of uniform distribution over all elements in $\Delta(\widehat{\underline{z}}^{t-1}, g)$.

their entry and innovation decisions are made on the basis of the technological environment that may no longer be relevant.

Given the four-stage structure, the process of intra-industry dynamics in period t starts with four groups of state variables. First, there exists a set of surviving firms from $t-1$, denoted S^{t-1}, where $S^0 = \emptyset$. The set of surviving firms includes those firms which were *active* in $t-1$ in that their outputs were strictly positive as well as those firms which were *inactive* with their plants shut down during the previous period. Let S_+^{t-1} and S_-^{t-1} denote, respectively, the set of *active* and *inactive* firms in $t-1$ such that $S_+^{t-1} \equiv \{\text{all } j \in S^{t-1} | q_j^{t-1} > 0\}$ and $S_-^{t-1} \equiv \{\text{all } j \in S^{t-1} | q_j^{t-1} = 0\}$, where $S_+^{t-1} \cup S_-^{t-1} = S^{t-1}$. The inactive firms in $t-1$ survive to t if and only if they have sufficient net capital to cover their fixed costs in $t-1$.

Second, each firm $i \in S^{t-1}$ possesses a production technology, $\underline{z}_i^{t-1}$, carried over from $t-1$, which gave rise to its marginal cost of c_i^{t-1} as defined in equation (4). In addition, the previous period's optimal technology $\widehat{\underline{z}}^{t-1}$ is carried over to period t since firms perceive the technological environment to remain the same as they make their entry decisions and innovation decisions prior to the opening of the market in t.

Third, each firm $i \in S^{t-1}$ has a current net capital of w_i^{t-1} which it carries over from $t-1$. The net capital is adjusted at the end of each period on the basis of the economic profit earned (which adds to it) or loss incurred (which subtracts from it) by the firm. It is this net capital which ultimately determines the firm's viability in the market.

Finally, there is a finite set of *potential* entrants, R^t, who contemplate entering the industry in the beginning of t. In this paper, we assume that the size of the potential entrants pool is fixed and constant at r throughout the entire horizon. We also assume that this pool of r potential entrants is renewed fresh each period. Each potential entrant k in R^t is endowed with a technology, $\underline{z}_k^t$, randomly chosen from $\{0,1\}^{N \cdot n}$ according to uniform distribution. Associated with the chosen technology is its marginal cost of c_k^t for all $k \in R^t$.

The definitions of the set notations introduced in this section and used throughout the paper are summarized in Table 1.

2.4.1 Stage 1: Entry Decisions

In stage 1 of each period, the potential entrants in R^t first make their decisions to enter. This decision depends on the profit that it expects to earn in t following entry, which is influenced by two beliefs: 1) the technological environment that prevailed in $t-1$ will continue to prevail in t; and 2) if it enters, its profit will be the static Cournot equilibrium profit based on the marginal costs of the active firms from $t-1$ and itself as the only new entrant in the market.[12] That the potential entrants would assume that they will be the only firm to enter if they find it profitable to do so is clearly a strong assumption. Nevertheless, this assumption is made for two reasons. First, it has the virtue of simplicity. Second, Camerer and Lovallo (1999) provides some support for this assumption by showing in an experimental setting of business entry that most subjects who enter tend to do so with overconfidence and excessive optimism. Furthermore, they find that "Excess entry is much larger when subjects volunteered to participate knowing that payoffs would depend on skill. These self-selected subjects seem to neglect the fact that they are competing with a reference group of subjects who all think they are skilled too."

[12] This requires: 1) a potential entrant is able to (correctly) perceive its own marginal cost from its chosen technology and the previous period's optimal technology; and 2) the market price and the active firms' production quantities in $t-1$ are common knowledge. Each active incumbent's marginal cost can be directly inferred from the market price and the production quantities as clearly shown in equation (12)

The decision rule of a potential entrant $k \in R^t$ is then:

$$\begin{cases} \text{Enter,} & \text{if and only if } \pi_k^e(\underline{z}_k^t) + b > 0, \\ \text{Do not enter,} & \text{otherwise,} \end{cases} \tag{17}$$

where π_k^e is the static Cournot equilibrium profit the entrant expects to make in the period of its entry and b is the fixed "start-up capital" common to all new entrants. The start-up capital may be viewed as a firm's available fund that remains after paying for the one-time set-up cost of entry.[13] For example, if one wishes to consider a case where a firm has zero fund available, but must incur a positive entry cost, it would be natural to consider b as having a strictly negative value.

Once every potential entrant in R^t makes its entry decision on the basis of the above criterion, the resulting set of *actual* entrants, $E^t \subseteq R^t$, contains only those firms with sufficiently efficient technologies which will guarantee some threshold level of profits given its beliefs about the market structure and the technological environment. Denote by M^t the set of firms ready to compete in the industry: $M^t = S^{t-1} \cup E^t$. We will denote by m^t the number of competing firms in period t such that $m^t = |M^t|$.

The entry decision rule indicates that an outsider will be attracted to enter the industry if and only if it is convinced that its net capital following entry will be strictly positive. Just as each firm in S^{t-1} has its current net capital of w_i^{t-1}, we will let $w_j^{t-1} = b$ for all $j \in E^t$. At the end of stage 1 of period t, we then have a well-defined set of competing firms, M^t, and the current net capital for all firms in that set, $\{w_i^{t-1}\}_{\forall i \in M^t}$.

2.4.2 Stage 2: Innovation Decisions

In stage 2, the surviving incumbents from $t-1$ – i.e., all active and inactive firms in S^{t-1} – engage in innovation in order to improve the efficiency of their existing technologies. Given that the new entrants in E^t entered with new technologies, they do not engage in innovation in t.

Each surviving incumbent in t gets *one* chance to innovate in that period with probability λ. With probability $(1-\lambda)$, it does not get the opportunity to innovate, in which case $\underline{z}_i^t = \underline{z}_i^{t-1}$. The opportunity, if it comes, comes at zero cost. λ then captures the exogenously specified firm's propensity (common to all firms in the industry) to innovate. This propensity may be determined by the institutions exogenous to the market competition or by the prevailing culture of innovation within the industry that is not specified in the model. From here on, I will refer to λ as the "propensity to innovate."

"Innovation" is said to occur when a firm with a given technology ($\underline{z}_k^{t-1}$) randomly picks one of its N tasks and considers for implementation an alternative method (randomly chosen out of 2^n potential methods) for that task. Implementing a new method is assumed to be costless, but it is limited to only one task at a time. Limiting innovation to a change in only one task is consistent with the assumption of bounded rationality. The firms are viewed as being purposive – i.e., they seek improvements in their positions – but are certainly not global optimizers. Let $\widetilde{\underline{z}}_k^t$ denote firm k's vector of experimental methods (i.e., a technology considered for potential

[13] The size of the one-time cost of entry is not directly relevant for our analysis. It may be zero or positive. If it is zero, then b is the excess fund the firm enters the market with. If it is positive, then b is what remains of the fund after paying for the cost of entry.

adoption) obtained through innovation. The adoption decision rule is as follows:

$$\underline{z}_k^t = \begin{cases} \underline{\widetilde{z}}_k^t, & \text{if and only if } c_k(\underline{\widetilde{z}}_k^t, \underline{\widehat{z}}^{t-1}) < c_k(\underline{z}_k^{t-1}, \underline{\widehat{z}}^{t-1}), \\ \underline{z}_k^{t-1}, & \text{otherwise,} \end{cases} \tag{18}$$

A proposed technology is adopted by a firm if and only if it lowers the marginal cost below the level attained with the current technology the firm carries over from the previous period.[14] This happens when the Hamming distance to the perceived optimal technology is lower with the proposed technology than with the current technology. Notice that this condition is equivalent to a condition on the firm profitability. When an incumbent firm takes all other incumbent firms' marginal costs as given, the only way that its profit is going to improve is if its marginal cost is reduced as the result of its innovation.

For concreteness, consider an example of a production process with 5 tasks ($N = 5$), the method for each task being represented with 4 bits ($n = 4$). Hence, there are 16 different methods for each task. Let us suppose that firm i currently has the following technology:

task (h) :	#1	#2	#3	#4	#5
firm i's technology ($\underline{z}_i^{t-1}(h)$):	1101	0010	1000	1001	1010

and the optimal technology from $t-1$ is:

task (h) :	#1	#2	#3	#4	#5
optimal technology ($\underline{\widehat{z}}^{t-1}(h)$):	1101	1110	1101	0101	1111

Further suppose that firm i had a chance to innovate and (randomly) chose task #3 as the target. It may decide to try another method "1100" rather than the current "1000" for that task. The experimental method under consideration, call it $\underline{\widetilde{z}}_i^t(h)$, is then:

task (h) :	#1	#2	#3	#4	#5
firm i's experimental technology ($\underline{\widetilde{z}}_i^t(h)$):	1101	0010	1100	1001	1010

With the original technology, $\underline{z}_i^{t-1}(h)$, the Hamming distance to the optimal technology, $\underline{\widehat{z}}^{t-1}(h)$, is 8 (and the marginal cost is 40) while with the experimental technology, $\underline{\widetilde{z}}_i^t(h)$, it is 7 (and the marginal cost is 35) Hence, this represents a gain in efficiency and firm i adopts the experimental technology – i.e., $\underline{z}_i^t = \underline{\widetilde{z}}_i^t$.

