A Non-Equilibrium Theory of Merger Waves[*]

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Abstract

Mergers are known to come in waves. This paper offers a computational model of industry dynamics, in which endogenously generated mergers exhibit a wave-like pattern. The root cause of this emergent behavior is random technological shocks which change the absolute and relative unit costs of existing firms' technologies. This mechanism induces other dynamic patterns consistent with several well-known empirical regularities. Through a comparative dynamics analysis, I investigate the impact of mergers on the steady-state structure and performance of the industry, and offer predictions on how industry-specific factors determine the between-industry variations in merger intensity.

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1. Introduction

Mergers are known to come in waves. The wave-like patterns, while most obvious in the aggregate merger series for the overall economy, are also in clear display at the individual industry level. However, the size and the shape – i.e., total number of mergers and the position of the peak – tend to vary significantly from industry to industry. In this paper, I offer a computational model of industry dynamics, in which endogenously generated mergers exhibit a wave-like pattern. The root cause of this emergent behavior is random technological shocks which change the absolute and relative unit costs of existing firms' technologies. This mechanism also induces other dynamic patterns that are consistent with a number of well-known empirical regularities in industrial organization. Most importantly, the model developed here allows a thorough investigation of the linkages between the industry-specific factors and the extent to which the causal mechanism drives the evolving dynamics of the industry.

Starting with Nelson (1959), a long line of empirical research has shown that merger activities tend to cluster in time and in sectors.[1] Five major merger waves have been identified.[2] The first three waves are described in Scherer (1980) – the first wave occurring around the turn of the last century (1893-1903), the second wave peaking in 1929, and the third wave starting around 1964 and ending by 1971. Ravenscraft (1987) identified the fourth merger wave during the early to mid-1980s. [See also Mitchell and Mulherin (1996).] Finally, a steady increase in merger activity over the 1990s, continuing through 2001, is often considered the fifth wave. [See Gugler *et al.* (2012).]

Nelson (1959) provided an in-depth analysis of the first merger wave, using a comprehensive and detailed time series of merger activity in manufacturing and mining for the period of 1895-1920. The second wave was covered by the series compiled by Willard Thorpe for the period of 1919-39.[3] The U.S. Federal Trade Commission (FTC) collected and published data on mergers in the manufacturing and mining sectors of the U.S. for the period of 1948-79. This series, hence, covered the third merger wave. Ravenscraft (1987) based his evidence for the fourth wave on the merger series constructed from both the periodical *Merger and Acquisition Journal* and W. T. Grimm & Co. for the period of 1979-86. Gugler *et al.* (2012) used the corporate transactions data from Thomson Financial Securities Data for the period of 1991-2004.

It is clear that the datasets used to identify these waves are not consistent with one another as the data sources as well as the criteria for inclusion vary widely. Nevertheless, within each series, the existence of a major wave, as well as other minor cycles, is quite noticeable. To illustrate this, the first three merger waves are portrayed in Figure 1. Figure 1(a) plots the aggregate merger series provided in Nelson (1959), while Figure 1(b) plots the merger series for manufacturing and mining

[1] A diverse set of econometric techniques have been used to formally *identify* the merger waves. Ravenscraft (1987) regressed measures of merger activity on four dummy variables, each representing one of the four merger waves. He found the merger activity to be significantly higher during the wave years than during the non-wave years. Golbe and White (1988) used a non-parametric "runs" test and found the number of mergers to cluster in adjoining periods of relatively high and relatively low activity. Both Town (1992) and Linn and Zhu (1997) tested the wave hypothesis for the US and UK time series data, using a two-state Markov regime switching model. Golbe and White (1993) used an alternative approach in which the wave hypothesis was tested using the sine curve estimations for the US merger time series. Yet another alternative approach was proposed by Barkoulas, Baum, and Chakraborty (2001), where they used a fractionally integrated process to model the wave-like pattern in the merger series. They observed that the dynamic structure in merger activity can be characterized as a strongly dependent or long-memory process.

[2] The data documenting these waves comes from a variety of sources with varying data collection protocols.

[3] Willard L. Thorp, "The Merger Movement," in *The Structure of Industry*, Temporary National Economic Committee, No. 27, table 1, p.233.

industries from 1919 to 1947 as presented by Weston (1953). The third wave is captured in Figure 1(c), which is based on the FTC series between 1948 and 1979.[4] In all cases, the three major waves, the first during 1893-1903, the second during 1923-1931, and the third during 1964-71, clearly stand out, although there are other minor waves in-between these major ones.

FIGURE 1 NEAR HERE

The aggregate merger waves are the result of individual industry merger waves that are not entirely synchronous nor of equal relative amplitude. Both timing and amplitude differences can offer insights and opportunities for using variation in model parameters to explain those difference. In order to investigate the between-industry variations, let us focus on the FTC merger data between 1948 and 1979. In Table 1, I provide the information on merger activity among manufacturing firms that belong to all two-digit SIC sectors between 20 and 39. The total number of mergers that occurred between 1948 and 1979 for each sector is presented in the first column. Because these sectors vary in size, I also provide information on the annual number of firms (establishments) for each of these sectors in four selected years, 1954, 1958, 1967, and 1972. The merger intensity in column 6 is computed by dividing the total mergers in column 1 by the simple average of the annual numbers of firms in those four years (columns 2-5). It is meant to capture the extent of merger activity relative to the overall size of the industry. Finally, the last two columns report the 4-firm concentration ratios of each sector in 1958 and 1982.[5]

TABLE 1 NEAR HERE

First, the total mergers vary greatly between industries, ranging from the low of 8 in furniture and fixtures (SIC 25) to the high of 201 in electrical equipment and supplies (SIC 36). Similarly, a significant variation is also observed for *merger intensity*, where the extent of merger activity is measured relative to the size of the industry. Recall from Figure 1 that the *aggregate* merger activity reaches the peak in 1968. Based on the 4-digit industry data collected from the FTC report, I plot in Figure 2 the industry-specific merger series for a subset of the manufacturing industries. It is clear that the merger waves reach their peaks at different points in time: For instance, the food industry (SIC 20) reaches its peak in 1978, the textile industry (SIC 22) in 1955, while the paper industry (SIC 26) displays multiple peaks, one in 1960 and another in 1969. Although these merger series at the industry level add up to the aggregate merger series with a single peak in 1968, the component series do not necessarily behave in the manner consistent with the aggregate series.

FIGURE 2 NEAR HERE

Second, the degrees of concentration, as measured by the four-firm concentration ratio (CR-4), tend to vary widely across industries. In 1958, the largest four firms possessed over 78% of the market in tobacco industry (SIC 21), while the largest four firms had only 12.5% of the market share in the

[4] The Nelson series is from Table 14 of Nelson (1959) and consist of all manufacturing and mining industries. The series from Weston (1953) combines the Thorp series, 1919-1939, with those from Smaller War Plants Corporation, 1940-1945, and from FTC, 1946-1947. The FTC series in Figure 1(c) was constructed from the data provided in Table 27 of *Statistical Report on Mergers and Acquisitions 1979* (published in July 1981 by Bureau of Economics, Federal Trade Commission). The table lists all manufacturing and mining companies acquired with assets of $10 million or more between 1948 and 1979. The companies are classified at the level of 4-digit SIC (Standard Industrial Classification). Although the table claims to be focused on "manufacturing and mining companies," it should be noted that the aggregate merger data also include a small number of firms outside of these sectors, such as agriculture, transportation, etc.

[5] The data is from Table 1 of Pryor (1994).

lumber industry (SIC 24). The relative ranking of the CR-4s in 1982 appears similar to that in 1958. What is more interesting is the relationship between the industry's concentration measure and its degree of merger intensity. In Figure 3, I plot merger intensity (column 6) against the 4-firm concentration ratio for each of the twenty manufacturing sectors in Table 1 – Figure 3(a) for CR-4 in 1958 and Figure 3(b) for CR-4 in 1982. The two variables are positively correlated at 0.58 and 0.53, respectively, for the two concentration measures. When the obvious outlier in the upper-left corner – the petroleum and coal industry (SIC 29) – is discarded, the correlation rises even further to 0.88 and 0.85 for CR-4 from 1958 and 1982, respectively.

