Cyclical Industrial Dynamics in a Model of Schumpeterian Competition with Fluctuating Demand*

Myong-Hun Chang
Department of Economics
Cleveland State University
Cleveland, OH 44115
216-687-4523, -9206 (Fax)
m.chang@csuohio.edu
http://academic.csuohio.edu/changm

May 20, 2013

Abstract

This paper proposes a computational model of Schumpeterian competition with endogenous R&D when the size of the market demand is stochastic. The fluctuation in the market demand induces cyclical patterns in firms' entry and exit behavior as well as their R&D intensities over time. Most significantly, we find that the industry concentration, market price, and the average price-cost margins are countercyclical, while the industry profits and the aggregate R&D spending are procyclical. These patterns are explained in terms of the cyclicalities in the degree of competition and the production efficiencies resulting from the endogenous entry, exit, and R&D activities of firms.

*I would like to thank Ed Bell, Doug Stewart, and the session participants of the 2013 Eastern Economic Association Conference (New York) for many helpful comments. I am particularly grateful to Chris Ruebeck for his careful reading of an earlier version of this paper. Charlotte DeKoning provided capable research assistance during this project.

1 Introduction

The fluctuations of many industries often correlate with those in the aggregate economy (business cycle), though to a varying degree of sensitivity. For example, a large body of empirical literature has found: 1) Firm entry and business formation tend to be procyclical;[1] 2) the price level and the average mark-ups by firms tend to be countercyclical;[2] 3) aggregate profits are procyclical;[3] and 4) the R&D activities tend to be procyclical.[4] While various models have been proposed to explain these patterns, most of them specialize in explaining a single specific pattern without any reference to other observed patterns. This paper offers a general model of industry dynamics that is capable of replicating all of the above-mentioned empirical observations, and identifies an underlying mechanism that gives rise to these patterns.

One way in which the fluctuations at the industry-level is connected to those at the economy-level is through the movement in the size of the market demand that results from the economy-wide fluctuations. This paper focuses on how fluctuations in market demand (whatever their cause) affect the evolutionary dynamics of an industry. It uses a computational model of an industry which allows firms to enter, exit, and perform R&D. Central to the model is a series of exogenous random shocks to the technological environment, which induces the individual firms to perform adaptive R&D in order to improve the efficiency of their production methods. This feature gives rise to the Schumpeterian process of *creative destruction*, in which the structure of the industry evolves over time as the equilibrating force of the market competition acts on the disequilibrating tendency of the technology shocks. This process allows the innovative firms with greater efficiency to continually replace those that lag behind. The main contribution of the paper is in showing how the variation in the market demand affects the interactive dynamics of firms' entries and exits, as well as their R&D activities, thereby inducing patterns in the time series movements of those variables that describe the structure and performance of the industry.

The proposed model is capable of generating *persistent* entries and exits of firms, even without any fluctuation in market demand. Such movements of firms, induced solely by the random technology shocks, display patterns that are consistent with empirical observations. This, however, is merely a starting point. The ultimate goal of the paper is to identify the relationships between the demand movement and the adaptive behavior of firms over time. This entails systematically varying the size of the market demand, while allowing the firms to respond to these changes by adjusting their entry and exit decisions as well as the R&D investment and production decisions. I first consider a serially-correlated stochastic movement in market size with a parameter that captures the rate of *persistence* in demand. With this specification, I show that the model is capable of predicting cyclical industry dynamics consistent

[1] Chatterjee and Cooper (1993), Campbell (1998), Etro and Colciago (2010)

[2] Bils (1987, 1989), Cooley and Ohanian (1991), Chevalier and Scharfstein (1995), Chevalier, Kashyap, and Rossi (2003), Bagwell (2004), Barro and Tenreyro (2006), Edmond and Veldkamp (2008), Bilbiie, Ghironi, and Merlitz (2010)

[3] Barlevy (2007), Etro & Colciago (2010), Bilbiie, Ghironi, and Merlitz (2010)

[4] Gerosky and Walters (1995), Barlevy (2007), Francois and Lloyd-Ellis (2009)

with the empirical observation. In order to identify the causal and contributing factors of such cyclical patterns, I then focus on a deterministic demand cycle, in which the market size variable follows a sine wave. This specification, though restrictive, permits a clear look at the underlying process, in which firms systematically adapt to the changing market conditions, endogenously generating the cyclical patterns in the way the industry evolves.

For both specifications the computational exercise entails a series of simulation runs, each of which starts out with an empty industry targeted by a fixed pool of potential entrants (refreshed each period). Each run generates the behavior of firms over a horizon of 5,000 periods. I follow the movements of the firms into and out of the market as well as those of other endogenous variables. Central to our analysis is the identification and characterization of any cyclicalities in the movements of market price, price-cost margin, aggregate profits, and the firms' R&D spending. The simulation results indicate that the cyclicalities in price and price-cost margin are crucially related to the cyclicality in entry/exit dynamics as well as in R&D spending by the firms. First, both entry and exit are procyclical, but entry dominates during the boom, while exit dominates during the bust. This leads to countercyclical industry concentration, where the number of firms rises during a boom and declines during a bust. This change in industry structure has a significant implication for the degree of competition in the market. The increased number of firms during a boom reduces market concentration and raises the degree of competition, while the decrease in the number of firms during a bust increases market concentration and reduces the degree of competition. The result is that the market price displays "countercyclicality" while the aggregate output and revenue display "procyclicality."

The industry average marginal cost (defined as the sum of the operating firms' marginal costs, each weighted by the firm's market share) also displays countercyclicality – i.e., the average productivity of the firms is procyclical. There are two possible sources for this. First, the increased competition during a boom potentially raises the selection pressure on the firms, driving out the inefficient firms to a greater extent, hence reducing the marginal costs of surviving firms on average. The reduced degree of competition during a bust will have exactly the opposite effect. This "selection effect," if present, can induce the average marginal cost for the industry to move countercyclically. Second, any cyclical tendency in the endogenous R&D activities of the firms may induce cyclicality in the firms' marginal costs – i.e., "adaptation effect." The results obtained in this paper show that the countercyclicality in the average marginal cost is mainly due to the "adaptation effect" from the endogenous R&D and not the "selection effect." In fact, the model predicts the aggregate R&D spending to be procyclical such that there are more intense R&D activities during a boom than during a bust. Given that the role of R&D in this model is to reduce the marginal cost of production, the procyclical aggregate R&D induces countercyclical average marginal cost through the adaptation effect.

Although both the market price and the industry average marginal cost are countercyclical, the variation in price tends to exceed that in the average marginal cost so that the price/marginal cost markups or the price-cost margins are countercyclical. There is a large body of applied and theoretical works in macroeconomics and industrial organization that show countercyclical price and markups at the aggregate economy-level or at the industry-level.[5] This paper contributes to that literature by providing an explanation based on the process of firm entry and exit as well as the Schumpeterian process of creative destruction which fully endogenizes the R&D decisions of the firms.

The next section describes the model in detail. In Section 3, the design of the computational experiments as well as the parameter values used in these experiments are discussed. Section 4 offers as benchmark the special case of fixed demand. This assumption is relaxed in Section 5, where demand fluctuates according to a stochastic process with an embedded degree of persistence. Section 6 looks for the causal factors of endogenous industry dynamics by thoroughly exploring the case of deterministic variation in demand. Section 7 concludes.

2 The Model

The base model is the same as that employed in Chang (2012). It entails an evolving population of firms which interact with one another through repeated market competition. Central to this process are the heterogeneous production technologies held by the firms and the R&D mechanism through which they evolve over time.

A typical period t opens with two groups of decision makers: 1) a group of incumbent firms surviving from $t-1$, each of whom enters t with a technology chosen in $t-1$ and its net wealth carried over from $t-1$; 2) a group of potential entrants ready to consider entering the industry in t, each with an endowed technology and its start-up wealth. All firms face a common technological environment within which his/her technology will be used. The environment in t is fully represented by the exogenously specified optimal technology (in t) which is unknown to the firms.

[5] Recent media coverages of the pricing behavior during an economic downturn also confirm these findings:

> "Shoppers continue to pare back spending even on basic household staples, resulting in lower-than-expected sales for Procter & Gamble Co. and Colgate-Palmolive Co. The consumer-products giants are responding by raising prices to keep profits from plunging. ... To offset higher commodity prices and global currency swings, P&G and Colgate raised prices in the quarter through March. P&G said higher prices increased its total sales by 7%. Colgate raised prices by 8%." [Wall Street Journal (May 1, 2009), B1]
>
> "The nation's two largest brewers by sales are planning a new round of price increases this fall despite flat volumes, in a sign of their growing clout. **Anheuser-Busch InBev** NV, the largest U.S. beer seller by revenue, and **MillerCoors** LLC will increase beer prices in the majority of their U.S. sales regions, the two companies said Tuesday. 'We do plan on taking prices up in the fall on the majority of our volume in the majority of the U.S.,' said David Peacock, president of Anheuser's U.S. division. 'The environment is very favorable, we think.' ... **MillerCoors** also said it will raise prices. 'Se have seen very strong pricing to date this year, and we are projecting a favorable pricing environment moving forward,' said Brad Schwartz, a vice president at **MillerCoors** ... Both U.S. giants have reported strong profits this year, in part by raising prices to offset flat volumes." [Wall Street Journal (August 26, 2009), B1]

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 to vary from one period to the next in a systematic manner. The nature of the technology and the mechanism that guides the shift dynamic of the technological environment is described below.