2.4.3 Stage 3: Output Decisions and Market Competition

Given the innovation decisions made in stage 2 by the firms in S^{t-1}, all firms in M^t now have the updated technologies $\{\underline{z}_i^t\}_{\forall i \in M^t}$ as well as their current net capital $\{w_i^{t-1}\}_{\forall i \in M^t}$. Given these updated technologies, the firms engage in Cournot competition in the market, where we "approximate" the outcome with the Cournot equilibrium defined in Section 2.3.[15] Once the

[14] I assume that the evaluation of the technology by a firm in terms of its production efficiency (and the consequent marginal cost) is done with perfect accuracy. While this assumption is clearly unrealistic, it is made to avoid overloading the model which is already substantially complicated.

[15] Given the "limited rationality" assumption employed in this paper, I admit to the use of Cournot-Nash equilibrium as being inconsistent with it conceptually. A more consistent approach would have been to explicitly model the process of market experimentation. Instead of modelling this process, which would further complicate an already complex model, I implicitly assume that it is done instantly and without cost. Cournot-Nash equilibrium is then assumed to be a reasonable approximation of the outcome from that process. In further defense of its use, I

market opens for competition and production commences, the new technological environment, $\widehat{\underline{z}}^t$, is realized, so the *actual* profits for the firms are now computed on the basis of $\widehat{\underline{z}}^t$.

Note that the equilibrium in Section 2.3 was defined for m firms who were assumed to produce positive quantities in equilibrium. In actuality, given the asymmetric costs, there is no reason to think that all m^t firms will produce positive quantities in equilibrium. Some relatively inefficient firms may shut down their plants and stay inactive. What we need is then a mechanism for identifying the set of *active* firms out of M^t such that the Cournot equilibrium among these firms will indeed entail positive quantities only. This is accomplished in the following sequence of steps. Starting from the initial set of active firms, compute the equilibrium outputs for each firm. If the outputs for one or more firms are negative, then de-activate the least efficient firm from the set of currently active firms – i.e., set $q_i^t = 0$ where i is the least efficient firm. Redefine the set of active firms (as the previous set of active firms minus the de-activated firms) and recompute the equilibrium outputs. Repeat the procedure until all active firms are producing non-negative outputs. Each *inactive* firm produces zero output and incurs the economic loss equivalent to its fixed cost. Each *active* firm produces its Cournot equilibrium output and earns the corresponding profit. We then have π_i^t for all $i \in M^t$.

2.4.4 Stage 4: Exit Decisions

Given the single-period profits or losses made in stage 3 of the game, the incumbent firms in M^t consider exiting the industry in the final stage. The incumbent firms' net capital levels are first updated on the basis of the profits (or losses) made in t:

$$w_i^t = w_i^{t-1} + \pi_i^t. \tag{19}$$

The exit decision rule for each firm is:

$$\begin{cases} \text{Stay in} & \text{iff } w_i^t \geq d, \\ \text{Exit} & \text{otherwise,} \end{cases} \tag{20}$$

where d is the threshold level of net capital such that all firms with their current net capital below d exit the market. Once the exit decisions are made by all firms in M^t, the set of surviving firms from period t is then defined as:

$$S^t \equiv \{\text{all } i \in M^t | w_i^t \geq d\}. \tag{21}$$

I denote by L^t the set of firms which have decided to leave the industry:

$$L^t \equiv \{\text{all } i \in M^t | w_i^t < d\}. \tag{22}$$

The set of surviving firms, S^t, their current technologies, $\{\underline{z}_i^t\}_{\forall i \in S^t}$ and their current net capital, $\{w_i^t\}_{\forall i \in S^t}$, as well as the current optimal technology, $\widehat{\underline{z}}^t$, are then passed on to $t+1$ as state variables.

refer the readers to a small body of literature, in which experimental studies are conducted to determine whether firm behavior indeed converges to the Cournot-Nash equilibrium via best-reply dynamic. In their pioneering work, Fouraker and Siegel (1963) conducted experiments with participants who took the role of the quantity-adjusting Cournot oligopolists under incomplete information. They did find that the Cournot-Nash equilibrium was supported in many trials for the cases of duopoly and triopoly. Similarly, Cox and Walker (1998), using linear demand and contant marginal cost in Cournot duopoly, found that, if a stable equilibrium exists, then the participants in their experiments learn to play the Cournot-Nash equilibrium after only a few periods. Even though best reply dynamics do not necessarily converge in oligopolies with more than three firms [Theocharis (1960)], Huck, Normann, and Oechssler (1999) finds that the best reply process does converge if firms are assumed to exhibit some *inertia* in their choice of strategy.

3 Design of Computational Experiments

The values of the parameters used in this paper, including those for the baseline simulation, are provided in Table 2.[16] I assume that there are 24 separate tasks in the production process, where the method chosen for each task is represented by a 4-bit string. This implies that there are $2^4 (= 16)$ different methods for each task and $2^{96} (\cong 8 \times 10^{28})$ different combinations of methods for the complete production process. In each period, there are exactly 40 potential entrants who consider entering the industry, where a new firm enters with a start-up capital of 0. An incumbent firm will exit the industry, if his net capital falls below the threshold rate of 0. The demand intercept is fixed at 300. The maximum magnitude of a change in technological environment is 8 – that is, the Hamming distance between the optimal technologies at $t-1$ and at t can not be more than 8 bits. The time horizon is over 5,000 periods, where in period 1 the market starts out empty.

There are four parameters that are the focus of my analysis. The first two are the fixed cost of production, f, and the size of the market, s. The other two are the rate of change in technological environment, γ, and the propensity to innovate, λ. Note that f and s are the *structural* determinants of the market equilibrium, where lower (higher) values of f and higher (lower) values of s imply an industry with a capacity to sustain a greater (smaller) number of firms. [See Figure 2(a).] On the other hand, γ and λ determine the dynamic capability of firms to adapt to changing technological environment. For instance, a higher value of γ reflects more frequent changes in technological environment, which makes it tougher for firms to adapt given a fixed level of λ. On the other hand, a higher value of λ, given a fixed rate of γ, provides the firms with a potential to quickly adapt to the changing environment. As such, a lower value of γ and a higher value of λ imply an industry with a greater *adaptive potential*, while a higher value of γ and a lower value of λ imply one with lower adaptive potential. [See Figure 2(b).]

I consider four different values for each of these four parameters: $f \in \{100, 200, 300, 400\}$; $s \in \{4, 6, 8, 10\}$; $\gamma \in \{.1, .2, .3, .4\}$; $\lambda \in \{.25, .5, .75, 1\}$. The baseline values are chosen to be: $f = 100$; $s = 4$; $\gamma = 0.1$; and $\lambda = 0.5$. In carrying out the cross-industry analysis, I consider different values for a given parameter, while holding all other parameters at their baseline values.

Given a configuration of parameters, I track the movements of the following endogenous variables:

- $|E^t|$: number of firms actually entering the industry in the beginning of period t
- $|M^t| (= m^t)$: number of firms that are in operation in period t (including both active and inactive firms)
- $|L^t|$: number of firms leaving the industry at the end of period t[17]
- $|S^t|$: number of firms surviving at the end of period t $(= |M^t| - |L^t|)$
- P^t: market price at which goods are traded in period t
- $\{c_i^t\}_{\forall i \in M^t}$: realized marginal costs of all firms that were in operation in period t
- $\{q_i^t\}_{\forall i \in M^t}$: actual outputs of all firms that were in operation in period t

[16] The source code for the computational experiments was written in C^{++} and the simulation outputs were analyzed and visualized using Mathematica 7.0. The source code is available upon request from the author.

[17] I also collect the "ages" of all firms that exit the industry over the entire horizon.

I also construct an additional group of variables to facilitate the inter-industry comparisons later on. First, note that the two structural parameters, f and s, are likely to have significant influence on the number of firms that a given industry can sustain in the long run. Since the magnitude of firm turnovers must be viewed in relation to the size of the industry, I construct the *rates* of entry and exit, ER^t and XR^t, which are, respectively, the number of new entrants and the number of exiting firms as the fractions of the total operating firms in period t:

$$ER^t = \frac{|E^t|}{|M^t|} \text{ and } XR^t = \frac{|L^t|}{|M^t|}. \tag{23}$$

In order to measure the industry concentration, I use the Herfindahl-Hirschmann Index, H^t, which is

$$H^t = \sum_{\forall i \in M^t} \left(\frac{q_i^t}{\sum_{\forall j \in M^t} q_j^t} \cdot 100 \right)^2. \tag{24}$$

The third variable of interest is an aggregate measure of the industry's production efficiency. For this, I construct an industry marginal cost, WMC^t, where

$$WMC^t = \sum_{\forall i \in M^t} \left[\left(\frac{q_i^t}{\sum_{\forall j \in M^t} q_j^t} \right) \cdot c_i^t \right]. \tag{25}$$

WMC^t is, hence, a weighted average of the individual firms' marginal costs in period t, where the weights are the market shares of the firms in that period. Note that a firm's marginal cost enters into this variable only if it produces a positive output. As such, the industry marginal cost only captures the level of efficiency for those firms who are sufficiently efficient to produce positive outputs.