FIGURE 3 NEAR HERE

These observations, though admittedly casual, call for an improved understanding of the industry-specific factors that may lead to differential merger incentives and the consequent variation in the industrial structure and performance across industries. The economics literature related to mergers and merger waves varies in approach, but there are few dynamic models addressed to the dynamic of merger waves, per se.[6] Gort (1969) offered a theory of mergers based on economic shocks, in which major changes in technology and movements in security prices can increase the dispersion in valuations of firms, thereby raising the frequency of mergers. Along the same line, Mitchell and Mulherin (1996) tests the hypothesis that mergers are carried out as a response to changes brought about by economic shocks (e.g., changes in input costs, innovations, and deregulation). Hence, they predict cross-industry variations in the rate of mergers as being directly related to the variations in the shocks borne by those industries. Indeed, they find that the merger activity in the 1980s tends to cluster in the industries that experience shocks of the greatest magnitude.

Jovanovic and Rousseau (2002a) offers the "*q*-theory" of merger, in which mergers are treated as purchases of used plant and equipment and the widening gap between the *q*s (i.e., Tobin's *q*s) of potential acquiring firms and targets leads to a merger wave. In Jovanovic and Rousseau (2002b), they offer an alternative interpretation, where major innovations lead to increased opportunities for profitable mergers (as well as stock market boom and entries). Consistent with this theory, they find that the two periods of major technological change – electrification of 1890-1930 and the arrival of information technology of 1970-2002 –coincide with the observed merger waves and the rise in entry/exit rates.

Andrade and Stafford (2002) find evidence that merger activity clusters through time by industry. Focusing on the industry-level causes, they conclude that industries with strong growth prospects, high profitability, and near capacity experience the most intense merger activity. Toxvaerd (2008) proposes a dynamic model of merger activity in which waves occur as a game-theoretic equilibrium phenomenon. In the context of this model, merger waves are caused by the interaction between the economic factor (the option value of delaying a takeover) and the strategic factor (the risk of pre-emption by rivals). In a similar vein, Dimopoulos and Sacchetto (2014) presents an infinite horizon equilibrium model of a competitive industry in which firms with heterogeneous productivities may pursue mergers, entry, and exit over the business cycle. Their model generates pro-cyclical entry

[6] To be fair, there is a large body of theoretical studies that explore equilibrium models of merger incentives, both in static and dynamic framework, but few of these studies address the issue of *merger waves*. For instance, Gowrisankaran (1999) presents a dynamic model of mergers, where mergers, investment, entry, and exit are endogenous variables chosen by firms to maximize the present value of expected future profits. Due to the analytical complexity of the model, it is solved computationally, using the Markov-perfect Nash equilibrium (MPE) approach – for elaboration on this methodology, see Pakes and McGuire (1994), Ericson and Pakes (1995) and Doraszelski and Pakes (2007). Even with the computational approach, the maximum number of active firms considered in the paper is restricted to four due to the curse-of-dimensionality issue.

and merger activity and counter-cyclical exit, as have been documented by Andrade, Mitchell, and Stafford (2001), Harford (2005), and Campbell (1998).

My objective in this paper is to continue the line of research that explores the causal mechanism behind merger waves. However, my approach is substantially different from the work reviewed above. I propose a computational model of industry dynamics in which firms make their merger decisions endogenously but with bounded rationality. The industry is subject to persistent technological shocks that induce incumbent firms to consider merger as a way of adapting to the changing technological environment. Rather than treating merger waves as an equilibrium phenomenon, I view them as an out-of-equilibrium phenomenon driven by the adaptive moves of firms responding to external technology shocks and the changing landscape of the marketplace.

The computational model presented here extends the base model of industry dynamics proposed in Chang (2015). The extension entails adding a stage in which merger decisions of the incumbent firms are made fully endogenous. The feature of the model that is crucial for inducing merger waves is the persistent shocks to the technological environment within which the firms operate. These unexpected shocks tend to affect the firms differentially – i.e. some firms benefit from a given shock, while others may be adversely affected by the same shock. Immediately following such a shock, the variance in the efficiency levels among firms tends to increase. This induces a wave of mergers as lower cost firms acquire higher cost firms with the prospect of having the combined firm operate at the unit cost of the acquiring firm.

Using the base model of industry dynamics without the merger stage, Chang (2015) showed that the wave-like pattern is also observed in the rates of turnover (entry/exit) by firms – what is often referred to as "shakeouts." The mechanism underlying the shakeout is the same as that underlying the merger wave. As such, the full model with merger decisions as presented in this paper predicts co-movement of the rate of entry and the rate of mergers. Furthermore, the steady-state rates of these activities depend on the model parameters which capture the industry-specific factors. The computational analysis carried out in this research offers insights into the causal relationships between these factors and the steady-state merger/turnover dynamics of firms.

The model is described in detail in Section 2. The model parameters and the endogenous variables that form the basis of the computational experiments are introduced in Section 3. In Section 4, I focus on a special set of experiments that allow for only a single technological shock so as to focus on the precise impact that the shock has on merger dynamics. The steady-state dynamics in the presence of persistent technological shocks are then examined in Section 5. The impact of merger policies on the structure and performance of the industries is explored in Section 6. Section 7 concludes the paper.

2. The Model

The model entails an evolving population of firms which interact with one another through repeated market competition.[7] Each period consists of five decision stages. Figure 4 provides the sequence of decision stages that characterize a typical period *t*.

FIGURE 4 NEAR HERE

[7] The underlying base model is identical to the one presented in Chang (2015), except for the additional stage of merger decisions that follows the market competition stage and precedes the exit stage. As such, the description of the model in this section is very similar to that in Chang (2015).

Each period starts with two groups of decision makers: The group of incumbents surviving from the previous period, t-1, and the group of potential entrants who are considering entry into the industry at the beginning of period t. These decision makers are uniquely characterized by the technologies they are holding. In stage 1, each of the potential entrants makes an entry decision based on the technology it is endowed with. In stage 2, the surviving incumbents from t-1 decide whether or not to perform R&D and update their current technologies. Once the two groups of firms make their decisions, the market participants are well defined for the period. In stage 3, these firms (new entrants and the incumbents) compete against one another as Cournot oligopolists by choosing outputs on the basis of the technologies they are holding. The competition in stage 3 yields profits or losses for the firms. In stage 4, the firms make decisions to merge with one another. Upon completion of the mergers, the remaining firms consider whether or not to exit the industry in the final stage of the decision making. The surviving firms then move on to the next period t+1. With a fresh pool of potential entrants available in $t+1$, the entire process repeats itself.

The description of the model in this section is organized as follows: 1) In Section 2.1, I define "technology" in our modeling framework; 2) the mechanics of market competition among firms with heterogeneous technologies are described in Section 2.2; 3) the multi-stage decision making is fully explained in Section 2.3.

2.1. Technology

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 by $\underline{z}_i^t \in \{0,1\}^N$ firm i's technology in period t, where $\underline{z}_i^t \equiv (z_i^t(1), z_i^t(2), \dots, z_i^t(N))$ and $z_i^t(h) \in \{0,1\}$ is firm i's chosen method in task h. The degree of heterogeneity between two technologies, $\underline{z}_i^t$ and $\underline{z}_j^t$, is measured by "Hamming Distance," the number of positions for which the corresponding bits differ:

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

The efficiency of a given technology depends on the environment it operates in. In order to represent the technological environment that prevails in period t, I specify a unique methods vector, $\underline{\hat{z}}^t \in \{0,1\}^N$, which is defined as the *optimal technology* for the industry in t. The technological environment, $\underline{\hat{z}}^t$, is defined at the beginning of each period and remains fixed for that period.

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. To be specific, the marginal cost of firm i in t is specified to be a direct function of $D(\underline{z}_i^t, \underline{\hat{z}}^t)$, the Hamming distance between the firm's chosen technology, $\underline{z}_i^t$, and the optimal technology, $\underline{\hat{z}}^t$. The firms are uninformed about $\underline{\hat{z}}^t$ *ex ante*, but engage in search to get as close to it as possible by observing their marginal costs. The optimal technology is common for all firms – i.e., all firms in a given industry face the same technological environment. As such, once optimal technology is defined for an 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.