2.1 Technology and Technological Environment

In 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 two 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 the firm for a given task is represented by a bit (0 or 1) such that there are two possible methods available for each task and thus 2^N variants of the production technology. In period t, a firm's *technology* is then fully characterized by a binary vector of N dimensions which captures the complete set of methods it uses to produce the good. Denote it by $\underline{z}_i^t \in \{0,1\}^N$, where $\underline{z}_i^t \equiv (z_i^t(1), z_i^t(2), ..., z_i^t(N))$ and $z_i^t(h) \in \{0,1\}$ is firm i's chosen method in task h.

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

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

The efficiency of a given technology depends on the environment it operates in. In order to represent the technological environment in period t, I specify a unique methods vector, $\widehat{\underline{z}}^t \in \{0,1\}^N$, as the *optimal technology* for the industry in t. How well a firm's chosen technology performs in the current environment 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 specified to be 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 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 their marginal costs each period. The optimal technology is common for all firms – i.e., all firms in a given industry face the same technological environment. As such, once it is defined for a given industry, its technological environment is completely specified for all firms since the efficiency of any technology 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 such as technological innovations that originate from outside the given industry.[6] The external technology shocks *redefine* firms' production environment and 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 then 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, $\underline{\widehat{z}}^t$, 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.[7]

Consider a binary vector, $\underline{x} \in \{0,1\}^N$. Define $\delta(\underline{x}, l) \subset \{0,1\}^N$ 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

$$\Delta(\underline{x}, l) \equiv \bigcup_{i=0}^{l} \delta(\underline{x}, i). \tag{2}$$

The following rule governs the shift dynamic of the optimal technology:

$$\underline{\widehat{z}}^t = \begin{cases} \underline{\widehat{z}}' & \text{with probability } \gamma \\ \underline{\widehat{z}}^{t-1} & \text{with probability } 1-\gamma \end{cases} \tag{3}$$

where $\underline{\widehat{z}}' \in \Delta(\underline{\widehat{z}}^{t-1}, g)$ and γ and g are constant over all t.[8] Hence, with probability γ the optimal technology shifts to a new one within g Hamming distance from the current technology, while with probability $1-\gamma$ it remains unchanged at $\underline{\widehat{z}}^{t-1}$. The volatility of the technological environment is then captured by γ and g, where γ is the rate and g is the maximum magnitude of changes in technological environment.

The change in technological environment is assumed to take place in the beginning of each period before firms make any decisions. While the firms do not know what the optimal technology is for the new environment, they are assumed to get accurate signals of their *own* marginal costs based on the new environment when making their decisions to enter or to perform R&D.[9]

[6] In a framework closer to the neoclassical production theory, one could view an externally generated innovation 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 differential impacts 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.

[7] In any given period t, the optimal technology is specified to be 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] For the computational experiments reported in this paper, $\underline{\widehat{z}}'$ is chosen from $\Delta(\underline{\widehat{z}}^{t-1}, g)$ according to uniform distribution.

[9] This is clearly a strong assumption. A preferred approach would have been to explicitly model the process of learning about the new technological environment; it is for analytical simplicity that I abstract away from this process.

2.2 Demand, Cost, and Competition

In each period, there exists a finite number of firms that operate in the market. In this subsection, 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.

Let m^t be the number of firms operating in the market in period t. The firms are Cournot oligopolists, who choose production quantities of a homogeneous good. In defining the Cournot equilibrium in this setting, I assume that all m^t firms produce positive quantities in equilibrium.[10] The inverse market demand function is:

$$P^t(Q^t) = a - \frac{Q^t}{s^t}, \tag{4}$$

where $Q^t = \sum_{j=1}^{m^t} q_j^t$ and s^t denotes the size of the market.[11] The demand intercept, a, is assumed fixed, while the size parameter, s^t, can change from one period to the next.

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

$$C^t(q_i^t) = f_i^t + c_i^t \cdot q_i^t. \tag{5}$$

For simplicity, the firms are assumed to have identical fixed cost that stays constant over time: $f_1^t = f_2^t = ... = f_{m^t}^t = f$ for all t.

The firm's marginal cost, c_i^t, depends on how different its technology, $\underline{z}_i^t$, is from the optimal technology, $\widehat{\underline{z}}^t$. Specifically, c_i^t is defined as follows:

$$c_i^t(\underline{z}_i^t, \widehat{\underline{z}}^t) = 100 \cdot \frac{D(\underline{z}_i^t, \widehat{\underline{z}}^t)}{N}. \tag{6}$$

Hence, c_i^t increases in the Hamming distance between the firm's chosen technology and the optimal technology for the industry. It is at its minimum of zero when $\underline{z}_i^t = \widehat{\underline{z}}^t$ and at its maximum of 100 when all N bits in the two technologies are different from one another. The total cost can then be re-written as:

$$C^t(q_i^t) = f + 100 \cdot \frac{D(\underline{z}_i^t, \widehat{\underline{z}}^t)}{N} \cdot q_i^t. \tag{7}$$

Given the demand and cost functions, firm i's profit is:

$$\pi_i^t(q_i^t, Q^t - q_i^t) = \left(a - \frac{1}{s^t} \sum_{j=1}^{m^t} q_j^t \right) \cdot q_i^t - f - c_i^t \cdot q_i^t. \tag{8}$$

[10] This assumption is made strictly for ease of exposition in this section. In actuality, there is no reason to suppose that in the presence of asymmetric costs all m^t 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 Section 2.3.3

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

Taking the first-order condition for each i and summing over m^t firms, we derive the equilibrium industry output rate, which gives us the equilibrium market price, $\overline{P}^t$, through equation (4):

$$\overline{P}^t = \left(\frac{1}{m^t+1}\right)\left(a + \sum_{j=1}^{m^t} c_j^t\right). \tag{9}$$

Given the vector of marginal costs defined by the firms' chosen technologies and the optimal technology, $\overline{P}^t$ is uniquely determined and is independent of the market size, s^t. Furthermore, the equilibrium market price depends only on the *sum* of the marginal costs and not on the *distribution* of c_i^ts.

The equilibrium firm output rate is:

$$\overline{q}_i^t = s^t\left[\left(\frac{1}{m^t+1}\right)\left(a + \sum_{j=1}^{m^t} c_j^t\right) - c_i^t\right]. \tag{10}$$

Note that $\overline{q}_i^t = s^t\left[\overline{P}^t - c_i^t\right]$: A firm's equilibrium output rate depends on its own marginal cost and the equilibrium market price. Finally, the Cournot equilibrium firm profit is

$$\pi^t(\overline{q}_i^t) = \overline{P}^t \cdot \overline{q}_i^t - f - c_i^t \cdot \overline{q}_i^t = \frac{1}{s^t}\left(\overline{q}_i^t\right)^2 - f \tag{11}$$

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

2.3 Multi-Stage Decision Structure

At the outset of a period, the goal vector, $\underline{\widehat{z}}^t$, and the market size, s^t, are given. These variables are exogenously determined according to the pre-specified mechanisms: The movement of $\underline{\widehat{z}}^t$ follows the shift dynamic provided in (3), while that of s^t follows the stochastic or deterministic cycles as will be described in Sections 5 and 6, respectively.

Each period consists of four decision stages – see Figure 1. Denote by S^{t-1} the set of surviving firms from $t-1$, 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. The inactive firms in $t-1$ survive to t if and only if they have sufficient net wealth to cover their fixed costs in $t-1$. 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 (6). It also has a current net wealth of w_i^{t-1} it carries over from $t-1$.

Let R^t denote a finite set of *potential* entrants who contemplate entering the industry in the beginning of t. I assume that the size of the potential entrants pool is fixed and constant at r throughout the entire horizon. I 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 $\{0,1\}^N$ according to uniform distribution. In addition, each potential entrant has a fixed start-up wealth it enters the market with.

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

2.3.1 Stage 1: Entry Decisions

In stage 1 of each period, the potential entrants in R^t first make their decisions to enter. Just as each firm in S^{t-1} has its current net wealth of w_i^{t-1}, we will let $w_j^{t-1} = b$ for all $j \in R^t$ where b is the fixed "start-up" wealth common to all potential entrants. The start-up wealth, b, may be viewed as a firm's available fund that remains after paying for the one-time set-up cost of entry.[12] 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 negative value.

It is important to specify what a potential entrant knows as it makes the entry decision. A potential entrant k knows its own marginal cost, c_k^t, based on the new environment, $\widehat{z}^t$.[13] It observes the size of the market, s^t. It also has observations on the market price and the incumbent firms' outputs from $t-1$ – that is, P^{t-1} and $q_i^{t-1} \forall i \in S^{t-1}$. Given these observations and the fact that $\overline{q}_i^t = s^t[\overline{P}^t - c_i^t]$ from equation (10), k can infer c_i^{t-1} for all $i \in S^{t-1}$. While the surviving incumbent's marginal cost in t may be different from that in $t-1$ due to technological shocks, I assume that the potential entrant takes c_i^{t-1} to stay fixed for lack of information on $\widehat{z}^t$. The potential entrant k then uses c_k^t and $\{c_i^{t-1}\}_{\forall i \in S^{t-1}}$ in computing the post-entry profit expected in t.

Given the above information, the entry rule for a potential entrant takes the simple form that it will be attracted to enter the industry if and only if it perceives its post-entry net wealth in period t to be strictly positive. The entry decision then depends on the profit that it expects to earn in t following entry, which is assumed to 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.[14]

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

$$\begin{cases} \text{Enter,} & \text{if and only if } \pi_k^e(\underline{z}_k^t) + b > \underline{W}; \\ \text{Stay out,} & \text{otherwise,} \end{cases} \tag{12}$$

where π_k^e is the static Cournot equilibrium profit the entrant *expects* to make in

[12] 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.