Finally, to measure the industry's performance, I compute the usual price-cost margin. However, given the inter-firm variation in marginal costs, I construct an aggregate industry price-cost margin, PCM^t, as:

$$PCM^t = \sum_{\forall i \in M^t} \left[\left(\frac{q_i^t}{\sum_{\forall j \in M^t} q_j^t} \right) \cdot \frac{P^t - c_i^t}{P^t} \right].$$

PCM^t then measures the extent to which the prevailing market price departs from the firms' marginal cost levels, where each firm's price-cost margin is given the weight of its market share. It is a measure of the collective market power of firms and the allocative inefficiency of the industry, when firms have heterogeneous costs.

4 Representative Replication with Baseline Parameter Values

Let us start with a single representative replication based on the *baseline* parameter values as indicated in Table 2. Figure 3 captures the time paths of the five endogenous variables over the first 5,000 periods of the industry's development from its birth to full maturity: (a) the number of entrants, $|E^t|$; (b) the number of exiting firms, $|L^t|$; (c) the proportion of exiting firms that are of a given age or younger; (d) the number of operating firms, $|M^t|$; and (e) the market price, P^t. First note from Figure 3(a) the initial surge in the number of new entrants into the industry at its birth: The entire pool of potential entrants (40) jumps into the industry as it is newly born. This rush quickly slows down and the industry settles into a steady state where there are occasional entries that continue indefinitely over the horizon. Figure 3(b) shows that the initial surge of entries is immediately followed by a large number of exits, implying that a large number firms who initially entered the industry are soon forced out through a severe market competition – i.e., a "shakeout.". After the initial shakeout, the industry experiences a steady out-flow of firms that seems to accompany the steady in-flow of firms exhibited in Figure 3(a). Hence, the industry experiences a persistent series of entry and exit.

A more interesting observation is that these exits are predominantly of firms which have recently entered the industry. To see this, I examined the ages of all firms that exited between $t = 1,000$ and $t = 5,000$, excluding the exits that occurred during the initial transient phase (the first $1,000$ periods) of the industry's development.[18] There was a total of 856 exits which took place over the $4,000$ periods (the number of exits taking place over the first $1,000$ periods was 441). The ages of these 856 exiting firms ranged from 1 to 4,284. But more importantly, the age distribution was heavily right-skewed – that is, a large percentage of the firms exited at early ages. Figure 3(c) shows the proportion of the total exiting firms (856) whose ages were less than or equal to AGE on the horizontal axis. Almost 40% of the exiting firms were 10 periods or younger, while over 73% of them were 100 periods or younger. This is consistent with the "infant mortality" phenomenon often observed in the empirical data [Caves(1998), pp.1954-1959].

The continual streams of entries and exits interact to produce the time series in Figure 3(d) of the total number of operating firms, m^t, which include both the active and inactive firms. The time path shows that the number of operating firms moves with substantial volatility over time, though it moves around a steady mean ($\approxeq 70$) after about t = 1000. The corresponding time path of the market price is captured in Figure 3(e). Again, the path is volatile. The market price starts out high at the initial infant stage of the industry, but then declines sharply as the industry expands and matures, eventually reaching a steady state around $t = 1,000$, after which it fluctuates around a steady mean.

The time paths captured in Figure 3 are typical of all replications performed in this study. The time paths of interest almost always reach a steady state by $t = 3,000$ for all parameter configurations considered in this study. As such, when we examine the impact of industry-specific factors on the industry's performance, the steady-state value of an endogenous variable will be computed as an average over the two thousand periods between $t = 3,001$ and $t = 5,000$.

5 Time Series Properties along the Steady-State Path

Having examined the outputs from a typical run, I now engage in a more systematic exploration by performing multiple replications. For each parameter configuration, I have performed 500 independent replications, using a fresh sequence of random numbers for each replication. The time series values of the endogenous variables listed above were collected for the last two thousand periods from $t = 3,001$ to $t = 5,000$. These time series, hence, represent the steady-state paths of these endogenous variables. Table 3 presents the correlations between the time series of various endogenous variables, averaged over 500 replications, for each parameter configuration of (f, s, γ, λ). For ease of comparison, I change the value of one parameter at a time while holding fixed the values of all other parameters at their baseline levels.

For each parameter configuration, the first four columns in Table 3 report how the time series of the entry rate correlates with those of the exit rate, industry marginal cost, market price, and the industry price-cost margin, respectively. The next two columns show the correlations between the time series of the market price and the industry marginal cost and those between

[18] The first $1,000$ periods are excluded so as to remove the possible effects of the initial shakeout in the industry.

the time series of the market price and the industry price-cost margin. Finally, the last column reports the correlations between the time series of the industry price-cost margin and the industry marginal cost. Several patterns emerge from this table, the most relevant being the positive correlation between the contemporary rates of entry and exit for all parameter configurations, as indicated by the entries in the first column.

Property 1: The contemporary rates of entry and exit are positively correlated.

This property implies that within a given industry the period with a higher than average rate of entry is also likely to be the period with a higher than average rate of exit. This is consistent with the empirical findings in Dunne, Roberts, and Samuelson (1988). Also, note that this result is based only on the entries and exits that occurred over the last two thousand periods during which the industry is in a steady-state. Hence, this positive correlation is not just a transient phenomenon that is likely to arise during the initial shakeout period. Rather, it is a phenomenon that is observed along the industry's steady-state path. This result, together with the typical age distribution of the exiting firms in Figure 3(c), is then fully consistent with the observation of Caves (2007):

> "Turnover in particular affects entrants, who face high hazard rates in their infancy that drop over time. It is largely because of high infant mortality that rates of entry and exit from industries are positively correlated (compare the obvious theoretical model that implies either entry or exit should occur but not both). The positive entry-exit correlation appears in cross-sections of industries, and even in time series for individual industries, if their life-cycle stages are controlled." – p.9

Table 3 also shows that the rate of entry is positively correlated with the industry marginal cost. Recall that the technological environment is likely to shift with a probability of γ. Such a shift adversely affects many of the firms who have already adapted to the old environment, thereby temporarily raising the industry marginal cost. This sudden rise in industry marginal cost (in t) induces exits of the unfortunate incumbents, providing an opening for new entrants to come into the industry in $t+1$, and, hence, the positive correlation. The rise in the industry marginal cost pushes up the market price, but not enough to offset the rise in marginal cost itself. Consequently, the industry price-cost margin tends to drop. The fifth column, hence, shows that the market price is almost perfectly correlated with the industry marginal cost, but negatively correlated with the industry price cost margin.

Property 2: The rates of entry and exit are positively correlated with the market price, but negatively correlated with the industry price-cost margin.

Hence, the period of high price is actually the period of low price-cost margin for the firms. This property is driven by the fact that a shift in technological environment, in general, adversely affects the marginal costs of the firms which then leads to lower price-cost margins. The negative relationship between the industry marginal cost and the industry PCM is shown in the last column of Table 3. A high market price is then less a reflection of market power and more that of temporary inefficiency in firms' production process caused by sudden unexpected shifts in technological environment.

6 Steady-State Mean Properties Across Industries

In this section, I address the issue of how industry-specific factors affect the turnover of firms as well as their performance in the long run. The approach is to focus on the mean behavior of the relevant endogenous variables along the steady-state time path. For each of the five hundred (500) replications carried out for each parameter configuration, I compute the steady-state mean of the time series outputs for each endogenous variable. These steady-state means are then averaged over the 500 replications. For instance, given the time series of entry rates, $\{ER_k^t\}_{t=3001}^{5000}$, from a given replication, k, I compute the steady-state mean value of the rate of entry as:

$$\overline{ER} \equiv \frac{1}{500} \cdot \sum_{k=1}^{500} \left(\frac{1}{2000} \cdot \sum_{t=3001}^{5000} ER_k^t \right) \tag{26}$$

The steady-state means for other endogenous variables of interest are computed similarly:

$$\begin{aligned} \overline{XR} &\equiv \tfrac{1}{500} \cdot \textstyle\sum_{k=1}^{500} \left(\tfrac{1}{2000} \cdot \sum_{t=3001}^{5000} XR_k^t \right); & \overline{WMC} &\equiv \tfrac{1}{500} \cdot \textstyle\sum_{k=1}^{500} \left(\tfrac{1}{2000} \cdot \sum_{t=3001}^{5000} WMC_k^t \right); \\ \overline{m} &\equiv \tfrac{1}{500} \cdot \textstyle\sum_{k=1}^{500} \left(\tfrac{1}{2000} \cdot \sum_{t=3001}^{5000} m_k^t \right); & \overline{H} &\equiv \tfrac{1}{500} \cdot \textstyle\sum_{k=1}^{500} \left(\tfrac{1}{2000} \cdot \sum_{t=3001}^{5000} H_k^t \right); \\ \overline{P} &\equiv \tfrac{1}{500} \cdot \textstyle\sum_{k=1}^{500} \left(\tfrac{1}{2000} \cdot \sum_{t=3001}^{5000} P_k^t \right); & \overline{PCM} &\equiv \tfrac{1}{500} \cdot \textstyle\sum_{k=1}^{500} \left(\tfrac{1}{2000} \cdot \sum_{t=3001}^{5000} PCM_k^t \right); \end{aligned} \tag{27}$$

I first examine the entry and exit patterns across industries in section 6.1 by focusing on the mean rates of entry and exit for various parameter configurations. The endogenous industry concentration is then analyzed in section 6.2. Finally, in section 6.3, I look at the endogenous performance differences across industries and identify patterns in the relationships between these differences and the relevant parameters. As noted, there are two different types of parameters that are of interest to us. The first two parameters, f and s, have direct impacts on the endogenous market structure and performance by determining the structural capacity of the market. The other two, γ and λ, have indirect and dynamic impacts by specifying the firms' abilities to adapt to changing environment. My presentation of the results will be organized around these two types of parameters.