The technological environment may shift unexpectedly from one period to the next. These shifts are assumed to be caused by factors external to the industry in question such as technological innovations that originate from outside the given industry.[8] In my model, external technology shocks are applied at the beginning of each period, *redefining* firms' production environment within which other decisions are made. 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. I capture this kind of external shocks by allowing 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 is described in Section 2.3.1.

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.

2.2. Demand, Cost, and Competition

In each period, there exists a finite number of firms that operate in the market. In this section, I define the static market equilibrium among such firms. The static market equilibrium defined here is then used to *represent* the outcome of market competition in stage 3 of each period.

Let m^t be the number of firms 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 tentatively that all m^t firms produce positive quantities in equilibrium. This assumption is made strictly for expositional convenience 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 choose to be *inactive* by producing zero quantity. The algorithm used to distinguish among active and inactive firms based on their production costs is described in Section 2.3.2.

<u>Demand</u>

The inverse market demand function is:

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

[8] 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 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.

where $Q^t = \sum_{j=1}^{m^t} q_j^t$ and s^t denotes the size of the market in *t*. Note that this function can be inverted to $Q^t = s^t(a - P^t)$. Hence, for a given market price, doubling the market size then doubles the quantity demanded. The demand intercept, *a*, is assumed fixed throughout.

<u>Cost</u>

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

$$C^t(q_i^t) = f + c_i^t \cdot q_i^t \tag{3}$$

All firms have identical fixed cost, f, that stays constant over time.

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

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

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 $\underline{z}_i^t = \underline{\hat{z}}^t$ and at its maximum of 100 when all N bits in the two technologies are different from one another. The total cost can be re-written as:

$$C^t(q_i^t) = f + 100 \cdot \frac{D(\underline{z}_i^t, \underline{\hat{z}}^t)}{N} \cdot q_i^t. \tag{5}$$

I assume that the size of the fixed cost is independent of the technology.

<u>Short-Run Market Equilibrium</u>

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

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

Taking the first-order condition with respect to output 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 (2):

$$\overline{P}^t = \left(\frac{1}{m^t + 1}\right)\left(a + \sum_{j=1}^{m^t} c_j^t\right). \tag{7}$$

Given the vector of marginal costs, $\overline{P}^t$ 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 [Bergstrom and Varian (1985)].

The equilibrium firm output rate is:

$$\overline{q}_i^t = s^t \left[\left(\frac{1}{m^t + 1} \right) \left(a + \sum_{j=1}^{m^t} c_j^t \right) - c_i^t \right]. \tag{8}$$

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 market price. Finally, the Cournot equilibrium firm profit is

$$\pi^t\left(\overline{q}_i^t\right) = \overline{P}^t \cdot \overline{q}_i^t - f - c_i^t \cdot \overline{q}_i^t = \frac{1}{s^t}\left(\overline{q}_i^t\right)^2 - f \tag{9}$$

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 $\underline{\hat{z}}^t$ 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, $\pi^t\left(\overline{q}_i^t\right) \geq \pi^t\left(\overline{q}_k^t\right) \forall i, k \in \{1, \ldots, m^t\}$.

The use of Cournot-Nash equilibrium to represent the market outcome is arguably inconsistent with the "bounded rationality" assumption. However, explicitly modeling the process of market experimentation would further complicate an already complex model. Therefore, I implicitly assume that experimentation is done instantly and without cost. A Cournot-Nash equilibrium is assumed to be a reasonable approximation of the outcome from that process.

2.3. Dynamic Structure

In the beginning of any typical period *t*, the industry opens with two groups of decision makers who face a common market environment as specified by the demand size, s^t: 1) a group of incumbent firms surviving from $t-1$, each of whom enters *t* with a technology, $\underline{z}_i^{t-1}$, and its net wealth, w_i^{t-1}, carried over from $t-1$; and 2) a group of potential entrants ready to consider entering the industry in *t*, each with an endowed technology of $\underline{z}_j^t$ and its start-up wealth. All firms face a common technological environment within which his/her technology will be used. This environment is fully represented by the prevailing optimal technology, $\underline{\hat{z}}^t$, which is exogenously given to the industry in the beginning of period *t*. The optimal technology is *ex ante* unknown to the firms and is not necessarily the same as $\underline{\hat{z}}^{t-1}$.

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 – i.e., the technology which was optimal in one period is not necessarily optimal in the next period. This is captured by allowing the optimal technology, $\underline{\hat{z}}^t$, to vary from one period to the next in a systematic manner. The mechanism that guides this shift dynamic is described next.

2.3.1. Turbulence in the Technological Environment

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

$$\Delta(\underline{x}, l) \equiv \bigcup_{i=0}^{l} \delta(\underline{x}, i). \quad (10)$$

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

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

where $\underline{\hat{z}}' \in \Delta(\underline{\hat{z}}^{t-1}, g)$ and γ and g are constant over all t. Hence, with probability γ the optimal technology shifts to a new one within g Hamming distance from the current technology, $\underline{\hat{z}}^{t-1}$, while with probability $1-\gamma$ it remains unchanged at $\underline{\hat{z}}^{t-1}$. 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. For the computational experiments reported in this paper, $\underline{\hat{z}}'$ is chosen from $\Delta(\underline{\hat{z}}^{t-1}, g)$ according to the uniform distribution.

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. 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.

2.3.2. Multi-Stage Decision Structure

The technological environment, $\underline{\hat{z}}^t$, is defined at the start of each period before firms engage in their decision making. Each period consists of five decision stages – see Figure 4. 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 (4). It also has the 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 entrant pool is fixed 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 the uniform distribution. In addition, each potential entrant has a fixed start-up wealth with which it enters the market.

I describe below the decision-making process in each of the five stages.

Stage 1: Entry Decisions

In stage 1 of each period, the potential entrants in R^t first make their decisions to enter. We will denote by b the fixed "start-up" wealth common to all potential entrants. The start-up wealth, b, may be viewed as a firm's available funds that remain after paying for the one-time set-up cost of entry. 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, which is based on its technology, $\underline{z}_k^t$, and the new environment, $\underline{\hat{z}}^t$: It is not that the potential entrant k knows the content of $\underline{\hat{z}}^t$ (the optimal method for each activity), but only that it gets an accurate signal on c_k^t (which is determined by $\underline{\hat{z}}^t$). The potential entrant also has observations on the market price and the incumbent firms' outputs from $t-1$ – i.e., $\overline{P}^{t-1}$ and $\overline{q}_i^{t-1} \forall i \in S^{t-1}$ – as well as the mergers that were consummated in the previous period. Given these observations and the fact that $\overline{q}_i^t = s^t[\overline{P}^t - c_i^t]$ from equation (8), 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 changing environment, I assume that the potential entrant takes c_i^{t-1} to stay fixed for lack of information on $\underline{\hat{z}}^t$. 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. 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) provide 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: "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."

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

$$\begin{cases} Enter, & \text{if and only if } \pi_k^e(\underline{z}_k^t) + b > \underline{W}; \\ Stay\ out, & otherwise; \end{cases} \tag{11}$$

where π_k^e is the static Cournot equilibrium profit the entrant *expects* to make in the period of its entry and $\underline{W}$ is the threshold level of wealth for a firm's survival (common to all firms).

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 to guarantee some threshold level of profits given its belief about the market structure and the technological environment. Denote by Ω^t the set of firms ready to compete in the industry: $\Omega^t \equiv S^{t-1} \cup E^t$. At the end of stage 1 of period t, we have a well-defined set of competing firms,

Ω^t, with their current net wealth, $\{w_i^{t-1}\}_{\forall i \in \Omega^t}$ and their technologies, $\underline{z}_i^{t-1}$ for all $i \in S^{t-1}$ and $\underline{z}_j^t$ for all $j \in E^t$.

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. The modeling of this transformation process is described separately and in full detail in Appendix-1.