[13] It is not that the potential entrant k knows the content of $\widehat{z}^t$ (the optimal method for each activity), but only that it gets an accurate signal on c_k^t (which is determined by $\widehat{z}^t$).

[14] That each potential entrant assumes itself to be the only firm to enter 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.

the period of its entry and $\underline{W}$ is the threshold level of wealth for a firm's survival (common to all firms).[15]

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 belief about the market structure and the technological environment. Denote by M^t the set of firms ready to compete in the industry: $M^t \equiv S^{t-1} \cup E^t$. At the end of stage 1 of period t, we then have a well-defined set of competing firms, M^t, with their current net wealth, $\{w_i^{t-1}\}_{\forall i \in M^t}$ and their technologies, $\underline{z}_i^{t-1}$ for all $i \in S^{t-1}$ and $\underline{z}_j^t$ for all $j \in E^t$.

2.3.2 Stage 2: R&D Decisions

In stage 2, the surviving incumbents from $t-1$, S^{t-1}, engage in R&D to improve the efficiency of their existing technologies. Given that the entrants in E^t entered with new technologies, they do not engage in R&D in t. In addition, only those firms with sufficient wealth to cover the R&D expenditure engage in R&D. I will denote by I_i^t the R&D expenditure incurred by firm i in t.

The R&D process transforms the incumbent's technology from $\underline{z}_i^{t-1}$ to $\underline{z}_i^t$, where $\underline{z}_i^t = \underline{z}_i^{t-1}$ if either no R&D is performed in t or R&D is performed but its outcome is not adopted. This transformation process involves endogenizing the R&D-related decisions by specifying a set of choice probabilities that evolve over time on the basis of a reinforcement learning mechanism. If a firm decides to pursue R&D, it can do so through either *innovation* or *imitation*. The size of R&D expenditure depends on which of the two modes a given firm chooses: *Innovation* costs a fixed amount of K_{IN} while *imitation* costs K_{IM}. Hence, the necessary condition for a firm to engage in R&D is:

$$w_i^{t-1} \geq \max\{K_{IN}, K_{IM}\}.^{16} \quad (13)$$

Figure 2 illustrates the various stages of the R&D process. The crucial part of this model is how the various components of the R&D decision are carried out. First, each firm i has two probabilities, α_i^t and β_i^t, which evolve over time via a reinforcement learning mechanism. Each period, firm i chooses to pursue R&D with probability α_i^t and not to pursue R&D with probability $1 - \alpha_i^t$. If she chooses not to purse R&D, she simply keeps the old technology and, hence, $\underline{z}_i^t = \underline{z}_i^{t-1}$. However, if she chooses to pursue R&D, then she has a probability β_i^t with which she chooses to "innovate" and $1 - \beta_i^t$ with which she chooses to "imitate." (As mentioned, both α_i^t and β_i^t are endogenous – how they are updated from one period to the next is discussed below.)

Innovation occurs when the firm considers changing the method (i.e., flipping the bit) in *one* randomly chosen activity. *Imitation* occurs when the firm (i) picks another firm (j) from a subset of S^{t-1} and considers copying the method employed by j in *one* randomly chosen activity while retaining his (i's) current methods in all

[15] Naturally, $\underline{W}$ may also be viewed as the opportunity cost of operating in the given industry.
[16] The computational experiments reported in this paper assume $K_{IN} > K_{IM}$.

other activities.[17] Only those surviving firms which were profitable in $t-1$, i.e., $\pi_k^{t-1} > 0$, are considered as the potential targets for imitation. Let S_*^{t-1} denote the set of these *profitable* firms, where $S_*^{t-1} \subseteq S^{t-1}$. The choice of a firm to imitate is made probabilistically using the "roulette wheel" algorithm. To be specific, the probability of firm $i \in S^{t-1}$ observing a firm $j \in S_*^{t-1}$ is denoted p_{ij}^t and is defined as follows:

$$p_{ij}^t \equiv \frac{\pi_j^{t-1}}{\sum_{\forall k \in S_*^{t-1}, k \neq i} \pi_k^{t-1}} \tag{14}$$

such that $\sum_{\forall j \in S_*^{t-1}, j \neq i} p_{ij}^t = 1 \forall i \in S^{t-1}$. Hence, the more profitable firm is more likely to be imitated.

Let $\underline{\widetilde{z}}_k^t$ denote firm k's vector of experimental methods (i.e., a technology considered for potential adoption) obtained through "innovation" or through "imitation." The adoption decision rule is as follows:

$$\underline{z}_k^t = \begin{cases} \underline{\widetilde{z}}_k^t, & \text{if and only if } c_k^t(\underline{\widetilde{z}}_k^t, \underline{\widehat{z}}^t) < c_k^t(\underline{z}_k^{t-1}, \underline{\widehat{z}}^t) \\ \underline{z}_k^{t-1}, & \text{otherwise.} \end{cases} \tag{15}$$

Hence, 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.[18] This happens when the Hamming distance to the 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 (as assumed to be part of its belief), the only way that its profit is going to improve is if its marginal cost is reduced as the result of its innovation.

Note that firm i's R&D expenditure in period t depends on the type of R&D activity it pursued:

$$I_i^t = \begin{cases} 0 & \text{if no R\&D was pursued;} \\ K_{IN} & \text{if R\&D was pursued and innovation was chosen;} \\ K_{IM} & \text{if R\&D was pursued and imitation was chosen.} \end{cases} \tag{16}$$

Let us get back to the choice probabilities, α_i^t and β_i^t. Both probabilities are endogenous and specific to each firm. Specifically, they are adjusted over time by individual firms according to a reinforcement learning rule. I adopt a version of the *Experience-Weighted Attraction (EWA)* learning rule as described in Camerer and Ho

[17] Hence, the imitating firm is capable of copying only a small part of the entire technology. This is one aspect of the cognitive limitation assumed in this research. An issue that can be investigated in the future is to relax this assumption and examine the impact that a firm's cognitive capacity has on the various outcomes at the firm and industry level. This is not pursued in this paper.

[18] I assume that the evaluation of the technology by a firm in terms of its production efficiency (as representd by the level of its 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.

(1999). Under this rule, a firm has a numerical *attraction* for each possible course of action. The learning rule specifies how attractions are updated by the firm's experience and how the probabilities of choosing different courses of action depend on these attractions. The main feature is that a positive outcome realized from a course of action reinforces the likelihood of that same action being chosen again.

Using the *EWA*-rule, α_i^t and β_i^t are adjusted at the end of each period on the basis of evolving attraction measures: A_i^t for *R&D* and $\overline{A}_i^t$ for *No R&D*; B_i^t for *Innovation* and $\overline{B}_i^t$ for *Imitation*. Table 2 shows the adjustment dynamics of these attractions for the entire set of possible cases. According to this rule, A_i^t is raised by a unit when R&D (either through innovation or imitation) was productive and the generated idea was adopted. Alternatively, $\overline{A}_i^t$ is raised by a unit when R&D was unproductive and the generated idea was discarded. In terms of the choice between innovation and imitation, B_i^t is raised by a unit if R&D via innovation was performed and the generated idea was adopted or if R&D via imitation was performed and the generated idea was discarded. Hence, the attraction for innovation can increase if either innovation was productive or imitation was unproductive. Conversely, $\overline{B}_i^t$ is raised by a unit if R&D via imitation generated an idea which was adopted – i.e., imitation was productive – or R&D via innovation generated an idea which was discarded – i.e., innovation was unproductive. If no R&D was performed, all attractions remain unchanged.

Given A_i^{t+1} and $\overline{A}_i^{t+1}$, one derives the choice probability of *R&D* in period $t+1$ as:

$$\alpha_i^{t+1} = \frac{A_i^{t+1}}{A_i^{t+1} + \overline{A}_i^{t+1}}. \tag{17}$$

In $t+1$, the firm then pursues *R&D* with probability α_i^{t+1} and *No R&D* with probability $1 - \alpha_i^{t+1}$. Hence, a success that raises the attraction level of a given course of action raises the probability that the same course will be taken in the following period.

Given B_i^{t+1} and $\overline{B}_i^{t+1}$, one derives the choice probability of innovation in period $t+1$ as:

$$\beta_i^{t+1} = \frac{B_i^{t+1}}{B_i^{t+1} + \overline{B}_i^{t+1}}. \tag{18}$$

The probability of pursuing imitation is $1 - \beta_i^{t+1}$.

Finally, all new entrants in E^t are endowed with the initial attractions that make them indifferent to the available options. Specifically, I assume that $A_i^t = \overline{A}_i^t = 10$ and $B_i^t = \overline{B}_i^t = 10$ for a new entrant such that $\alpha_i^t = \beta_i^t = 0.5$ for all i – i.e., it has equal probabilities of choosing between *R&D* and *No R&D* as well as between *innovation* and *imitation*. Of course, these attractions will diverge from one another as the firms go through differential market experiences as the result of their R&D decisions made over time.

2.3.3 Stage 3: Output Decisions and Market Competition

Given the R&D 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 wealth $\{w_i^{t-1}\}_{\forall i \in M^t}$. With the updated technologies, the firms engage in Cournot competition in the market, where we "approximate" the outcome with the Cournot equilibrium defined in Section 2.2.[19]

Note that the equilibrium in Section 2.2 was defined for m^t firms under the assumption that all m^t firms produce positive quantities. In actuality, given the asymmetric costs, there is no reason to think that all firms in M^t will produce positive quantities in equilibrium. Some relatively inefficient firms may shut down their plants and stay inactive. What we need is 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 done 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. Re-define 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 equilibrium output and earns the corresponding profit. We then have π_i^t for all $i \in M^t$.