6.1 Entry and Exit Patterns

Figure 4 captures how f and s affect (a) the mean rate of entry ($\overline{ER}$) and (b) the mean rate of exit ($\overline{XR}$). It shows that an industry with a higher fixed cost has both a higher rate of entry and a higher rate of exit for all $s \in \{4, 6, 8, 10\}$. Furthermore, an industry with a smaller market size (s) has both a higher rate of entry and a higher rate of exit for all $f \in \{100, 200, 300, 400\}$. Note that the mean rate of exit is the mean fraction of operating firms that exit the industry per period. The inverse of this rate is the mean fraction of operating firms that *survive* in the industry per period. As such, the fact that the mean rate of exit is higher for those industries with greater f and/or smaller s directly indicates that the mean rate of firm survival is *lower* in those same industries. This would also imply that the firms must exit at younger ages in those industries. This intuition is directly confirmed in the following exercise. I collected the ages of the exiting firms for all those who leave the industry between $t = 3001$ and 5000. I then compute the proportion of those whose ages are less than or equal to $AGE \in \{200, 400, ..., 2000\}$. The results are presented in Figure 5: (a) for $f \in \{100, 200, 300, 400\}$ and (b) for $s \in \{4, 6, 8, 10\}$. It clearly shows that a larger proportion of exiting firms are of younger ages in those industries having higher rates of firm turnovers (higher f and/or lower s).

Similarly, looking at the rates of entry and exit in Figure 6(a)-(b), we find that both rates are higher in more turbulent (higher γ) and less adaptable industries (lower λ). This is straightforward. Since a turbulent industry shifts the technological environment more frequently, there are more opportunities for new firms to come in. But, of course, the same turbulence tends to push the firms out of the market more frequently as well, thereby raising the rate of firm turnover on average. As discussed before, a higher rate of firm turnover implies a lower rate of firm survival, which should also imply an increase in "infant mortality." Figure 7 confirms this. Figures 7(a) and 7(b) show that the proportion of exiting firms with their age lower than a given AGE increases in γ and decreases in λ, respectively. Hence, more firms tend to exit at a young age in an industry with a greater technological turbulence.

Property 3: The mean rates of entry and exit are both higher and the mean rate of survival is lower when: 1) the fixed cost (f) is larger; 2) the market size (s) is smaller; 3) the rate of change in the technological environment (γ) is higher; or 4) firms' propensity to innovate (λ) is lower.

The findings reported here then indicate that the mean rates of entry and exit move together for all parameter configurations. This has an important implication for comparative studies involving a population of heterogeneous industries. This implies that *an industry with a higher-than-average rate of entry is also likely to have a higher-than-average rate of exit*. Again, this is fully consistent with the empirical findings that report positive correlations between rates of entry and exit across industries [Dunne *et al.* (1988)]. Since the rate of entry and the rate of exit tend to go together, I will simply refer to either one as the "rate of firm turnover."

6.2 Industry Concentration

I now examine the impacts that the four parameters have on the long-run structure of the industry. Figure 8(a) shows the steady-state number of operating firms as a function of f and s. Recall that the number of operating firms includes both the active firms (who produce positive quantities) and the inactive firms (who shut down their production and only pay the fixed cost). Figure 8(b) shows the number of *active* firms as a function of f and s. As expected, both the number of operating firms and the number of active firms are lower in industries with higher fixed cost (f) and/or smaller market size (s). This is an outcome that a static model of Cournot oligopoly with symmetric costs would have predicted. My model confirms these findings in a dynamic setting with entry, exit, and heterogeneous firm costs. In order to further confirm that the number of active firms inversely affects the industry concentration, I plot in Figure 8(c) the steady-state mean values of Herfindahl-Hirschman Index, $\overline{H}$, for all relevant values of f and s. As expected, an industry with a higher f and/or smaller s tends to be more concentrated.

Examining the long-run industry structure for industries having different values of γ and λ, Figure 9(a) shows that the number of operating firms is generally higher in those industries having greater rate of change in technological environment and/or lower firms' propensity to innovate. In other words, there are more firms (active and inactive) in the industry if the firms are less adaptive to their technological environment. This result is counter-intuitive and requires a closer look. Note that the operating firms include both active and inactive firms. If we separate the active firms from the inactive firms, the result becomes much more sensible. As shown in Figure 9(b), the number of *active* firms is lower in those industries with high γ and low λ. This then implies that the industries in less adaptable environment tend to have more *inactive* firms who are unable to operate profitably and are simply waiting to exit once they exhaust their net capital. Given that the concentration measure is defined over only those firms that produce positive quantities, the mean HHI, $\overline{H}$, is higher in those industries with less adaptable technological environment.

Property 4: An industry is more concentrated on average when: 1) the fixed cost (f) is larger; 2) the market size (s) is smaller; 3) the rate of change in technological environment (γ) is higher; or 4) firms' propensity to innovate (λ) is lower.

It should be noted that the conditions on the four parameters that support greater industry concentration are the same ones as those that support greater firm turnover rates. The implications of this property will be further discussed in Section 7.

6.3 Industry Performance

The next issue is how the four parameters affect the industry performance. In Figure 10, I first plot the mean industry marginal cost, $\overline{WMC}$, for all f and s. Notice that the mean industry marginal cost is higher in those industries with a higher f or smaller s. In other words, the industries that exhibit high rate of firm turnovers tend to suffer from lower production efficiency and higher marginal costs. This may seem surprising as we traditionally think of the dynamic process of entry-competition-exit as cleansing the market of inefficiencies and, thereby, leading it toward optimal production techniques. The fact is that the strength of the market's selective force is itself dependent on these parameters. Those industries with higher f and lower s are not likely to induce a large number of entries by efficient firms as their sustaining capacity tends to be small. Even though the *rate* of entry – the number of entry as a proportion of the number of operating firms – may be high for higher f or smaller s, the smallness in the absolute number of entries tends to limit the extent to which the turnover process can effectively select the more efficient firms.

Because firms in high-turnover industries tend to have higher marginal costs, the market price tends to be higher as well. This is shown in Figure 10(b). Most interestingly, however, the industry price-cost margin, $\overline{PCM}$, tends to be higher in an industry with a higher rate of turnover. While the production is, in general, inefficient in those industries, the higher market price, resulting from the concentrated structure and the associated market power, raises the price-cost margins for the firms.

Finally, Figure 11(a) shows that the industry marginal cost is higher in an industry with a greater rate of change in technological environment. This is obvious and does not require an explanation. The high marginal costs tend to raise the market price, as shown in Figure 11(b). However, quite contrary to the case of structural parameters, f and s, the industry price-cost margin is now lower for those industries that are subject to more turbulent technological environment as shown in Figure 11(c). In other words, the firms' performance is mainly affected (adversely) by the rising marginal cost and less by the increased market power from concentration.

Property 5: The industry marginal cost and the market price are both higher when: 1) the fixed cost (f) is larger; 2) the market size (s) is smaller; 3) the rate of change in technological environment (γ) is higher; or 4) firms' propensity to innovate (λ) is lower.

Property 6: The industry price-cost margin is higher when: 1) the fixed cost (f) is larger; 2) the market size (s) is smaller; 3) the rate of change in technological environment (γ) is lower; or 4) firms' propensity to innovate (λ) is higher.

These properties have an implication for the cross-sectional studies in industry performance. If the industries in the sample are differentiated in terms of their fixed cost or market size, then we are likely to observe that the market prices and the industry price-cost margins across industries are positively correlated – that is, those industries with a higher than average market price will also have higher than average price-cost margin. However, if the industries in the sample are differentiated in terms of the firms' adaptive potential (γ and λ in this model), then the prices and price-cost margins are likely to be *negatively* correlated across industries – that is, those industries with higher-than-average price should have lower-than-average price-cost margins. In a broad sample of industries that are heterogeneous in all four parameters, it is unlikely that one would find any strong relationship between price and price-cost margin.

7 Endogenous Relationships between Turnover, Concentration, and Performance

The conventional industrial organization literature focused on the market structure as the main determinant of firm performance. Much of the empirical research belonging to this structural school were cross-sectional studies aimed at identifying the relationship between the degree of market concentration and the price-cost margin (or some form of accounting profit as its proxy). The model presented in this paper, with its ability to track the movements over time of the various endogenous variables, allows me to address the concentration-margins question in a straightforward manner. The results obtained on firm turnovers also allow identification of the linkage between an industry's turnover rate and its concentration.

How the structural parameters (f and s) and the adaptive potential parameters (γ and λ) affect the rate of firm turnovers were captured in Figures 4 and 6. Their impacts on the steady-state HHI, $\overline{H}$, were captured in Figure 8(c) and Figure 9(c), respectively. Likewise, their impacts on the steady-state market price and the industry PCM were captured in Figures 10 and Figure 11. These observations can be summarized as follows:

Parameters	Rate of Turnover	Concentration ($\overline{H}$)	Market Price ($\overline{P}$)	PCM ($\overline{PCM}$)
f	+	+	+	+
s	−	−	−	−
γ	+	+	+	−
λ	−	−	−	+

Hence, firms' fixed cost (f) affects the above four endogenous variables positively, while the market size (s) affects all of them negatively. The rate of change in the technological environment (γ) positively affects the rate of turnover, industry concentration, and the market price, while it negatively affects the industry price-cost margin. The firms' propensity of innovate (λ) has the exact opposite effects on these variables: It negatively affects the rate of turnover, industry concentration, and the market price, while it positively affects the industry price-cost margin.