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 Ω^t now have the updated technologies $\{\underline{z}_i^t\}_{\forall i \in \Omega^t}$. With the updated technologies, the firms attain their corresponding marginal costs, c_i^t, for all $i \in \Omega^t$. They engage in Cournot competition in the market, given the heterogeneous marginal costs. The outcome is represented by the Cournot equilibrium as described in Section 2.2.

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 Ω^t will produce positive quantities in equilibrium. Some relatively inefficient firms may shut down their plants and stay inactive (but still pay the fixed cost). What we need is a mechanism for identifying the set of *active* firms out of Ω^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 re-compute 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, $\pi^t(\bar{q}_i^t)$, as defined in (9), where $\bar{q}_i^t$ is the equilibrium firm output rate for all $i \in \Omega^t$.

At the end of stage 3, each firm's net wealth is updated on the basis of the R&D expenditure incurred in stage 2 as well as the profits (or losses) made in stage 3:

$$w_i^t = w_i^{t-1} + \pi_i^t - I_i^t \tag{12}$$

where I_i^t is the firm's R&D expenditure made in stage 2.[9]

Stage 4: Merger Decisions

[9] It does not matter whether R&D expenditure is subtracted from the net wealth in stage 2 or in stage 3. 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.

Given all firms in t, active or inactive, we now consider the possibility of mergers among them. While it is certainly possible that three or more firms may consider merging simultaneously at any given point in time, we restrict our attention to 2-firm mergers only for analytical simplicity.[10] The dynamics of mergers taking place in stage 4 of a given period is then represented by an endogenous sequence of 2-firm mergers taking place among the initial set of firms, Ω^t.

Each merger entails a fixed one-time cost of F_{MA}, which is purely a transactional cost. After a merger is consummated, one of the firms disappears from Ω^t. Let me denote by $\Omega^t(k)$ the set of remaining firms after *k*th merger. Suppose the total number of mergers consummated in a given period is n^*. At the end of stage 4, the resulting set of firms in the industry will be $\Omega^t(n^*)$, all of which then move on to stage 5 in which they make the exit decisions.

The sequential decision process for each merger event is described next. In the context of our model, a merger is viable if the static equilibrium profit of the post-merger firm minus the fixed cost of merger exceeds the *sum* of the pre-merger profits of the two participants. To implement the viability condition into the computational model, we take the static version of the market characterized in Section 2.2. The time superscript is ignored here for expositional convenience.

Let Ω and m denote the set and the number, respectively, of firms in the market. Given the inverse demand function as described in (2) and the total cost for firm i in (3), the Cournot-Nash equilibrium firm output rate is fully described in (8) as a function of the marginal costs of all firms.

For expositional ease in this section, I denote by $\overline{q}_{i:m}$ the equilibrium output of firm i when there are m firms competing in the market. Additionally, we shall denote by $\overline{q}_{i:m\backslash j}$ the equilibrium output of firm i when there are m firms minus firm j – i.e., it is the equilibrium output of firm i in the same industry but excluding firm j. Finally, we denote by C_{-ij} the sum of marginal costs of all firms except for firms i and j such that $C_{-ij} \equiv \sum_{k=1}^{m} c_k - c_i - c_j$.

Suppose firm i and firm j consider merging with one another, where $i, j \in \Omega$. For the reason that will soon become clear, I will call firm i a "buyer" and firm j a "target." The expression for firm i's equilibrium output (prior to the merger with j), provided in (8), can be re-written as:

$$\overline{q}_{i:m} = s\left[\left(\frac{1}{m+1}\right)\left(a + C_{-ij} + c_i + c_j\right) - c_i\right] \tag{13}$$

Since the merger will take out firm j (target) from the market, there will be m-1 firms after the merger with $c_j = 0$. Transforming (13) to reflect the disappearance of j through merger, we get:

$$\overline{q}_{i:m\backslash j} = s\left[\left(\frac{1}{m}\right)\left(a - mc_i + C_{-ij} + c_i + c_j\right)\right] \tag{14}$$

Using (13), we can re-write (14) into:

[10] In our framework, a merger involving three or more firms may then be thought of as resulting from a sequence of 2-firm mergers. For instance, a merger involving four firms, *a*, *b*, *c*, and *d*, in which firm *c* is the final survivor, may be viewed as the result of three sequential mergers: firm *a* acquires firm *b* (firm *b* disappears); firm *c* acquires firm *a* (firm *a* disappears); firm *c* acquires firm *d* (firm *d* disappears).

$$\overline{q}_{i:m\backslash j} = \bar{q}_{i:m} + \frac{1}{m}\bar{q}_{j:m} \tag{15}$$

From (9), the Cournot-Nash equilibrium profit for firm *i* after it acquires firm *j* is:

$$\overline{\pi}_{i:m\backslash j} = \frac{1}{s}\left(\bar{q}_{i:m\backslash j}\right)^2 - f. \tag{16}$$

Denote by Δ_{ij} the gains to the merger between firms *i* and *j*, exclusive of the one-time cost of merger, F_{MA}. It is defined by:

$$\Delta_{ij} \equiv \overline{\pi}_{i:m\backslash j} - \left(\bar{\pi}_{i:m} + \bar{\pi}_{j:m}\right). \tag{17}$$

Putting the relevant profit expressions into (17) yields

$$\Delta_{ij} = \frac{1}{s}\left[\left(\frac{2}{m}\right)\bar{q}_{j:m}\left(\bar{q}_{i:m} - \frac{m^2-1}{2m}\bar{q}_{j:m}\right)\right] + f. \tag{18}$$

Several comments are in order. First, merger eliminates one of the fixed costs (shown as *f* in the above expression for the gain). This is a powerful incentive for merger in addition to the technological aspect. Second, the merger cost, F_{MA}, is a one-time cost, but the gain in profits continues, with some expected deterioration, for a number of periods. It is for the sake of simplicity and consistency with the rest of the model that I assume an extreme form of bounded rationality – i.e., limited foresight – for the firms that they ignore future gains beyond the next period. Finally, it is a strong assumption that the more efficient firm can perfectly clone its technology onto the firm it acquires. More realistically, the resulting technology of the combined firm may be some "melding" of the two technologies. Allowing this imperfect copying of the efficient technology is feasible within this model, but not pursued here.

It is clear from (18) that the gains to merger monotonically rises in $\bar{q}_{i:m}$ given $\bar{q}_{j:m}$. If firm *i* and firm *k*, both in Ω, contemplate merging with firm *j*, where $c_i \leq c_k$ and, hence, $\bar{q}_{i:m} \geq \bar{q}_{k:m}$, then $\Delta_{ij} \geq \Delta_{kj}$: firm *i* has a stronger incentive to merge with firm *j* than firm *k* does. This implies that, for a given target, the optimal buyer is the most efficient firm in the industry – i.e., the one with the lowest marginal cost. In the computational implementation of the merger process, we then utilize the above property and assume that the consideration of a potential merger starts with the most efficient firm and then proceeds in the decreasing order of efficiency.[11]

Stage 4 starts out with Ω^t, the set of all firms that competed (whether active or inactive) in stage 3. Let $\Omega^t(n)$ denote the set of all firms that remain after the *n*th merger. It is straightforward that $\Omega^t(0) = \Omega^t$. Each time a firm disappears through a merger, this set will shrink. Although the decision to merge is solely based on the possible gains to both parties over and above what they could have earned individually without the merger, it is convenient for expositional purposes to specify one of the firms as the buyer, denoted BUYER, and the other firms as the seller, denoted

[11] This approach is consistent with that used by Gowrisankaran (1999) in his model of endogenous mergers.

TARGET. In considering all possible mergers, we start with Ω^t ($\equiv \Omega^t(0)$) as the initial set of *potential* buyers.

The computational algorithm through which sequential merger decisions are made is described in detail in Appendix-2. I will only provide a brief sketch of it here.