2.3.4 Stage 4: Exit Decisions

Given the single-period profits or losses made in stage 3 of the game, the firms in M^t consider exiting the industry in the final stage. Each firm's net wealth is first updated on the basis of the profits (or losses) made in stage 3 as well as the R&D expenditure incurred in stage 2:[20]

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

where I_i^t is the firm's R&D expenditure. The exit decision rule for each firm is then:

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

where $\underline{W}$ is the previously-defined threshold level of net wealth such that all firms with their current net wealth below $\underline{W}$ exit the market. Define L^t as the set of firms

[19] I admit to the use of Cournot-Nash equilibrium as being conceptually inconsistent with the "limited rationality" assumption employed in this paper. However, explicitly modeling the process of market experimentation would further complicate an already complex model. As such, I implicitly assume that experimentation is done instantly and without cost. Cournot-Nash equilibrium is then assumed to be a reasonable approximation of the outcome from that process.

[20] It does not matter whether the R&D expenditure is subtracted from the net wealth in stage 2 or in stage 4. It is a sunk cost by the time market competition starts and, as such, it has no impact on the firm's output decision in stage 3.

which exit the market in t. Once the exit decisions are made by all firms in M^t, the set of surviving firms from period t is then defined as:

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

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

3 Design of Computational Experiments

A typical simulation starts in $t = 1$ with a brand new industry which has $S^0 = \emptyset$. The decision stages described in Section 2.3 are then repeated for each firm, while the state variables – i.e., S^{t-1}, $\{\underline{z}_i^{t-1}\}_{\forall i \in S^{t-1}}$, $\{w_i^{t-1}\}_{\forall i \in S^{t-1}}$ – are passed on from one period to the next as the industry evolves.

The dynamic path the industry takes is affected by the set of parameters that characterize the operating environment of the firms. The values of the relevant parameters used in this paper, with the exception of those that determine the movement of the market size, s^t, are provided in Table 3. The parameters that determine the movement of s^t will be discussed in full in Sections 5 and 6.

The growth and development of the industry from its birth are studied by tracing the changes in the following endogenous variables:

- $|E^t|$: number of firms actually entering the industry in the beginning of t
- $|M^t|$: number of firms that are in operation in t (including both active and inactive firms)
- $|L^t|$: number of firms leaving the industry at the end of t
- P^t : market price at which goods are traded in t
- $\{c_i^t\}_{\forall i \in M^t}$: realized marginal costs of all firms that were in operation in t
- $\{q_i^t\}_{\forall i \in M^t}$: actual outputs of firms that were in operation in t
- $\{\pi_i^t\}_{\forall i \in M^t}$: realized profits (losses) of all firms that were in operation in t
- $\{I_i^t\}_{\forall i \in M^t}$: R&D expenditure of all firms that were in operation in t

Using the above variables, I construct an additional group of endogenous variables that characterize the aggregate behavior of the firms in an industry. First, as a concentration measure, I use the Herfindahl-Hirschmann Index, H^t:

$$H^t = \sum_{\forall i \in M^t} \left(\frac{q_i^t}{\sum_{\forall j \in M^t} q_j^t} \cdot 100 \right)^2. \tag{22}$$

For an aggregate measure of the industry's production efficiency, I construct an industry marginal cost, WMC^t, where

$$WMC^t = \sum_{\forall i \in M^t} \left[\left(\frac{q_i^t}{\sum_{\forall j \in M^t} q_j^t} \right) \cdot c_i^t \right]. \tag{23}$$

WMC^t is, hence, the weighted average of the individual firms' marginal costs in period t, where the weights are the market shares of the firms in that period.

Finally, I construct an industry average price-cost margin, PCM^t, where

$$PCM^t = \sum_{\forall i \in M^t} \left[\left(\frac{q_i^t}{\sum_{\forall j \in M^t} q_j^t} \right) \cdot \left(\frac{P^t - c_i^t}{P^t} \right) \right]. \tag{24}$$

PCM^t is the weighted average of the individual firms' price-cost margins in period t, where the weights are the market shares of the operating firms in that period.

In the next two sections, I examine the time series values of a subset of these endogenous variables from 100 independent replications based on the baseline parameter values. Let $X^t(r)$ be the value of an endogenous variable X in period t in replication r. For the analysis provided in the remaining part of the paper, I will use the time series of replication-average values, $\{X^t\}_{t=1}^{5,000}$, where

$$X^t = \frac{1}{100} \sum_{r=1}^{100} X^t(r) \tag{25}$$

4 Benchmark: Steady-State with Fixed Demand

As a benchmark, consider the case where there is no fluctuation in demand – that is, $s^t = \widehat{s}(= 4)$ for all t. Hence, any movement of firms over time is caused by the random shocks in the technological environment only. The technological shocks induce entry and exit of firms by directly influencing their current marginal costs, but they also give rise to adaptation by firms through R&D in their search for the new technological optimum. After the initial transition period following its birth, the industry settles into a steady-state in which each endogenous variable representing the industry structure fluctuates around a constant mean with finite variance. Figure 3 shows the movement of three main variables as they are averaged over 100 replications: (a) Number of operating firms; (b) market price; (c) aggregate R&D spending. All three endogenous variables reach steady-state by $t = 1,000$.

Given the industry's convergence to a steady-state, I focus on the values of the endogenous variables for the last 2,000 periods between $t = 3001$ and $t = 5,000$. As a step toward understanding the role of endogenous R&D on the industry dynamics, I run two separate simulations; one *with* endogenous R&D and another *without* any R&D.[21] When there is no endogenous R&D, the industry evolves purely on the

[21] All parameter values remain the same for both simulations. The only difference is that the case with no R&D requires the R&D decision to be turned off so that there is no updating of marginal costs for the incumbent firms.

basis of market competition among firms with heterogeneous endowed technologies (with heterogeneous efficiencies). The intra-industry variation in firms' efficiencies is guaranteed by the continual entry of new firms with distinct technologies.[22] Once entered, the firms have no way of improving their endowed technologies. Table 4 presents the steady-state mean and standard deviation of the endogenous variables over the 2,000 periods from both simulations.

The impact of R&D on the industry is captured by the difference in the steady-state behavior of an endogenous variable between the two scenarios; this is reported in the last column of the table. First, the R&D by firms has a stabilizing effect on the market structure: Both the number of entrants and the number of exits are lower when the firms perform R&D. That the net entry is approximately zero on average implies that the market structure is in the steady state for the relevant periods.

The number of operating firms is lower on average when firms perform R&D – i.e., R&D tends to raise the industry concentration. Based on this observation, one may conclude that the higher concentration under endogenous R&D confers higher degree of market power to the firms and, hence, a higher market price along the steady-state. This is not the case. As shown in Table 4, the market price is actually lower with R&D. The difference in the levels of the industry average marginal cost provides an explanation for this. Note that there are two countervailing forces that R&D exerts on price. The first is the increase in market power that results from the higher industry concentration as shown previously; this tends to raise the price. The second is the increase in production efficiency that comes from the improvements the firms are able to make on their operations; the corresponding reduction in the marginal costs tends to pull the price downward. [Table 4 shows that the R&D reduces the industry marginal cost through this effect and expands the industry output.] Given the two countervailing forces, the reduction in marginal cost dominates the increase in market power, leading to a net reduction in market price. Though the industry revenue is lower with R&D, both the industry profits and the profit for each individual firm tend to be higher. The dominance of the efficiency effect over the market power effect is also responsible for the positive impact R&D has on the price-cost margin.

5 Stochastic Variation in Demand

Given the impact of endogenous R&D on the steady-state structure of the industry, we proceed to examine the industry dynamics in the presence of inter-temporal variation in market demand. Our objective is to establish the relationships between the movement of the market size, s^t, and the relevant endogenous variables such as price (P^t), average price-cost margin (PCM^t), aggregate profit ($\sum_{\forall i \in M^t} \pi_i^t$), and aggregate R&D expenditure ($\sum_{\forall i \in M^t} I_i^t$).

As the first step toward understanding such relationships, we consider a stochastic

[22] To use the evolutionary terminology, the sole driving mechanism is the process of selection imposed on a population of firms having variation in their production efficiencies. There exists no adaptation at the level of individual firms in the population.

variation (of relative generality) in market size as specified next:

$$s^t = \begin{cases} \widehat{s} & \text{for } 1 \leq t \leq 2,000 \\ \max\{0, (1-\theta)\widehat{s} + \theta s^{t-1} + \varepsilon^t\} & \text{for } t \geq 2,001 \end{cases} \tag{26}$$

where θ is the rate of persistence in demand and ε^t is the random noise. ε^t is assumed to be uniformly distributed between $-1/2$ and $1/2$: $\varepsilon^t \sim U[-1/2, 1/2]$. Note that a higher value for θ implies a demand which is more sticky. An important issue is how the persistence in demand affects the cyclicality of various endogenous variables.

For the simulations reported here, five different values were considered for θ : $\theta \in \{0.5, 0.7, 0.9, 0.925, 0.95\}$. All other parameters were held at the baseline levels as indicated in Table 3. For each value of θ, one hundred independent replications were performed, each with a fresh set of random numbers.

Figure 4 plots the typical movements of the four main endogenous variables – number of operating firms, price, industry profits, and the aggregate R&D spending – against the movement of the market size variable, s^t, over a randomly chosen interval of 100 consecutive periods from a single randomly chosen replication. The persistence parameter, θ is set at 0.95 for this particular run. A casual look at these time series tells us that the number of operating firms is procyclical, the market price is countercyclical, the industry profit is strongly procyclical, and the aggregate R&D spending is weakly procyclical.