Observe from the above table that the rate of turnover and the industry concentration have the same signs for all parameters; hence, they always move together. The first implication is then on the endogenous relationship between the rate of firm turnover and the industry concentration.

Property 7: The rate of firm turnover and the industry concentration are positively related.

Davies and Geroski (1997) provide some empirical support for this property. They estimated the market shares of leading firms in a sample of three-digit industries in U.K. in 1979 and 1986.

Defining market turbulence as the degree of market share changes among the largest five firms in each industry and measuring market concentration with the 5-firm concentration ratio, they found that "turbulence tends to be higher in more concentrated industries, and it is inversely (if weakly) correlated to changes in concentration." More recently, Brynjolfsson, McAfee, Sorell, and Zhu (2008) found evidence that turbulence (as measured by the intra-industry rank change in sales) and concentration (H-index) tended to move together in IT-intensive U.S. industries over the period of 1995-2006. Although the context and the measurement of turnover are slightly different from those in my model, these papers do show that there is a positive relationship between the turnover rate and concentration.

The second implication is on the concentration-performance relationship. The traditional cross-sectional studies find the presumed positive relationship between concentration and price to be much stronger than that between concentration and price-cost margin. [Weiss (1989)] The results obtained here confirm these findings. First note that the concentration measure and the market price have the same signs for all parameters.

Property 8: The industry concentration and the market price are positively related.

A more concentrated industry is, hence, likely to have higher market price, consistent with the findings of the cross-sectional studies. The results on the relationship between concentration and PCM are not so straightforward. The concentration measure and the price-cost margin move in the same direction when the industries vary in terms of f and s: As often claimed in the conventional literature, a more concentrated industry tends to exhibit higher price-cost margin. However, when industries vary in terms of their adaptive potential, γ and λ, the concentration measure and the price-cost margin move in the opposite direction so that a more concentrated industry exhibits a lower price-cost margin and vice versa. This then implies that a sample of industries that are differentiated in terms of all four parameters is unlikely to show any significant relationship between concentration and PCM, confirming the difficulty that the old cross-sectional studies faced.

8 Concluding Remarks

This paper presented a dynamic model of industry competition that is capable of generating the various empirical regularities on firm turnovers and market structure over time and across industries. The primary objective was to deepen our understanding of how the dynamics of firm entry and exit affect the endogenous market structure and firm performance. The driving force behind the dynamic process that generated the persistent firm turnovers in this model was the turbulent nature of the technological environment within which firms must operate. The adverse effect that sudden unexpected technological shocks have on the cost positions of the firms repeatedly set in motion the process of market selection as it operates on the evolving population of heterogeneous firms who adapt through independent innovations. The implications for the standard questions in industrial organization were then explored through the computational analysis of the firm turnovers as well as the evolving industry structure and performance over time. The computational methodology utilized here had the flexibility to exploit the various features of the model to the fullest extent, thus making feasible the comparative dynamics exercises that formed the basis of the reported results.

More work remains to be done. I will conclude by offering some thoughts on one possible avenue that this line of research may take. As emphasized by Baldwin (1995), there are different types of entry and exit. A firm can enter an industry by building a new capacity (greenfield entry) or by acquiring existing capacity (acquisition) or by transferring capacity from another industry. A firm can exit an industry through the closure of capacity (closedown) or through the divestiture of existing capacity (divestiture) or through transfer of the capacity to another industry. In this paper, I focused only on greenfield entries and closedown exits by assuming single-product single-plant firms in the model. A useful avenue for future exploration will be to consider multi-market firms which may expand its operation by entering new markets either through building a new capacity or through acquiring existing capacity from an exiting firm. Likewise, an exit from an industry may not be permanent and total as it is in the current model. It may withdraw from one market but retain its operations in other markets, or simply move its operation from one market to another by transferring its capacity. Incorporating these possibilities into a multi-market model will enable one to investigate the issue of firm turnover in a much more comprehensive framework in which multi-market firms make the underlying entrepreneurial decisions on which market(s) to enter and exit. The rates of entry and exit will then be viewed more as the rate of firm's mobility from one market to another, a perspective that is more in line with the reality – entrepreneurs never leave the business arena; they merely move from one profit-making venture to another profit-making venture, willingly embracing the risk of failure along the way in return for the compensating monetary gains. Such an extension will further widen the scope of the model presented here and enable us to study the dynamic patterns of mergers and acquisitions as well as of diversifications in a comprehensive but coherent framework.

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Table 1: Set Notations

Notation	Definition
S^t	Set of surviving firms at the end of t
S^t_+	Those in S^t which were active in t
S^t_-	Those in S^t which were inactive in t
R^t	Set of potential entrants at the beginning of t
E^t	Set of actual entrants in t
M^t	Set of firms poised to compete in t $(= S^{t-1} \cup E^t)$
L^t	Set of firms which exit the industry at the end of t

Table 2: List of Parameters and Their Values

Notation	Definition	Baseline Value	Parameter Values Considered
N	Number of tasks	24	24
n	Length of a task bit string	4	4
r	Number of potential entrants per period	40	40
b	Start-up capital for a new entrant	0	0
d	Threshold level of net capital for exit	0	0
a	Demand intercept	300	300
g	Maximum magnitude of change in technological environment	8	8
T	Time horizon	5,000	5,000
f	Fixed cost	100	{100, 200, 300, 400}
s	Market size	4	{4, 6, 8, 10}
γ	Rate of change in technological environment	0.1	{0.1, 0.2, 0.3, 0.4}
λ	Propensity to innovate	0.5	{0.25, 0.5, 0.75, 1}

Table 3: Correlations between Time Series

Parameter Values				$\{ER^t\}$				$\{P^t\}$		$\{PCM^t\}$
f	s	γ	λ	$\{XR^t\}$	$\{WMC^t\}$	$\{P^t\}$	$\{PCM^t\}$	$\{WMC^t\}$	$\{PCM^t\}$	$\{WMC^t\}$
100	4	.1	.5	.284937	.398509	.395442	−.28539	.977908	−.789878	−.645999
200	4	.1	.5	.31348	.376209	.36633	−.298891	.96678	−.837812	−.672337
300	4	.1	.5	.339491	.356287	.336038	−.301161	.951639	−.854802	−.656053
400	4	.1	.5	.355623	.335234	.303141	−.299694	.937364	−.870013	−.646072
100	4	.1	.5	.284937	.398509	.395442	−.28539	.977908	−.789878	−.645999
100	6	.1	.5	.270565	.403223	.401352	−.275935	.982099	−.762557	−.62868
100	8	.1	.5	.266159	.402005	.400724	−.266367	.983945	−.744574	−.615187
100	10	.1	.5	.262572	.400654	.400161	−.259899	.985321	−.736931	−.612299
100	4	.1	.5	.284937	.398509	.395442	−.28539	.977908	−.789878	−.645999
100	4	.2	.5	.346953	.431321	.420779	−.27822	.95064	−.709933	−.457777
100	4	.3	.5	.383019	.400632	.37602	−.255282	.925422	−.666061	−.334994
100	4	.4	.5	.403101	.36682	.329832	−.242067	.9053	−.650294	−.267051
100	4	.1	.25	.27442	.396182	.390065	−.24958	.94974	−.715406	−.462881
100	4	.1	.5	.284937	.398509	.395442	−.28539	.977908	−.789878	−.645999
100	4	.1	.75	.304875	.347468	.342866	−.26738	.987476	−.827779	−.730583
100	4	.1	1.	.310206	.283446	.279143	−.224193	.99117	−.858451	−.784837

Stage 1

Entry decisions by potential entrants
based on
the *previous* period's tech. optimum ($\widehat{\underline{z}}^{t-1}$)

$\downarrow$

Stage 2

Innovation decisions by incumbents
based on
the *previous* period's tech. optimum ($\widehat{\underline{z}}^{t-1}$)

$\downarrow$

$\widehat{\underline{z}}^{t}$ realized

$\downarrow$

Stage 3

Market competition and profit realization
based on
the *current* period's tech. optimum ($\widehat{\underline{z}}^{t}$)

$\downarrow$

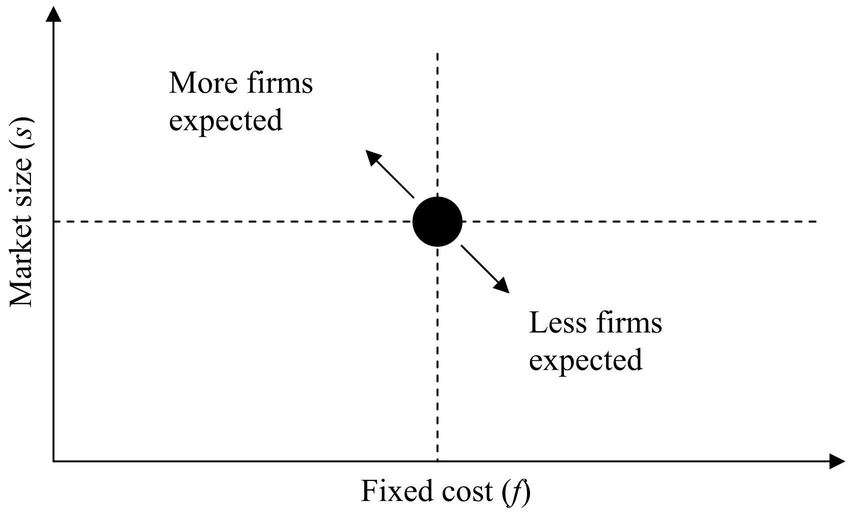
Stage 4

Exit decisions by incumbents and new entrants
based on
the *updated* net capital levels (w_i^t)