Let us consider the process after some arbitrary number of mergers, $n \geq 0$. After n mergers, the set of firms available for merger is $\Omega^t(n)$. Rank the firms in this set in the increasing order of marginal costs; hence, the most efficient firm is ranked first and the next efficient firm is ranked second, and so forth down to the most inefficient firm at the bottom of the ranking. The consideration of mergers proceeds from the most efficient firm on the basis of the logic implied by equation (18) that the gains to a merger is highest for a given target when it is acquired by the most efficient firm.

The most efficient firm, BUYER, considers merging with each of the remaining firms in the set of available firms. After identifying those firms that would generate positive net gains, BUYER will select the one that will yield the largest net gain as TARGET. A merger is consummated between BUYER and TARGET by shifting the net wealth of TARGET to BUYER after paying for the cost of merger. The firm identified as TARGET will then disappear from the set of available firms; hence, giving us $\Omega^t(n+1)$. With the merger thus consummated, the market structure is revised. The BUYER will once again evaluate the gains from merging with each and every firm in $\Omega^t(n+1)$ other than itself. Further mergers will take place on the basis of the criteria defined above, each time the set of available firms being refreshed.

Once the firm identified as BUYER can no longer find a viable partner, it is removed from the consideration of mergers. The firm with the next highest efficiency is now designated as BUYER and the process repeats itself until all firms have exhausted merger possibilities.

The industry at the end of the merger process is characterized by the final set of remaining firms, $\Omega^t(n^*)$, where n^* is the total number of mergers that have been consummated from the initial set of firms, Ω^t, who competed in the market in stage 3. We will denote by $\widehat{\Omega}^t$ the final set of firms at the end of stage 4 such that $\widehat{\Omega}^t = \Omega^t(n^*)$.

Stage 5: Exit Decisions

The firms that remain after the process of mergers and acquisitions in stage 4 – those in $\widehat{\Omega}^t$ – consider whether or not to exit the industry in the final stage. The exit decision rule for each firm is based purely on the current net wealth of the firm:

$$\begin{cases} Stay\ in, & if\ and\ only\ if\ \ w_i^t \geq \underline{W}; \\ Exit, & otherwise; \end{cases} \tag{13}$$

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 which exit the market in t. Once the exit decisions are made by all firms in $\widehat{\Omega}^t$, the set of surviving firms from period t is then defined as:

$$S^t \equiv \{\text{all } i \in \widehat{\Omega}^t \mid w_i^t \geq \underline{W}\}. \tag{14}$$

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. Computational Set-up

A particular industry is characterized by the set of parameters specified in the model. The values of the parameters used in this study, including those for the baseline simulation, are in Table 2.

TABLE 2 NEAR HERE

The production process is specified to have 96 separate tasks (*N* = 96), where the method chosen for each task is represented by a single bit. This implies that there are $2^{96}(\cong 8 \times 10^{28})$ 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 wealth (b) of zero. An incumbent firm will exit the industry if his net wealth falls below the threshold level $(\underline{W})$ of zero. The demand intercept (*a*) is fixed at 300. The cost of innovation, K_{IN}, is fixed at 100, while the cost of imitation, K_{IM}, is fixed at 50: Hence, innovation is twice as costly as imitation. The one-time fixed cost of merger between two firms, F_{MA}, is set at 10.

All initial attractions for R&D activities are such that the new entrants are indifferent between *R&D* and *No R&D* ($A_i^0 = \bar{A}_i^0 = 10$) as well as between *Innovation* and *Imitation* ($B_i^0 = \bar{B}_i^0 = 10$). The rate of change in the technological environment is set at γ = 0.1. The maximum magnitude of a change in technological environment, g, is held fixed at 8 – i.e., the Hamming distance between the optimal technologies at $t-1$ and at t cannot be more than 8 bits. The time horizon (*T*) is over 5,000 periods, where in period 1 the market starts out empty. The examination of the simulation outputs shows that the horizon of 5,000 periods is more than enough for an industry to achieve a steady-state for all parameter values considered in this research.

For the analyses of the baseline and the long-run steady-state, I fix the size of the market over time such that $s^t = s$ for all *t*. I perform two sets of comparative dynamics exercise. The first set explores the impact of the market size (s) and the fixed cost (f) on merger dynamics. I consider four different values for the two parameters: $s \in \{3,4,5,6\}$ and $f \in \{200,300,400,500\}$. The second set examines the impact technological turbulence has on merger dynamics. This entails varying the values of γ and g: I consider $\gamma \in \{0.01, 0.05, 0.1, 0.2\}$ and $g \in \{4, 8, 16, 32\}$. An increase in γ raises the frequency with which technological change occurs, while an increase in g raises the average magnitude of technological changes. In addition, I explore the mutually counteractive nature of mergers and R&D by allowing the cost of R&D to vary: $(K_{IN}: K_{IM}) \in \{(100: 50), (300: 150), (500: 250), (700: 350)\}$.

Starting from an empty industry with the above configuration of parameters, I evolve the industry and trace its development by keeping track of the following endogenous variables:

- $|E^t|$: number of firms that entered the industry in the beginning of t
- $|L^t|$: number of firms that left the industry (via solo exit) at the end of t
- $|\Omega^t|$: number of firms (active and inactive) that competed in the industry prior to mergers
- $|\widehat{\Omega}^t|$: number of firms remaining after all the mergers
- $NM^t \equiv |\Omega^t| - |\widehat{\Omega}^t|$: total number of mergers in period *t*

- $|S^t|$: number of firms that survived at the end of $t\left(=\left|\widehat{\Omega}^t\right|-|L^t|\right)$
- P^t: market price at which goods were traded in t
- $\{c_i^t\}_{\forall i\in\Omega^t}$: realized marginal costs of all firms in the industry in t
- $\{q_i^t\}_{\forall i\in\Omega^t}$: actual outputs of all firms in the industry in t
- $\{\pi_i^t\}_{\forall i\in\Omega^t}$: realized profits (or losses) of all firms in the industry in t
- $\{age_i^t\}_{\forall i\in\Omega^t}$: ages of all firms in the industry in t
- $\{\alpha_i^t\}_{\forall i\in\Omega^t}$: *R&D* intensities of all firms in the industry in t
- $\{\beta_i^t\}_{\forall i\in\Omega^t}$: *innovation* intensities of all firms in the industry in t
- $\{I_i^t\}_{\forall i\in\Omega^t}$: R&D spending of all firms in the industry in t ($I_i^t=0$ if a firm did not perform any R&D; $I_i^t=K_{IN}$ if firm *i* performed innovation; $I_i^t=K_{IM}$ if firm *i* performed imitation.)

Using the above variables, I construct an additional group of endogenous variables that characterize the aggregate behavior of the firms in an industry. First, denote by Q^t and Π^t the aggregate output and the aggregate profit of all firms in period *t*: $Q^t=\sum_{\forall j\in\Omega^t}q_j^t$ and $\Pi^t=\sum_{\forall j\in\Omega^t}\pi_j^t$.

Note that both the size of the market (s) and the fixed cost (f) 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 number of firms in period t:

$$ER^t=\frac{|E^t|}{|\Omega^t|}\text{ and }XR^t=\frac{|L^t|}{|\Omega^t|}. \tag{15}$$

The rate of firm survival in period t is then $1-XR^t$.