To show that these cyclical tendencies are inherent to the system and not just limited to the single run, I report the correlation between the time series on the realized market demand (s^t) and the time series output of the endogenous variable over the period of $t = 3,001 - 5,000$. For each endogenous variable, such correlation coefficient was calculated for each replication. Table 5 reports the average of those correlations from 100 independent replications for each variable. First, note that the number of entrants is positively correlated with the market demand, while the number of exits is weakly or not at all correlated. As the result, the net entrants is positively correlated with the market demand. This leads to the number of operating firms being *positively* correlated with the market demand. Hence, the number of operating firms shows a procyclical tendency, while the degree of industry concentration shows a countercyclical tendency.

As glimpsed from the time series in Figure 4(b), the market price is countercyclical – i.e., it is *negatively* correlated with the market demand. Industry marginal cost is *negatively* correlated, though the correlation is rather weak. The aggregate R&D spending is procyclical. Both the aggregate output and the aggregate revenue are almost perfectly correlated with the market demand. The industry profit is also strongly positively correlated. On the other hand, the industry price-cost margin is negatively correlated with the market demand, showing a countercyclical tendency.

All of the results are consistent with the stylized facts reported in the empirical literature. Furthermore, the degree of demand persistence, θ, appears to affect the cyclicality of these variables in a systematic manner. Comparing the correlations between the different values of θ, an increase in θ generally strengthens the cyclicality – i.e., with the exceptions of the number of exits and net entrants, the correlations (positive or negative) are uniformly stronger for a higher value of θ.

6 Deterministic Variation in Demand

To delve into the underlying causal factors of the cyclical patterns, I now consider a rather special deterministic path for s^t, as defined by a sine wave:

$$s^t = \left\{ \begin{array}{ll} \widehat{s} & \text{for } 1 \leq t \leq 2,000 \\ \widehat{s} + \sigma \sin\left[\frac{\pi}{\tau} - t\right] & \text{for } t \geq 2,001 \end{array} \right| \tag{27}$$

where $\widehat{s}$ is the pre-specified mean market size, σ is the amplitude of the wave, and τ is the period for half-turn (hence, one period is 2τ).

For simulations reported in this paper, we set $\widehat{s} = 4$, $\sigma = 2$, and $\tau = 500$: The size of the market is held fixed at 4 for the first $2,000$ periods in order to give the industry sufficient time to attain its structural stability – i.e., the number of operating firms achieves a steady state in which it fluctuates around a steady mean. Starting with $t = 2,001$, the market size then follows a sine wave with amplitude of 2 and the half-turn of 500 periods. After allowing another $1,000$ periods for the industry to adjust to the cyclical movement in demand, our analysis focuses on the last $2,000$ periods from $t = 3,001$ to $t = 5,000$. Figure 5 captures the demand cycle over the relevant period. As noted before, the reported value of an endogenous variable at each point in the time series is the average of the corresponding values from the 100 independent replications.

We first examine the movement of the market price, given the cyclical movement of the market size. Figure 6(a) shows the price path, along with the deterministic path taken by the market size, s^t – the dotted curve.

Property 1: Market price is countercyclical.

While the price is countercyclical, the industry profit is approximately, though not perfectly, procyclical – see Figure 6(b): The aggregate profits cycle tends to precede the demand cycle such that it peaks when the market size is still rising.

Property 2: Industry aggregate profits are procyclical.

In order to understand these properties, we explore the impact of demand cycle on the movement of firms and the evolving structure of the industry. Figures 7(a) and 7(b) show the number of entrants and the number of exits over time. A rise (fall) in consumer demand generally increases (decreases) the number of entrants, though the two movements are not perfectly correlated. When the demand is increasing, the number of entrants tends to rise as long as the demand rises at an increasing rate. When the demand rises at a diminishing rate, the number of entrants tends to fall. Likewise, along the downward segment of the demand cycle, the number of entrants falls as long as the demand falls at an increasing rate; once the fall in demand slows down, firms start to enter in rising numbers. Together, these properties imply that the entry cycle tends to precede the demand cycle.

More interestingly, the number of exits tends to follow the same cyclical pattern – see Figure 7(b). This indicates *co-movement* of entry and exit over time such that the period with a relatively high number of entrants also has a relatively high number of exits. That is, the industry during a boom is characterized by a greater degree of *turbulence* than during a bust. However, the net entry (i.e., the number of entrants minus the number of exits) exhibits procyclicality such that the number of operating firms in a given period tends to be procyclical as well – see Figure 7(c). Naturally, the time series on the Herfindahl-Hirschmann index (measuring the concentration of the industry) follows a countercyclical path, as shown in Figure 7(d).

Property 3: The number of operating firms is procyclical.

An implication of this property is that the degree of competition is higher during a boom than during a bust. This offers a market power-based explanation as to why we observe countercyclicality in market price in Property 1: The higher number of new entrants during a boom leads to more intense oligopolistic competition, putting a downward pressure on the market price. Conversely, the decline in the net entry during a bust reduces the competition, pushing the price up.

Figure 8(a) shows that the average price-cost margin is countercyclical.

Property 4: The industry average price-cost margin is countercyclical.

This property can be explained solely on the bases of the countercyclical price, if the firms' marginal costs remain stationary in the presence of demand cycle. However, the marginal costs of the operating firms do not follow a stationary path; they tend to fluctuate over time as the degree of competition fluctuates according to: 1) the cyclical firm entries and exits; and 2) any movement in the R&D activities of the surviving firms. Indeed, Figure 8(b) shows that the industry marginal cost, WMC^t, is countercyclical: Firms are more efficient during a boom than during a bust.

Property 5: The industry average marginal cost is countercyclical.

This result would seem consistent with our observation on the entry/exit dynamics, which showed that the market is more (less) competitive – hence, more (less) selective – during a boom (bust): more selective market during a boom should push out the inefficient firms and bring the average marginal cost to a lower level, while the less selective market during the bust may allow the inefficient firms to linger on. A closer look at the source of cyclicality in the firm efficiency reveals that this explanation is incorrect. For more detailed investigation I performed two separate simulations (as done in Section 4), where the R&D decisions were turned on for one while they were turned off for another. Figure 9 reports the industry average marginal costs over the period of $3,001 - 5,000$, given the demand cycle (with the dotted line representing the period of peak and the solid line representing the trough) – the upper series from the simulation *without* the R&D and the lower series from the one *with* the R&D. The average marginal cost is stationary when there is no R&D, even in the presence of the demand cycle. In contrast, the time series from the model with the endogenous R&D clearly show countercyclicality. It is then clear that the cyclical pattern in the industry average marginal cost is caused by the cyclicality of endogenous R&D; the changing extent of market selection has little impact on the efficiencies of the operating firms. The time series on the aggregate R&D spending captured in Figure 10 reinforces this interpretation: the aggregate R&D spending by the firms takes a procyclical pattern such that the R&D activities are more intense during a boom than during a bust, which contributes to the countercyclicality in the industry average marginal cost.

Property 6: The aggregate R&D is procyclical.

That firms tend to be more efficient during a boom than a bust then has an adaptation-based explanation rather than a selection-based explanation. This cyclical tendency is likely to be weaker in those industries in which R&D spending makes up a smaller portion of its total production cost.

Note that the countercyclicality in the average price-cost margin is not obvious, given countercyclicality in both price (Property 1) and the average marginal cost (Property 5). What is clear is that the firms raise their markups over marginal cost during a bust and reduce them during a boom, which implies that the intertemporal variation in price is greater than that in the industry average marginal cost.

7 Concluding Remarks

The Schumpeterian process of *creative destruction* is often conceptualized as the Darwinian evolutionary process. The model proposed here can be viewed in a similar framework. To be specific, it has two interacting mechanisms that jointly determine how a given industry will evolve over time. The first is the mechanism that generates and maintains variation in the population of firms, where the variation comes in the form of heterogeneous production technologies (and, hence, the varying degrees of production efficiency on the supply-side). What guarantees the generation and maintenance of such variation is the inherent tendency of the firms to pursue available profit opportunities – e.g., the persistent entry by new firms and the R&D efforts of the existing firms. The exogenous shocks to the technological environment guarantees a steady supply of such opportunities for R&D. The second component, acting on the first component, is the market competition of sufficient severity that induces the selection of a subset of firms from the existing population, where the survival advantage goes to those producing a given product at lower cost by using more efficient technology. It is then the continuing interaction of these two mechanisms that drive the process of industrial dynamics in this model.

Given the underlying framework for the industrial dynamics, the focus of the paper was on investigating how fluctuations in market demand affect the long-run dynamics of the industry. Two specifications were considered for the inter-temporal movement of market demand. The first was a serially correlated stochastic movement with a parameter that captures the rate of persistence in demand. The second, used for the purpose of identifying the causal factors, was a deterministic cycle, in which the market size variable followed a sine wave, thereby capturing the regular boom-bust cycle with a fixed frequency.

The simulation results under both specifications were consistent with the cyclical patterns observed empirically for many of the relevant variables. In particular, the entry/exit dynamics that respond to the fluctuation in market demand generated countercyclical industry concentration. The cyclical concentration had implications for fluctuations in the market power of the operating firms, which in turn lead to countercyclical market price. The aggregate R&D spending was shown to be procyclical, generating countercyclical industry marginal cost (and countercyclical price). The markups over marginal costs were greater during a bust than a boom, which gave rise to the countercyclical price-cost margins. Finally, the more persistent the market demand, the stronger was the degree of cyclicality in these endogenous variables.