Figure 1: Decision Structure in Period t

Figure 2: Industry-Specific Parameters

(a) Industry's *structural* parameters (*f* and *s*)



(b) Industry's *adaptive potential* parameters (γ and λ)

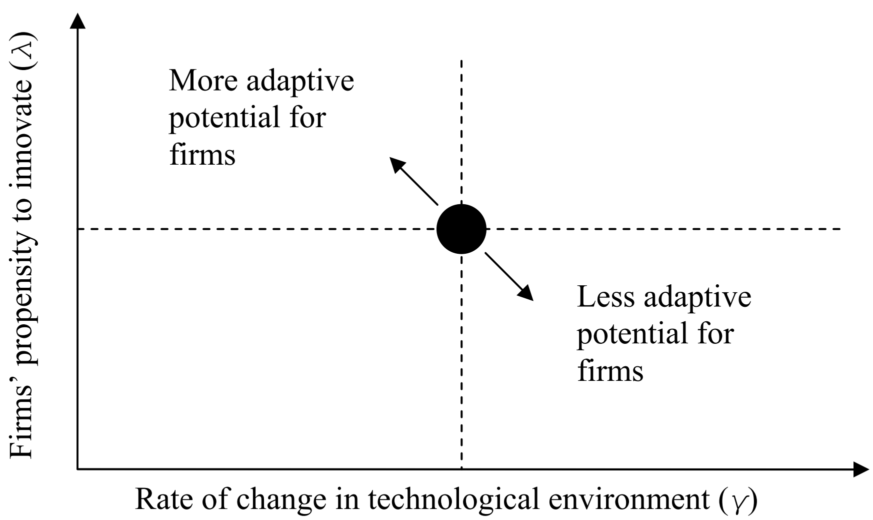
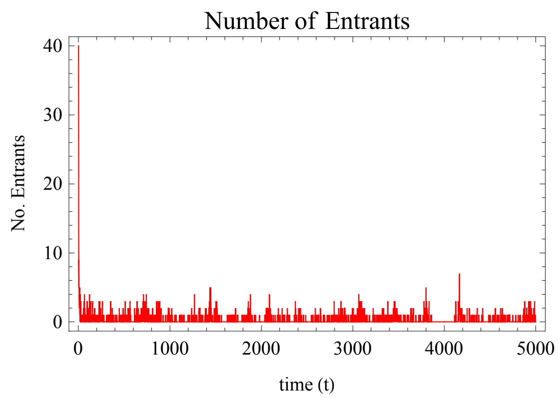
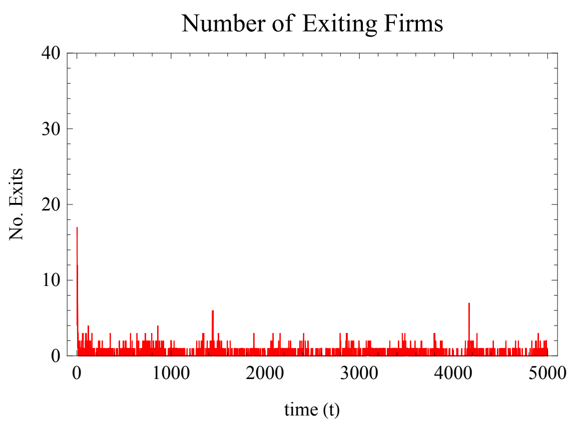


Figure 3: Time Paths from a Representative Replication

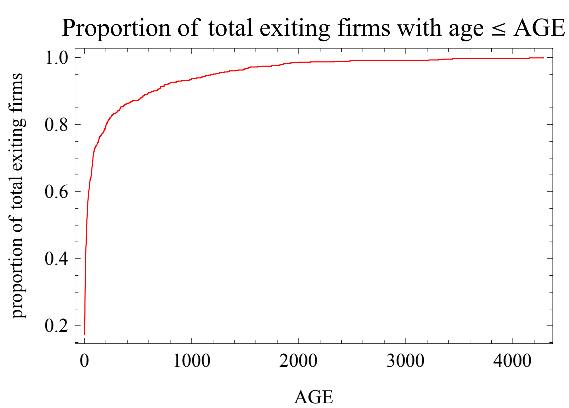
(a)



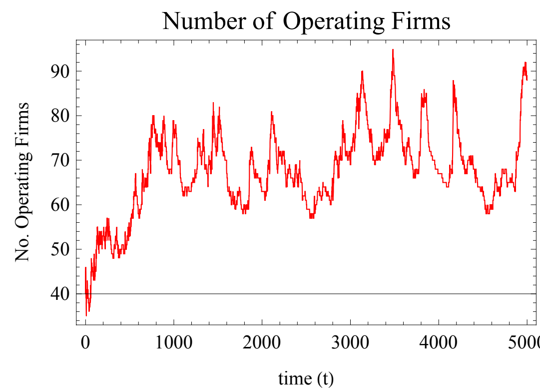
(b)



(c)



(d)



(e)

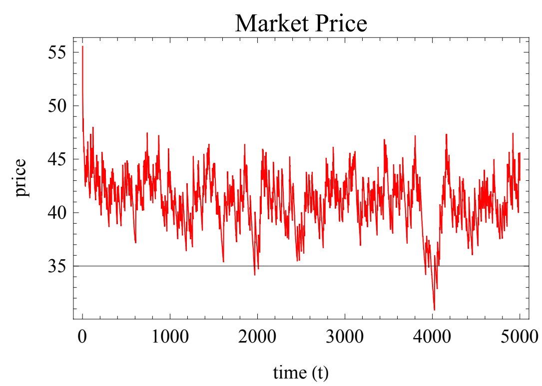
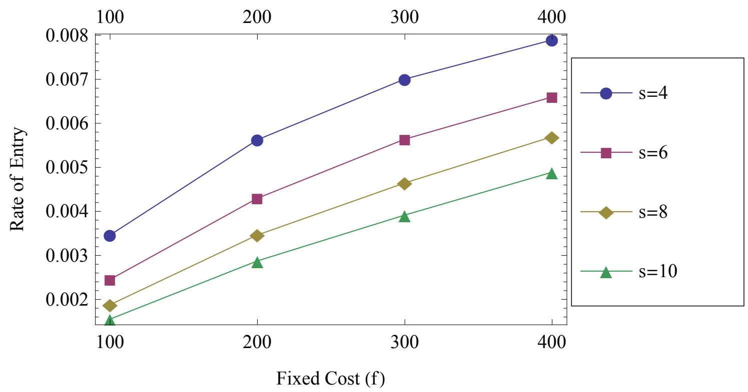


Figure 4: Rate of Entry and Rate of Exit
for $f \in \{100, 200, 300, 400\}$ and $s \in \{4, 6, 8, 10\}$

(a) Rate of Entry



(b) Rate of Exit

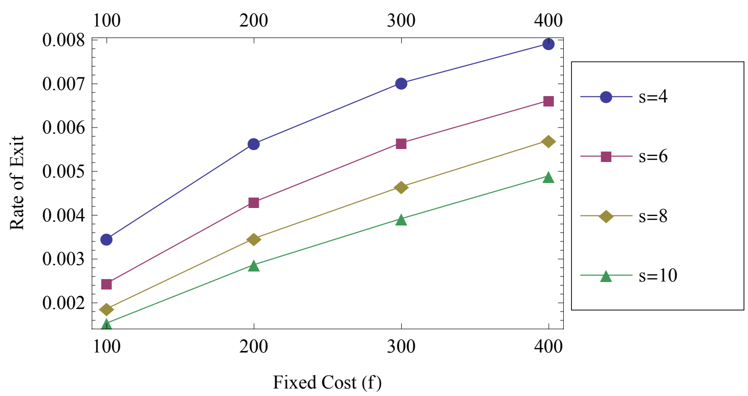
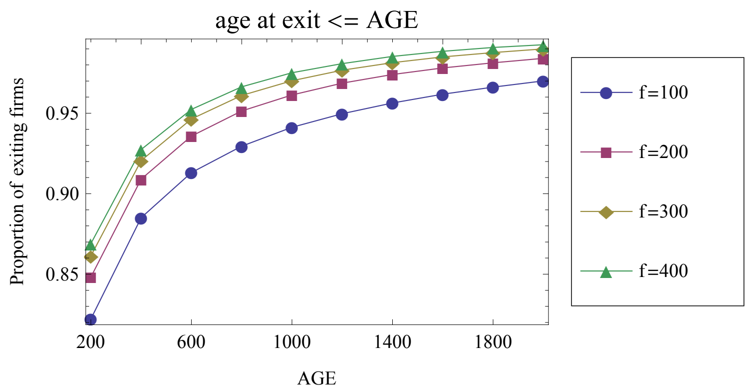