Likewise, the rate of merger (denoted RM^t) is defined as the number of mergers (NM^t) as the fraction of the total number of firms that competed in period *t*:

$$RM^t=\frac{|\Omega^t|-\left|\widehat{\Omega}^t\right|}{|\Omega^t|}. \tag{16}$$

As a concentration measure, I use the Herfidahl-Hirschmann Index, H^t:

$$H^t=\sum_{\forall i\in\Omega^t}\left(\frac{q_i^t}{Q^t}*100\right)^2 \tag{17}$$

A novel aspect of the model is how technological heterogeneity leads to cost asymmetries among firms. To investigate the evolving technological heterogeneity within the industry, I introduce a measure of the "degree of technological diversity," DIV^t. It is defined as the ratio of the mean technological difference in the population of all firms to the maximum possible difference. To be specific, first note that the maximum difference between any two technologies is when their Hamming distance is *N*. The mean Hamming distance, the numerator of the ratio, is computed as an average of the *Hamming* distances between all distinct pairs of firms within the population. Since the set of firms, Ω^t, contains a total of $|\Omega^t|$ firms, the total number of distinct pairs that can be formed among them is: $\frac{1}{2}|\Omega^t|(|\Omega^t|-1)$. The degree of technological diversity is then computed as:

$$DIV^t = \frac{2}{N|\Omega^t|(|\Omega^t|-1)} \sum_{\substack{\forall i,j \in \Omega^t \\ i \neq j}} D(\underline{z}_i^t, \underline{z}_j^t) \tag{18}$$

The practical implication of the heterogeneity in firms' technologies is the asymmetry it creates in terms of their production efficiency and the consequent market shares. Note that in each period *t*, the market share of a firm i is defined as $\frac{q_i^t}{Q^t}$. The inequality in market shares in *t* may then be represented by the *Gini* coefficient, $GINI^t$, which is computed as:

$$GINI^t = \frac{2\sum_{i=1}^{|\Omega^t|}\left(i * \frac{q_i^t}{Q^t}\right)}{|\Omega^t|} - \frac{|\Omega^t|+1}{|\Omega^t|}. \tag{19}$$

To examine the aggregate intensity of the R&D activities, I look at the total R&D spending in the industry, TRD^t:

$$TRD^t = \sum_{\forall i \in \Omega^t} I_i^t. \tag{20}$$

If a firm pursues R&D, it either innovates or imitates. The aggregate R&D expenditure, $\sum_{\forall i \in \Omega^t} I_i^t$, in period *t* then consists of the amount spent by the firms that innovate and the amount spent by those that imitate. [It should be noted that the inactive firms, producing zero output while paying the fixed cost, may still choose to pursue R&D and incur these expenses if they have sufficient net wealth.] Denote by TCN^t the aggregate amount spent on *innovation* (rather than imitation) by all firms in period *t*. Let NRD^t be the cost share of innovation in the aggregate R&D spending:

$$NRD^t = \frac{TCN^t}{TRD^t}. \tag{21}$$

NRD^t, hence, measures the industry's relative tendency to invest in innovation rather than in imitation.

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

$$WMC^t = \sum_{\forall i \in \Omega^t} \left[\left(\frac{q_i^t}{Q^t}\right) * c_i^t\right]. \tag{22}$$

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.

In order to evaluate the market power of the firms, I also construct an aggregate measure of firms' price-cost margins, PCM^t, where

$$PCM^t = \sum_{\forall i \in \Omega^t} \left[\left(\frac{q_i^t}{Q^t} \right) * \left(\frac{P^t - c_i^t}{P^t} \right) \right]. \quad (23)$$

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 firms.

For a measure of consumer welfare, I compute the consumer surplus as the usual triangular area under the demand curve above the market price:

$$CS^t = \frac{1}{2}(a - P^t)Q^t, \quad (24)$$

where P^t and Q^t are the realized price and aggregate output in period t.

Finally, the total surplus that captures the overall social welfare is computed as the sum of consumer surplus and the aggregate profit:

$$TS^t = CS^t + \Pi^t. \quad (25)$$

4. Impact of Technological Change on Merger Dynamics

The main feature of the model developed here involves persistent shocks to the technological environment within which the firms operate. In this section, I investigate the precise impact that such a shock has on the industry by allowing only a single shock to be applied at a fixed point in time. The procedure starts out by growing an industry from birth to maturity in the absence of any technological shock for the initial 3,000 periods. At t = 3,000, we apply a single shock of a given size and examine the behavior of firms and the evolving dynamics of the industry that follow the shock. All of the model parameters remain fixed over time at the baseline values. I perform 500 independent replications. Although all parameters are held fixed at the baseline values, each replication uses a fresh set of random numbers. Finally, the size of the shock at $t = 3{,}000$ can differ from one replication to another, except for the fact that it is bounded above by $g = 32$.

FIGURE 5 NEAR HERE

For expositional clarity, let us start by focusing on a single randomly selected replication. The number of firms operating at each point in time is shown in Figure 5. Two observations are made: 1) the infant phase of the industry is characterized by a severe shakeout; 2) there is another shakeout immediately following the external shock to the technological environment at $t = 3{,}000$. The shakeout following the technological change at $t = 3{,}000$ is the result of two things. First, the changing environment induces a wave of entry into the market by those potential entrants who are technologically well-suited for the new environment. At the same time, the unfortunate incumbents who are adversely affected by the shock will become relatively inefficient. These firms are the likely targets for mergers and acquisitions by the more efficient firms.

FIGURE 6 NEAR HERE

Figure 6 captures the two interacting forces. Figure 6(a) shows the number of mergers between $t = 2{,}500$ and at $t = 5{,}000$. The industry is in a steady state of zero merger until t=3,000, at which point the number of mergers suddenly jumps up. Though it tends to die out after a while, we observe a substantial number of mergers taking place following the shock. Figure 6(b) shows, for the same time period, the number of entries into the industry. Again, there are sudden entries into the industry following the shock. The shakeout pattern observed in Figure 5 can be understood as a joint outcome of the two interacting dynamics.

The merger wave and the shakeout caused by the technological shock are not just limited to the single replication. They are common to all replications. The time series of mergers and of entries, when averaged over the 500 replications, show the existence of the waves – see Figure 7.

FIGURE 7 NEAR HERE

The size of the merger wave – measured by the total number of mergers from $t = 3{,}000$ to $t = 5{,}000$) – and the size of the shakeout – measured by the total number of entries for the same time period – are both positively correlated with the realized size of the technological shock (which is bounded above by $g = 32$. Figure 8(a) plots the total number of mergers (vertical axis) against the size of the technological shock (horizontal axis) for each of the 500 replications; they are correlated at 0.77. Figure 8(b) displays the same information for the total entries of the firms and shows that they are correlated at 0.71. Hence, the larger the size of the technological shock, the bigger is the size of the merger wave and the shakeout.

FIGURE 8 NEAR HERE

In understanding the dynamic pattern captured in Figure 8, I propose the following causal mechanism. In this model, a technological shock entails a change in the optimal methods for a randomly selected set of tasks (the number of chosen tasks being bounded above by g). Since there are no shocks until $t = 3{,}000$ in this particular experiment, the firms are likely to have converged on the original (pre-shock) technological optimum, both through innovation (individual learning) and imitation (social learning). The sudden unexpected shock at $t = 3{,}000$, however, adversely affects a portion of the population, raising their marginal costs of production. This invites a wave of entry into the industry as the potential entrants with technologies that are more suited for the new environment find it attractive to enter.

The arrival of new firms with better adapted technologies should increase the degree of technological diversity within the industry, at least temporarily until the selective force of market competition drives out the relatively inefficient firms from the industry. While the selection mechanism will induce simple exits in the absence of options for mergers, it induces a wave of mergers in this model where mergers are a viable option. The inefficient firms that may linger on until they exhaust their accumulated net wealth now quickly disappear from the industry by merging with the more efficient firms.

FIGURE 9 NEAR HERE

If the proposed mechanism is valid, we should observe the following: 1) a wave of entry following the shock; 2) a sharp increase in the degree of technological diversity accompanying the entry wave; 3) a corresponding increase in the standard deviation of the firms' marginal costs within the industry; and 4) a wave of mergers that leads to a structural transformation of the industry. Indeed, the time series outputs from the computational experiment clearly display all of these patterns. Figure 9(a) plots the degree of technological diversity (DIV^t), averaged over 500 random replications. Note that technologies held by the firms prior to $t = 3{,}000$ are more or less homogeneous. The degree of diversity suddenly jumps up following the technological shock before gradually coming back down as the selective force of the market induces mergers and exits, hence, eliminating firms with inefficient technologies, all the while surviving firms are moving toward the common technological optimum through their R&D activity. That the variation in firms' marginal costs should display a similar pattern is confirmed in Figure 9(b) where the standard deviation of the marginal costs in each period is plotted.[12]

It should also be expected that the firms will be more active in R&D as the new technological environment, realized at $t = 3{,}000$, opens up new possibilities for discoveries. This is clearly shown in Figure 9(c), where the aggregate R&D expenditure is plotted for the same time period.[13] Finally, the rise in the degree of technological diversity and the consequent cost heterogeneity imply that the asymmetry among firms in terms of their market shares is likely to increase as the technological environment is hit with an unexpected shift. This is shown in Figure 9(d). After the sharp rise following the shock, the technological diversity as well as the market share inequality gradually decline as all firms adapt to the new environment through R&D and the industry evolves via selection of more efficient firms.