References

[1] Bagwell, K., "Countercyclical Pricing in Customer Markets," *Economica*, 71 (2004), 519-542.

[2] Barlevy, G., "On the Cyclicality of Research and Development," *American Economic Review*, 97 (2007), 1131-1164.

[3] Barro, R. J. and S. Tenreyro, "Closed and Open Economy Models of Business Cycles with Marked Up and Sticky Prices," *The Economic Journal*, 116 (2006), 434-456.

[4] Bilbiie, F. O., F. Ghironi, and M. J. Melitz, "Endogenous Entry, Product Variety, and Business Cycles," Working Paper.

[5] Bils, M., "The Cyclical Behavior of Marginal Cost and Price," *American Economic Review*, 77 (1987), 838-855.

[6] Bils, M., "Pricing in a Customer Market," *Quarterly Journal of Economics*, 104 (1989), 699-718.

[7] Camerer, C. and T.-H. Ho, "Experience-Weighted Attraction Learning in Normal Form Games," *Econometrica*, 67 (1999), 827-874.

[8] Camerer, C. and D. Lovallo, "Overconfidence and Excess Entry: An Experimental Approach," *American Economic Review*, 89 (1999), 306-318.

[9] Campbell, J., "Entry, Exit, Embodied Technology, and Business Cycles," *Review of Economic Dynamics*, 1 (1998), 371-408.

[10] Chang, M.-H., "Muddling through the Gales of Creative Destruction: A Non-Equilibrium Computational Model of Schumpeterian Competition," *Working Paper*, September 4, 2012.

[11] Chatterjee, S. and R. Cooper, "Entry and Exit, Product Variety and the Business Cycle," NBER Working Paper No. 4562.

[12] Chevalier, J. A., A. K. Kashyap, and P. E. Rossi, "Why Don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data," *American Economic Review*, 93 (2003), 15-37.

[13] Chevalier, J. A. and D. S. Scharfstein, "Liquidity Constraints and the Cyclical Behavior of Markups," *American Economic Review*, 85 (1995), 390-396.

[14] Cooley, T. F. and L. E. Ohanian, "The Cyclical Behavior of Prices," *Journal of Monetary Economics*, 28 (1991), 25-60.

[15] Edmond, C. and L. Veldkamp, "Income Dispersion and Counter-Cyclical Markups," NBER Working Paper No. 14452.

[16] Etro, F. and A. Colciago, "Endogenous Market Structures and the Business Cycle," *The Economic Journal*, 120 (2010), 1201-1233.

[17] Francois, P. and H. Lloyd-Ellis, "Schumpeterian Cycles with Pro-cyclical R&D," *Review of Economic Dynamics*, 12 (2009), 567-591.

[18] Geroski, P. A. and C. F. Walters, "Innovative Activity over the Business Cycle," *The Economic Journal*, 105 (1995), 916-928.

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 profitable 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 : Evolving Attractions

Decision Path			Updating of Attractions			
No R&D			$A_i^{t+1}= A_i^t$;	$\overline{A}_i^{t+1}=\overline{A}_i^t$;	$B_i^{t+1}= B_i^t$;	$\overline{B}_i^{t+1}=\overline{B}_i^t$
R&D	Innovate	Adopt	$A_i^{t+1}= A_i^t+1$;	$\overline{A}_i^{t+1}=\overline{A}_i^t$;	$B_i^{t+1}= B_i^t+1$;	$\overline{B}_i^{t+1}=\overline{B}_i^t$
		Discard	$A_i^{t+1}= A_i^t$;	$\overline{A}_i^{t+1}=\overline{A}_i^t+1$;	$B_i^{t+1}= B_i^t$;	$\overline{B}_i^{t+1}=\overline{B}_i^t+1$
	Imitate	Adopt	$A_i^{t+1}= A_i^t+1$;	$\overline{A}_i^{t+1}=\overline{A}_i^t$;	$B_i^{t+1}= B_i^t$;	$\overline{B}_i^{t+1}=\overline{B}_i^t+1$
		Discard	$A_i^{t+1}= A_i^t$;	$\overline{A}_i^{t+1}=\overline{A}_i^t+1$;	$B_i^{t+1}= B_i^t+1$;	$\overline{B}_i^{t+1}=\overline{B}_i^t$

Table 3 : List of Parameters and Their Values

Notation	Definition	Baseline Value
N	Number of tasks	96
r	Number of potential entrants per period	40
b	Start-up wealth for a new entrant	0
$\underline{W}$	Threshold level of net wealth for survival	0
a	Demand intercept	300
f	Fixed production cost	200
K_{IN}	Fixed cost of innovation	100
K_{IM}	Fixed cost of imitation	50
A_i^0	Initial attraction for R&D (all i)	10
$\overline{A}_i^0$	Initial attraction for No R&D (all i)	10
B_i^0	Initial attraction for Innovation (all i)	10
$\overline{B}_i^0$	Initial attraction for Imitation (all i)	10
g	Maximum magnitude of change in technological environment	8
T	Time horizon	5,000
γ	Rate of change in technological environment	0.1

Table 4: Firm and Industry Behavior in Steady-State When Demand is Fixed

Endogenous Variables	Steady-State Mean (Std. Dev.) Without R&D	With R&D	Impact of R&D
No. Entrants	1.01317(0.11518)	0.68359(0.09735)	−0.32958(0.15000)
No. Exits	1.01310(0.11525)	0.68420(0.09509)	−0.32890(0.15181)
Net Entrants	0.00007(0.12890)	−0.00061(0.11176)	−0.00068(0.17482)
No. Operating Firms	42.8374(0.40140)	41.1352(0.44332)	−1.70217(0.56168)
Concentration (HHI)	332.331(2.24527)	357.282(2.59841)	24.951(3.32877)
Price	46.9558(0.11048)	45.9190(0.15072)	−1.03677(0.18602)
Industry Marginal Cost	38.5471(0.11350)	36.8408(0.17661)	−1.70632(0.21117)
Industry Output	1012.18(0.44193)	1016.32(0.60290)	4.14707(0.74408)
Industry Revenue	47522.6(90.9316)	46659.7(125.549)	−862.829(154.367)
Industry Profit	−57.023(120.509)	−51.985(158.77)	5.03779(190.753)
Per-Firm Profit	1.09666(2.89925)	3.14115(4.07088)	2.04449(4.80525)
Price-Cost Margin	0.17911(0.00118)	0.19800(0.00172)	0.01889(0.00207)

Table 5: Correlations between the Market Size and the Endogenous Variables

Endogenous Variables	θ 0.5	0.7	0.9	0.925	0.95
No. Entrants	0.08716	0.10106	0.12513	0.12914	0.13009
No. Exits	−0.03295	−0.01920	0.01004	0.01675	0.02041
Net Entrants	0.10746	0.10805	0.10477	0.10249	0.10054
No. Operating Firms	0.03777	0.07552	0.22989	0.28358	0.36162
Concentration (HHI)	−0.05889	−0.09705	−0.29603	−0.36049	−0.45420
Price	−0.03216	−0.05057	−0.15002	−0.19594	−0.27785
Industry Marginal Cost	−0.00542	−0.00629	−0.01088	−0.01818	−0.04768
Industry Output	0.99759	0.99833	0.99934	0.99951	0.99965
Industry Revenue	0.95264	0.96622	0.98587	0.98937	0.99232
Industry Profit	0.39015	0.42844	0.51695	0.54738	0.59269
Price-Cost Margin	−0.03656	−0.06125	−0.19847	−0.24692	−0.31020
Aggregate R&D Spending	0.01237	0.03740	0.12352	0.15632	0.20727