Figure 5: Proportion of Exiting Firms of Age <= AGE
for $f \in \{100, 200, 300, 400\}$ and $s \in \{4, 6, 8, 10\}$

(a)



(b)

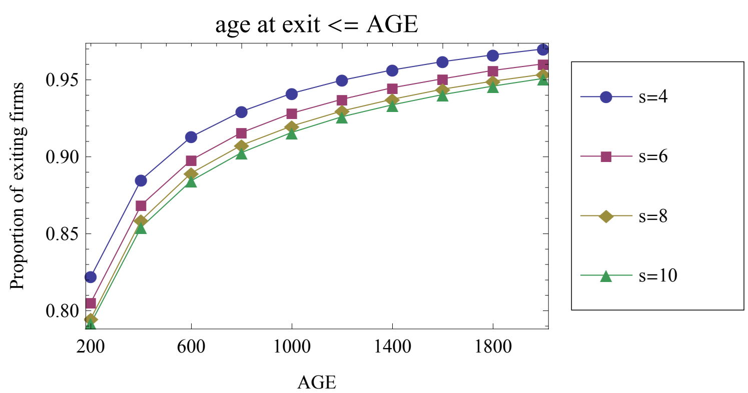
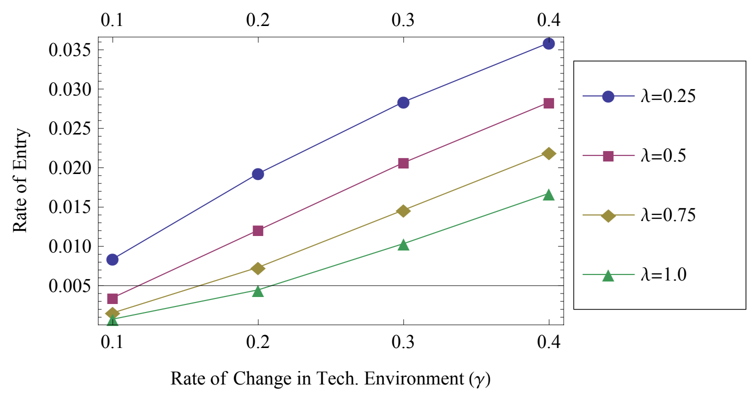


Figure 6: Rate of Entry and Rate of Exit
for $\gamma \in \{0.1, 0.2, 0.3, 0.4\}$ and $\lambda \in \{0.25, 0.5, 0.75, 1.0\}$

(a) Rate of Entry



(b) Rate of Exit

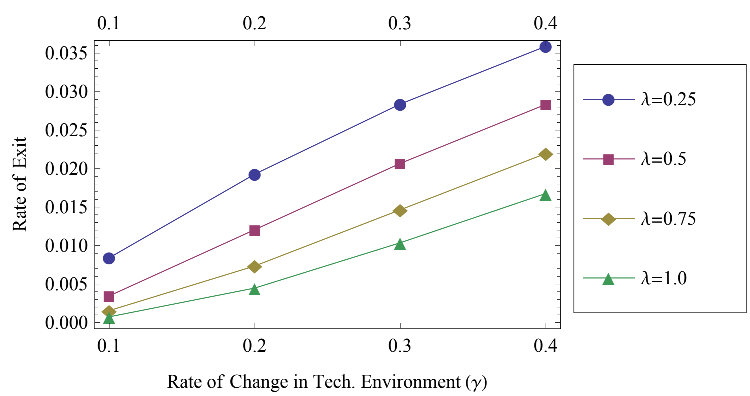
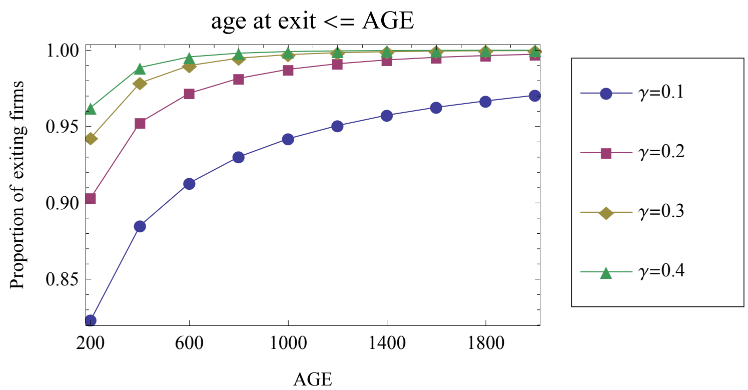


Figure 7: Proportion of Exiting Firms of Age <= AGE
for $\gamma \in \{0.1, 0.2, 0.3, 0.4\}$ and $\lambda \in \{0.25, 0.5, 0.75, 1.0\}$

(a)



(b)

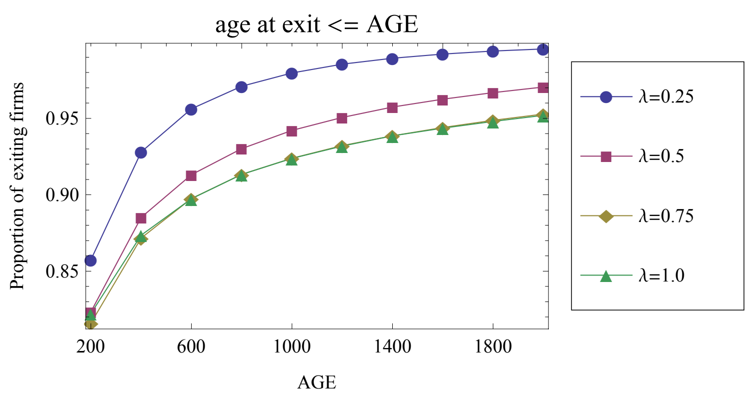


Figure 8: No. Operating Firms, No. Active Firms, and HHI for $f \in \{100, 200, 300, 400\}$ and $s \in \{4, 6, 8, 10\}$

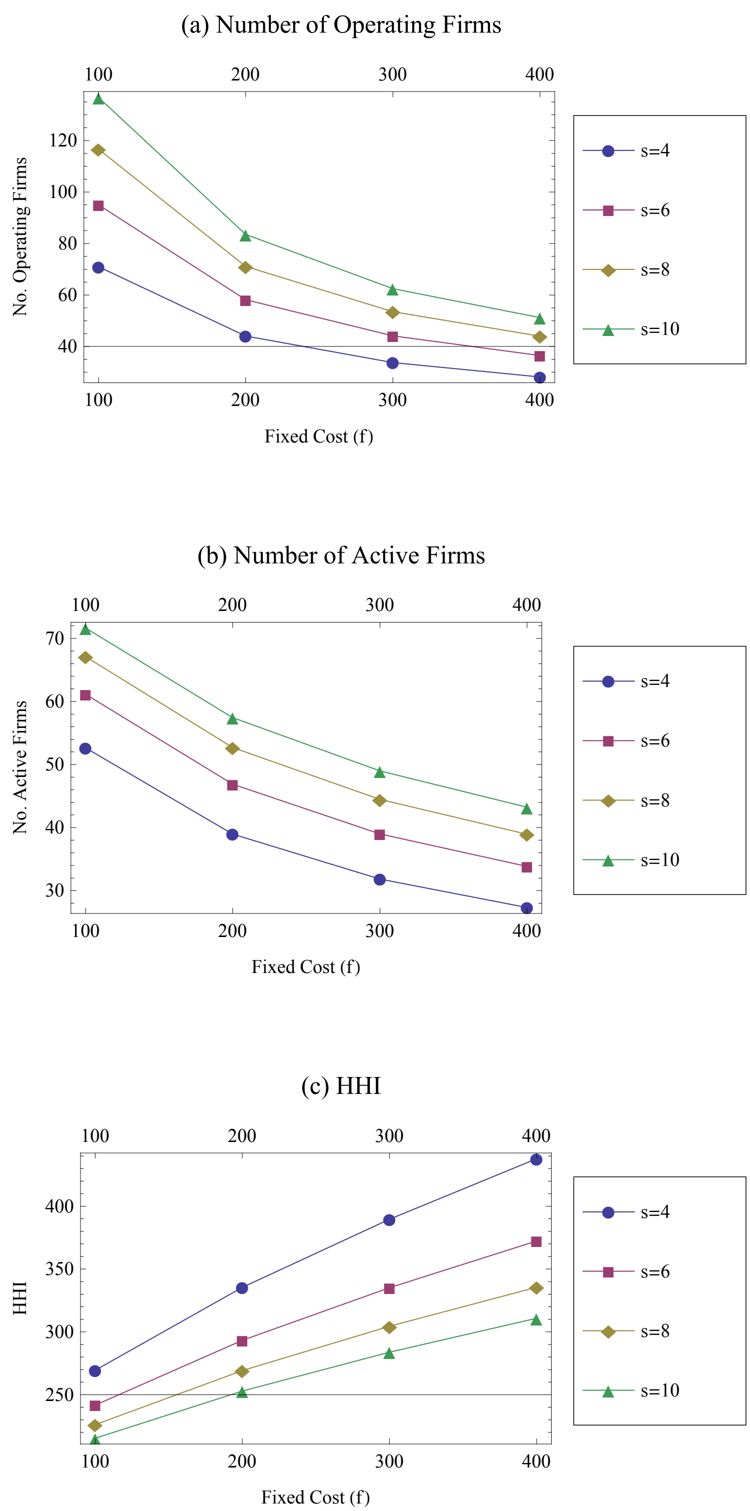


Figure 9: No. Operating Firms, No. Active Firms, and HHI
for $\gamma \in \{0.1, 0.2, 0.3, 0.4\}$ and $\lambda \in \{0.25, 0.5, 0.75, 1.0\}$