5. Persistent Technological Shocks and the Steady State Dynamics

The previous section focused on a special case where there was a single shock applied to the environment at a fixed point in time. Such a controlled experiment allowed me to isolate the effect of the technological shock on the evolving dynamics of mergers and entries. Generally, the unexpected changes tend to occur repeatedly over time and the firms must continually adapt for survival. In this section, I explore the dynamics of mergers and firm turnovers in the presence of technological shocks that persist over time.

We start by examining the endogenous cyclical dynamics of mergers and entries for when the model parameters take the baseline values in a single randomly chosen replication. The wave-like patterns in the time series of the relevant endogenous variables and the correlations among them are then investigated in a larger scale experiment involving 500 independent replications. Following the baseline analysis, I report in sections 5.2 and 5.3 the comparative dynamics results. These results show the impacts of the industry-specific factors – e.g., the size of the market (s), the size of the fixed cost (f), and the nature of the technological shocks (γ, g) – on the cyclical dynamics identified in the earlier part of the section.

5.1. Baseline: Shakeouts and Merger Waves

Let us now assume that the technological environment, $\underline{\hat{z}}^t$, is subject to change at the rate of γ and the magnitude of up to g: In each period t, there is a probability γ that $\underline{\hat{z}}^t$ can change and, if it does, the optimal methods will change for up to g component tasks. Given the persistent technological shocks thus specified, I first examine the evolution of a typical industry as characterized by the baseline parameter values indicated in Table 2.

[12] The time series used to plot Figure 9(b) is an average over only 20 replications. While other results presented in this paper are based on 500 replications, the computation of standard deviations of intra-industry distribution of marginal costs proved to be computationally quite intensive. Consequently, I present the time series in this figure as an average over 20 randomly chosen replications, but there is no reason to suspect that the qualitative results will be any different if we had used all 500 replications.

[13] One may question what happens to the *average* R&D expenditure per firm, as the number of firms itself increases following the shock. Its time series, unreported here, also revealed that it follows the same pattern as the aggregate R&D expenditure. Hence, the technological shock induces a sudden increase in the intensity of R&D both at the firm- and at the industry-level.

The baseline case assumes that the market size is completely fixed at $s^t = 4$ for all t. Any shift in the firms' decision environment is solely due to the random shocks to the technological environment. The external technological shocks affect the industry structure in three different ways: 1) they induce more entry and exit of firms by directly influencing the current marginal costs of the incumbent firms; 2) they provide fresh incentives for mergers by altering the distribution of the firms' marginal costs within the industry; 3) they give rise to more intensive R&D in the firms' search for the new technological optimum.

FIGURE 10 NEAR HERE

Let us start by focusing on a single randomly chosen replication and observing the time paths of the relevant endogenous variables. In Figure 10, I plot the number of firms, $|\Omega^t|$, and the number of mergers, NM^t ($\equiv |\Omega^t| - |\widehat{\Omega}^t|$). The upper solid curve captures the total number of firms in each period, both active and inactive, while the lower dashed curve captures the total number of mergers that occur along the same time horizon. The plot is in a log-linear format in order to focus on what happens during the initial transitory phase. The presence of a shakeout is clear in the time series of the total number of firms. As soon as the new industry is born, all 40 potential entrants jump in to compete, only to be shaken out after the first few periods.

The merger time series exhibits a similar pattern. The number of mergers starts out high at the birth of the industry and remains at that level (i.e., 10-15 mergers per period) for the first few periods, after which it quickly drops down. It is, however, clear from the figure that mergers persist even in the long run. Since the intensity of the merger activities should be seen relative to the overall size of the market (as represented by the total number of firms), I plot in Figure 11 the *rate* of mergers, RM^t, over the same horizon. The substantial degree and the persistence of turbulence in the endogenous merger activities relative to the size of the industry is quite striking.

FIGURE 11 NEAR HERE

Both Figures 10 and 11 show that the endogenous variables – i.e., the number of firms, the number of mergers, and the rate of mergers – all reach a steady-state after the initial 1000 periods, where the value of an endogenous variable fluctuates around a steady mean. In this model, the persistence of firm entries, exits, and mergers over time comes from the unexpected shifts in the technological environment surrounding the firms (which occur at the rate of $\gamma = 0.1$ for the baseline case). To see the impact that technological shifts have on the firms' merger activities in detail, I ask, for each period over the 4,000 periods between t =1,001 and t = 5,000, how many periods have elapsed since the last technological shift. This allows me to examine the relationship between the endogenous rate of mergers and the elapsed time since the last technological shift.

Figure 12 captures this information by plotting for each of the 4,000 periods the rate of mergers along the vertical axis and the time since the last technological shift along the horizontal axis. On average, the rate of merger tends to fall as the given period is further away from the last technological shift. [The correlation between the rate and the time since the last technological shock is -0.427111 as noted in the figure.]

FIGURE 12 NEAR HERE

Similar to the merger rates, the rate of entry is also negatively correlated with the time since the last technological shift. This information is captured in Figure 13, where the rate of entry tends to be high immediately following a technological shock, but then gradually falls as stability prevails in the technological environment until the next shock. The entry rate and the time since technological shift are correlated at -0.383428.

FIGURE 13 NEAR HERE

That the rate of mergers and the rate of entry respond similarly to the technological shocks implies the following property:

Property 1: The rate of entry and the rate of mergers are positively related over time.

The results in Figures 12 and 13 indicate that the industry becomes much more turbulent immediately following a technological shock: There is a sudden influx of new firms into the industry, but it is also accompanied by the disappearance of many incumbent firms through a wave of mergers. Hence, one can infer a heightened degree of structural turbulence from the sudden increase in the simultaneous appearance (via entry) and disappearance (via mergers) of firms. The impacts of technological shifts on other market variables are qualitatively identical to those reported in Chang (2015).[14] As such, I will refrain from reporting all of the available results here.

5.2. Between-Industry Variation in Mergers and Merger Waves

In identifying the recurrence of merger waves, I focused on a single randomly chosen replication in 5.1. More generally, the baseline computational experiments performed for this research involve running 500 independent replications using fresh random numbers for each replication. All of the replications exhibited the wave-like patterns reported above. In order to explore the average behavior of the industry over time, I take the simple average of the time series from the 500 replications. To be specific, denote by X_k^t the value of the endogenous variable X at t in replication k. The mean behavior of X over time is then captured by the time series outputs of the same variable as the average over 500 independent replications: $\left\{\frac{1}{500}\sum_{k=1}^{500} X_k^t\right\}_{t=1}^{5000}$.

FIGURE 14 NEAR HERE

Figure 14 plots the mean time series of the number of mergers that are consummated over the time horizon. As was the case for the single baseline replication, the mean over 500 independent replications clearly shows that the number of mergers is much higher in the beginning of the horizon when the industry is in its infancy. More importantly, the number of mergers, while declining over time to a steady-state level by $t = 100$, remains strictly positive on average for the remainder of the horizon. While the intensity of merger activity remains relatively low along the steady state, these low-level mergers have substantial impact on the evolution of the industry as demonstrated below.

FIGURE 15 NEAR HERE

[14] For instance, both the market price and the industry marginal cost are negatively correlated with the time since the last technological shift. The industry price-cost margin, on the other hand, is positively correlated with the time since the last technological shift. Hence, the market price tends to be high and firms relatively inefficient during the turbulent periods immediately following a technological shock. The price-cost margin tends to be low during the same periods, but it is driven by the drop in the efficiency of the firms caused by the sudden change in the technological environment.