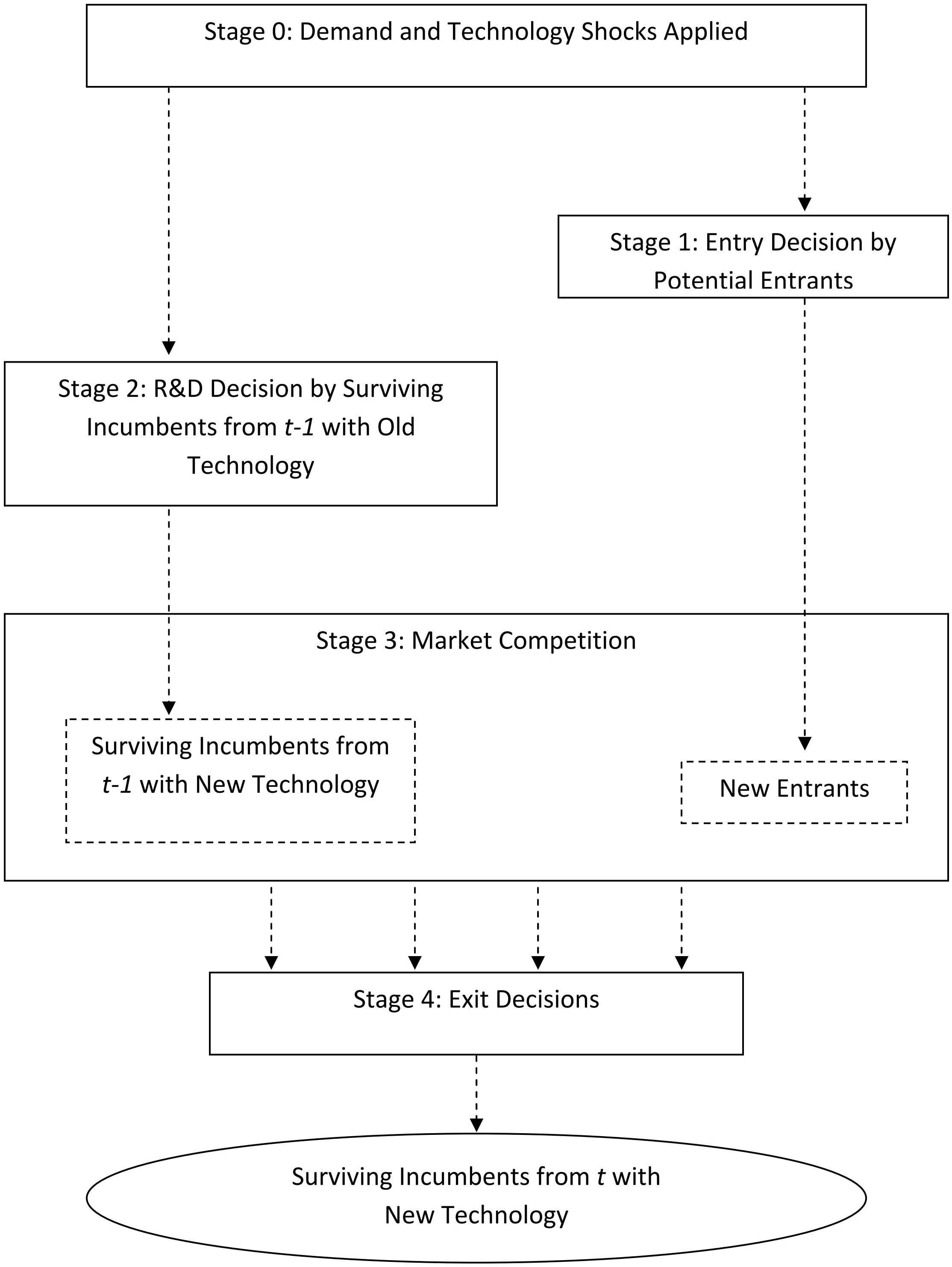


Figure 1: Four Stages of Decision Making in Period *t*

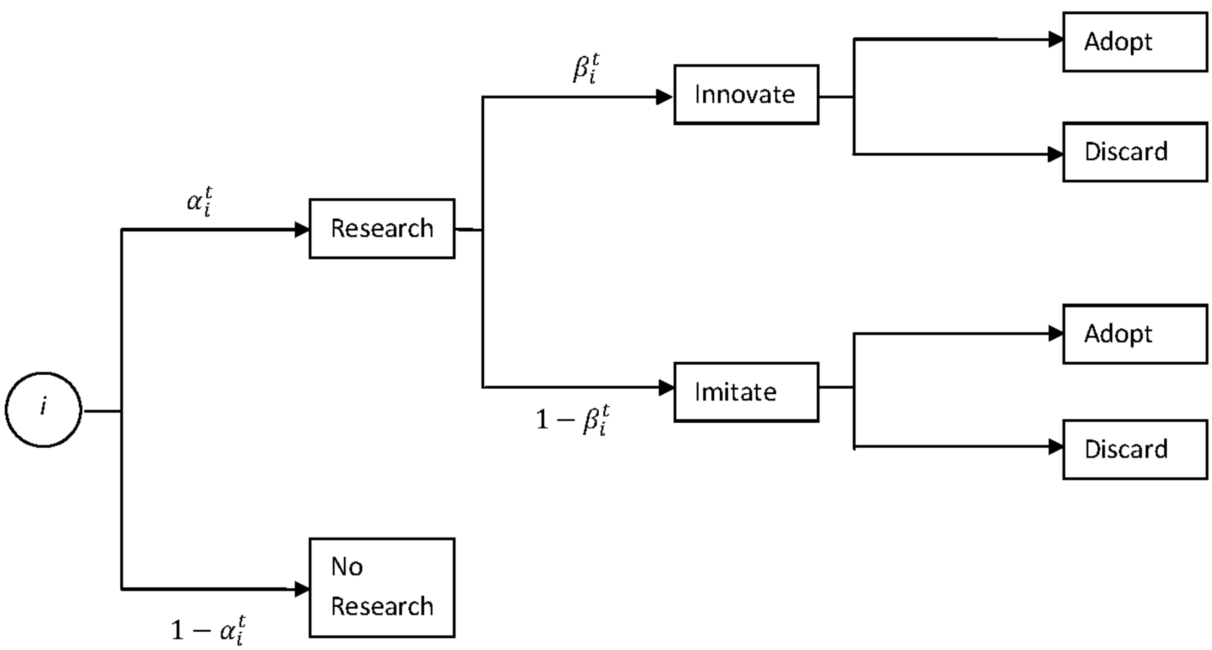


Figure 2: R&D Decision in Stage 2

Figure 3: Endogenous R&D with fixed demand

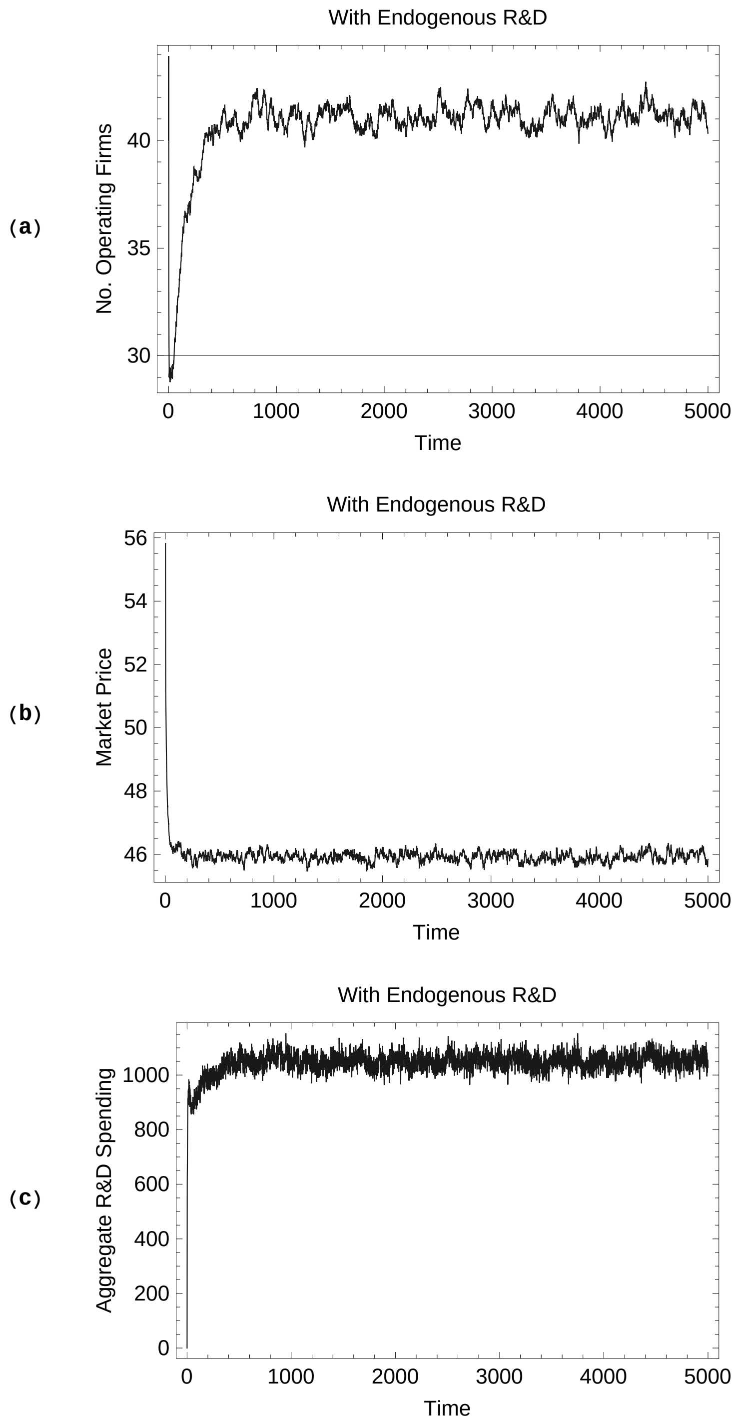
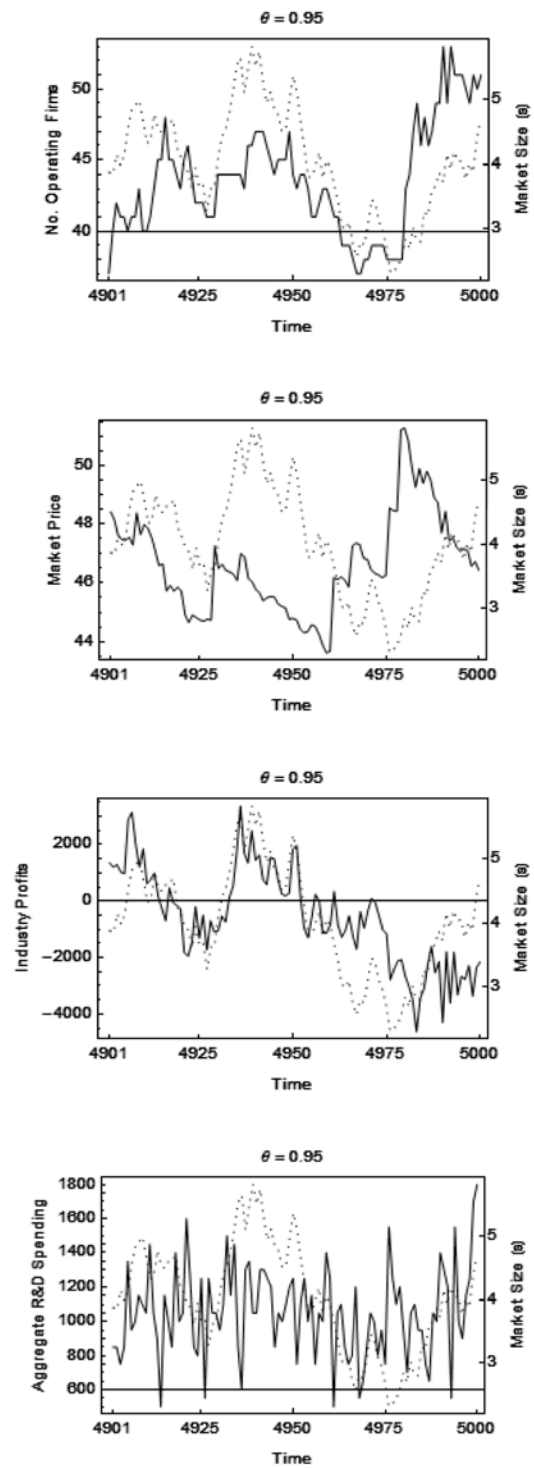