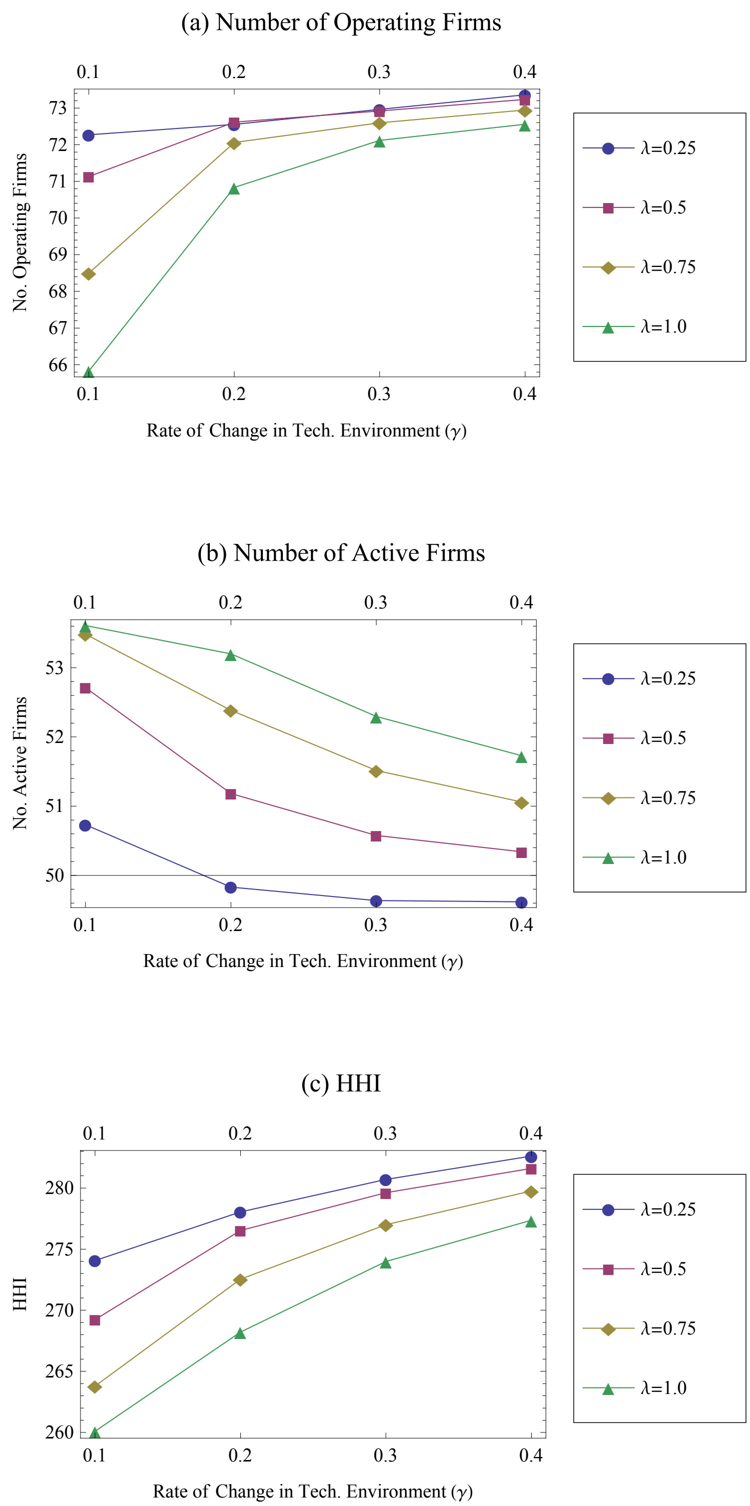
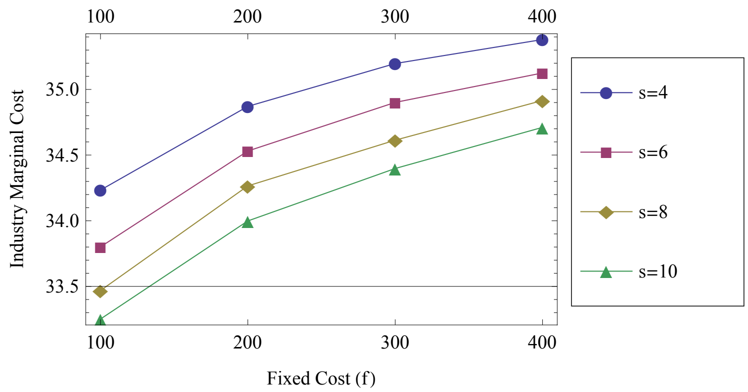
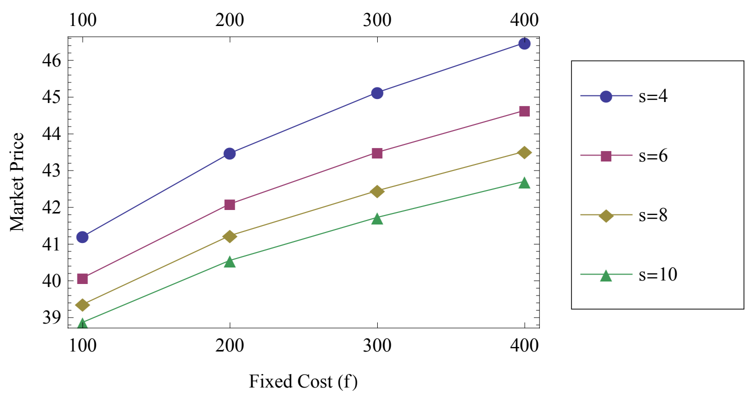


Figure 10: Industry Marginal Cost, Market Price, and Industry Price-Cost Margin for $f \in \{100, 200, 300, 400\}$ and $s \in \{4, 6, 8, 10\}$

(a) Industry Marginal Cost



(b) Market Price



(c) Industry Price-Cost Margin

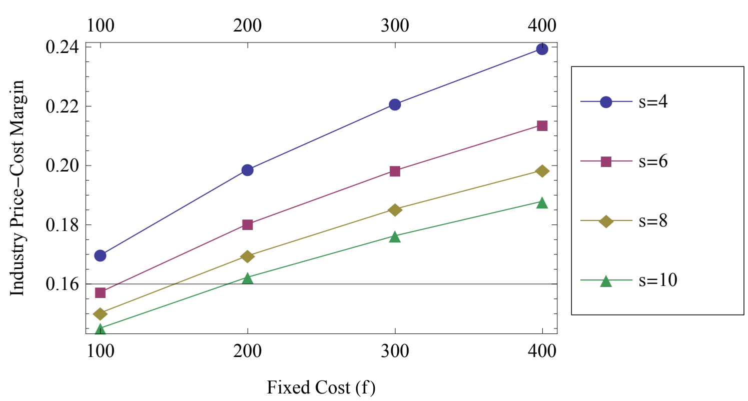
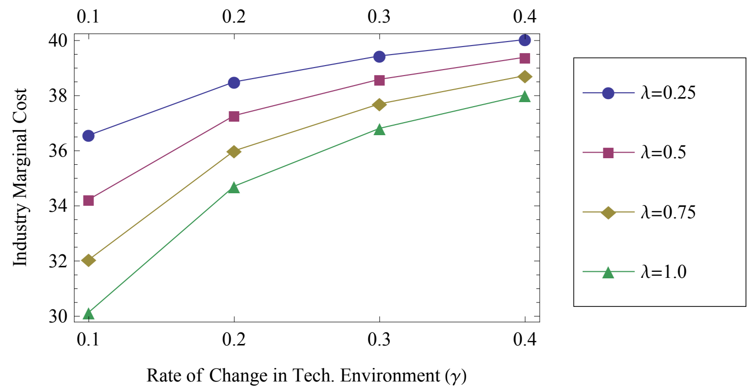
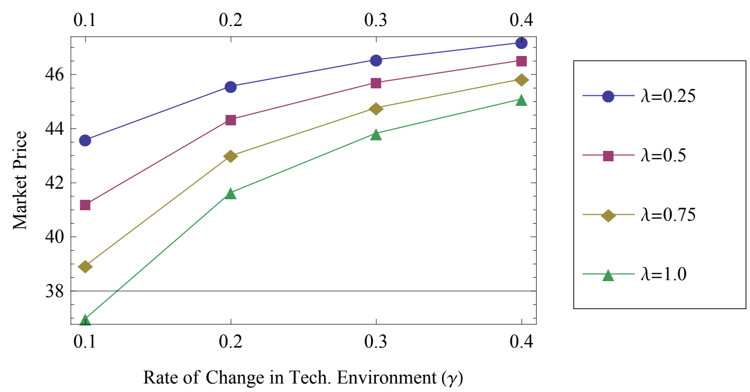


Figure 11: Industry Marginal Cost, Market Price, and Industry Price-Cost Margin for $\gamma \in \{0.1, 0.2, 0.3, 0.4\}$ and $\lambda \in \{0.25, 0.5, 0.75, 1.0\}$

(a) Industry Marginal Cost



(b) Market Price



(c) Industry Price-Cost Margin