Figure 4: Industry structure when demand is stochastic



(a)

(b)

(c)

(d)

Figure 5: Deterministic demand cycle

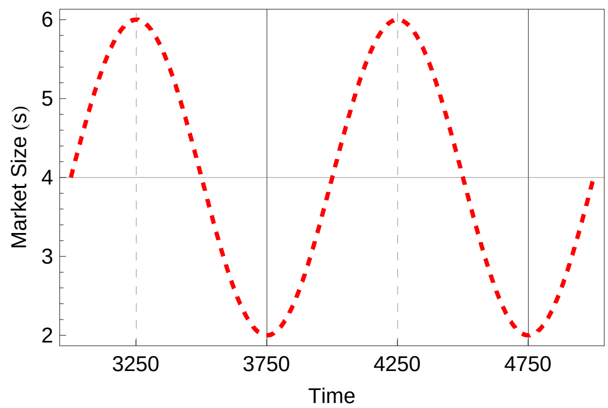
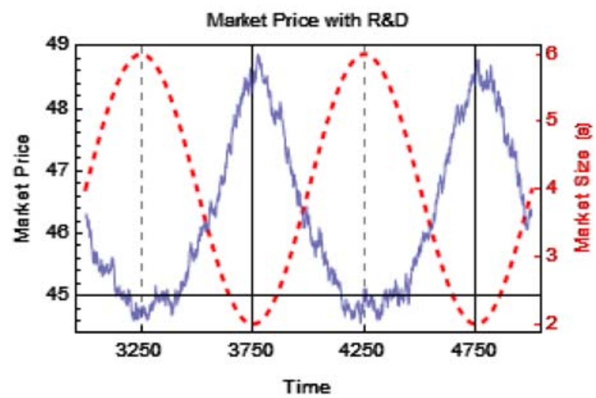


Figure 6: Entry and exit dynamics

(a)



(b)

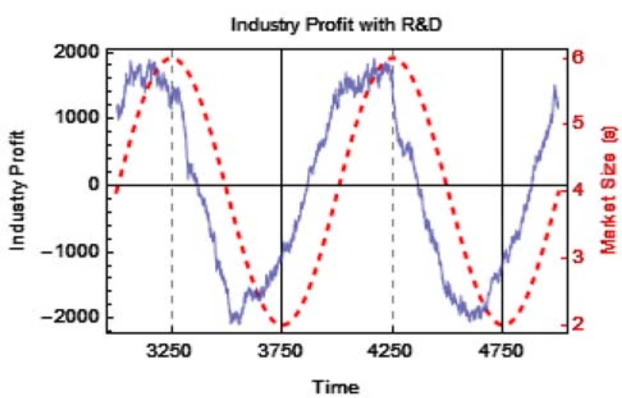
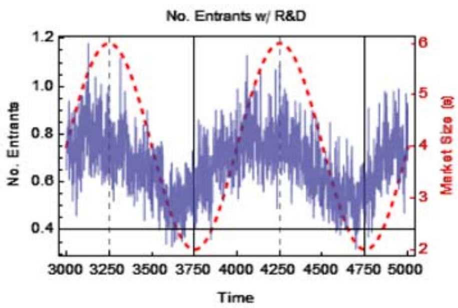
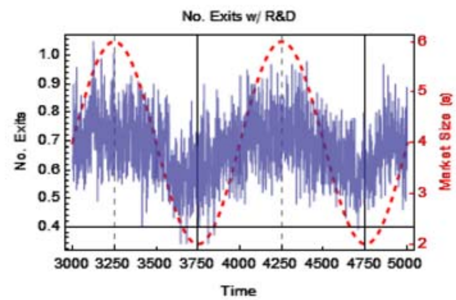


Figure 7: Market structure

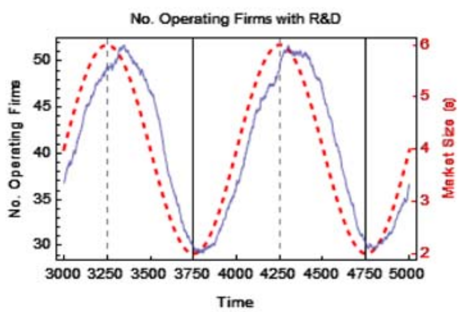
(a) Number of entrants



(b) Number of exits



(c) Number of operating firms



(d) Industry concentration (HHI)

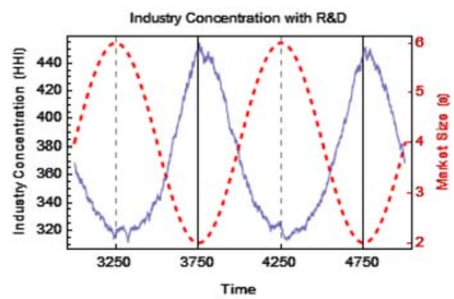


Figure 8: Price-cost margin and industry marginal cost

(a)

(b)

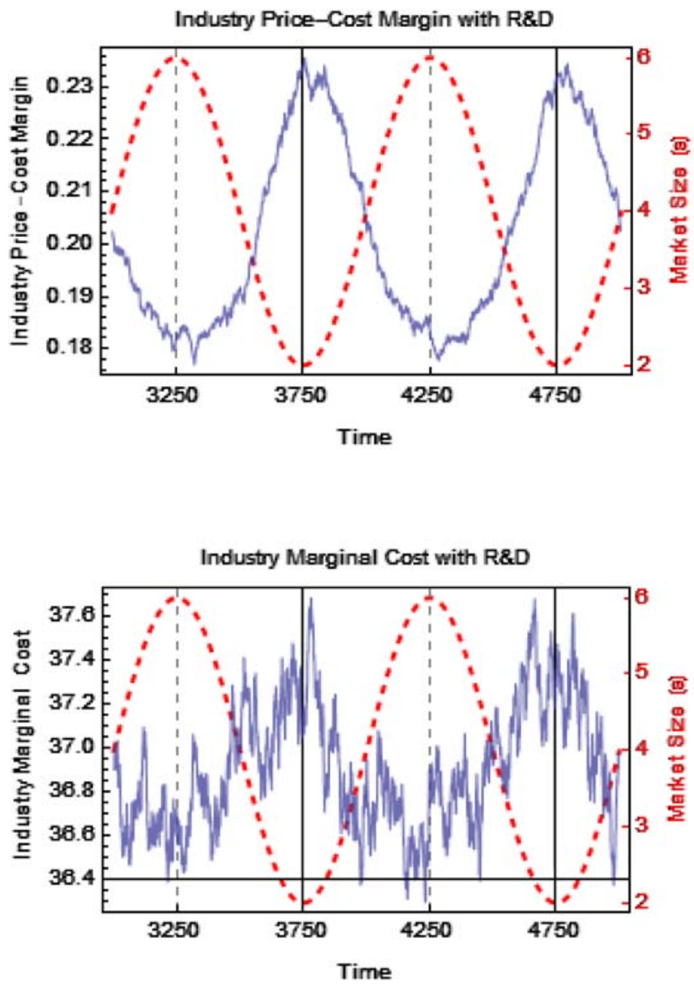


Figure 9: Industry marginal cost with and without R&D

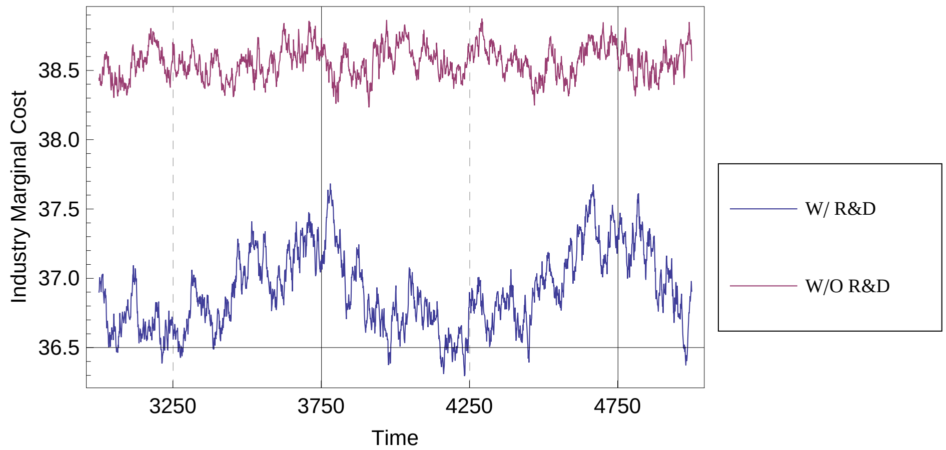


Figure 10: Aggregate R&D spending