The mean time series of the total number of firms is shown in Figure 15. The solid curve is the number of all firms (active and inactive), while the dashed curve is the number of active firms only. The vertical distance between the two curves – the shaded region – represents the number of "inactive" firms which shut down their plants and simply pay the fixed cost, while probabilistically performing R&D in an effort to improve their efficiency and be re-activated. It is straightforward to see that the inactive firms are noticeable only during the infant phase of the industry. After the first few periods, most firms in the industry are active and produce positive quantities at all times.

The time series data on the number of firms in Figure 15 show that the industry, even with the persistent shocks to the firms' technological environment, eventually reaches a steady state in which a typical endogenous variable fluctuates around a constant mean. In this subsection, I examine the mean behavior of the relevant endogenous variables along the steady state when the industry is characterized by different parameter configurations, particularly in terms of the size of the market, *s*, and the size of the fixed cost, *f*.

I start by providing a precise description of the process through which I study the mean behavior along the steady state. For a given parameter configuration, I perform 500 independent replications, using fresh sequence of random numbers for each replication. The time series values of the endogenous variables are collected for the last 2,000 periods from t = 3,001 to t = 5,000. These time series characterize the steady-state paths of these endogenous variables.

Suppose a given replication k generated time series values for an endogenous variable X as $\{X_k^t\}_{t=1}^{5,000}$, where X_k^t is the value of X in period t from replication k. The steady-state mean of X for the given replication k is denoted $\bar{X}_k$, where $\bar{X}_k = \frac{1}{2,000}\sum_{t=3,001}^{5,000} X_k^t$. For each endogenous variable, X, there will then be 500 steady-state means (from 500 independent replications), $\{\bar{X}_k\}_{k=1}^{500}$. The mean and the standard deviation of these means, generated under the baseline parameter configuration, are reported in Table 3 for both when mergers are allowed and when they are not.[15]

TABLE 3 NEAR HERE

Before engaging in the comparative dynamics analysis with respect to the parameters, *s* and *f*, it is instructive to examine the impact of mergers on the steady states as reported in Table 3. Some of the main impacts are: 1) mergers raise the rate of entry; 2) mergers reduce the number of firms and raise the industry concentration; 3) mergers raise the aggregate industry profitability; 4) mergers reduce the industry marginal cost (hence, raise the average production efficiency); 5) mergers reduce the aggregate R&D spending; 6) mergers increase the market share inequality. A more thorough and descriptive analysis of the impact mergers have on the industry dynamics is provided in Section 6.

We now perform the comparative dynamics analysis. The average behavior of the industry with respect to a given endogenous variable X is captured by averaging $\bar{X}_k$ over all replications: $\bar{X} = \frac{1}{500}\sum_{k=1}^{500} \bar{X}_k$. The mean steady state behavior, $\bar{X}$, is then computed for each parameter configuration of *s* and *f*, where $s \in \{3, 4, 5, 6\}$ and $f \in \{200, 300, 400, 500\}$.

FIGURE 16 NEAR HERE

[15] The case of "no mergers" entails running the same set of computational experiments as when there are mergers, but with the one-time fixed cost of mergers being so prohibitive that no firm ever pursues a merger over the relevant horizon.

I first look at the steady-state structure of the industry by comparing the number of firms across all parameter configurations. Figure 16(a) shows that the number of firms (sum of the active and inactive firms) increases with the size of the market, *s*, and decreases with the size of the fixed cost, *f*. Conversely, the industry concentration (*HHI*), shown in Figure 16(b), decreases with *s* and increases with *f*.

Property 2: The industry concentration decreases with the size of the market and increases with the size of the fixed cost.

These results are fully in line with the predictions from a static free-entry equilibrium model with symmetric firms, where the long-run equilibrium number of firms is higher in larger markets and/or when the fixed costs are lower.

FIGURE 17 NEAR HERE

The degree of structural turbulence is captured by the rate at which new firms enter the industry and the rate at which inefficient firms get acquired via merger or simply exit the industry. In Figure 17, I look at the steady-state means of the following variables for various parameter configurations: a) the rate of entry; b) the rate of solo exits; and c) the rate of mergers. I find that all three rates uniformly decrease with the size of the market and increase with the size of the fixed cost.

Property 3: The steady-state rate of entry and the steady-state rate of mergers decrease with the size of the market and increase with the size of the fixed cost.

Property 3 indicates that the industry tends to be more turbulent – i.e., there is a greater degree of turnover – when the market is smaller and/or the fixed cost of production is larger. In conjunction with Property 1, we therefore conclude that a more concentrated industry tends to exhibit a greater rate of turnover as well as a higher intensity of merger activities.

Property 4: The steady-state rate of entry and the steady-state rate of mergers are both positively related to the degree of industry concentration.

In cross-industry studies, we should then find that the industries with higher-than-average degree of concentration have higher-than-average rate of mergers as well as of entries. Note that this prediction is consistent with the positive relationship between the merger intensity and the four-firm concentration ratio observed in Table 1 (and Figure 3) for the US manufacturing sectors.

5.3. Technological Turbulence and the Intensity of Mergers

The analysis in Section 5.1 of the temporal behavior of firms indicated that the merger waves are driven by the extent to which firms experience sudden shifts in their technological environment. The heterogeneous impacts the shocks have on the firms – especially on their marginal costs – provide incentives for them to merge with one another in order to eliminate the relative inefficiency in one of the partners and realize additional gains. In this section, I directly examine how the *rate* and the *magnitude* of technological shocks affect the steady-state rate of mergers.

There are two parameters in my model that control the nature of the technological shocks. The first is γ, the rate at which technological shift occurs, and the second is g, the maximum number of tasks for which the optimal practice may change. I consider four different values for each parameter: $\gamma \in \{0.01, 0.05, 0.1, 0.2\}$ and $g \in \{4, 8, 16, 32\}$. To examine the impact of γ, I perform 500 independent replications of the simulation (hence obtaining 500 different steady-state values of the merger rate) for each value of γ, while holding g fixed at the baseline value of 8. Likewise, I repeat the same procedure for the four different values of g, holding γ fixed at the baseline value of 0.1. The histograms of the steady-state mean rates of mergers (from 500 replications) are provided in Figure 18 for these two sets of computational experiments.

FIGURE 18 NEAR HERE

Figures 18(a) and 18(b) show, respectively, that the rate of mergers is higher in an industry with a higher rate of technological shifts and/or a greater magnitude of technological shifts.

Property 5: The steady-state rate of mergers is higher when the rate and/or the size of the technological turbulence is greater.

One aspect of the model which allows the firms to overcome the negative effects of the unexpected shock is the ability to perform R&D so as to adapt to the new environment. As such, a determinant of the (endogenous) intensity of R&D is likely to have an indirect impact on the rate of merger as well. Of course, one obvious determinant is the cost of R&D, K_{IN} and K_{IM}. In order to see the connection between the R&D intensity and the rate of mergers, I consider four different pairs of values for K_{IN} and K_{IM}: $(K_{IN}: K_{IM}) \in \{(100: 50), (300: 150), (500: 250), (700: 350)\}$. Hence, in all cases, K_{IN} is twice as large as K_{IM}.

FIGURE 19 NEAR HERE

While the aggregate R&D spending, TRD^t, is a measure of R&D intensity, it is not ideal when we consider the impact of K_{IN} and K_{IM}, since TRD^t depends both on the number of R&D attempts and the cost of R&D. As such, we focus solely on the “number” of R&D attempts in this particular experiment. In Figure 19(a), the histograms of the total numbers of R&D (sum of both innovative and imitative R&D) are presented for the four different pairs of the R&D costs. Clearly, the firms engage in less R&D overall, when the cost of R&D is higher. Since firms are engaging in less R&D, they are poorly adapted to the changing environment. This provides a stronger incentive for mergers on the part of the firms. Figure 19(b) clearly shows that the rates of mergers are higher when the costs of R&D are higher.

Property 6: The rate of mergers is higher in industries with higher fixed cost of R&D.

At the industry level, mergers and R&D may then be viewed as substitutes. A market condition that induces more aggressive R&D activity tends to reduce the merger intensity and vice versa.

6. Impact of Mergers on Industry Dynamics

In the U.S., potential mergers are scrutinized and/or challenged on the basis of the Horizontal Merger Guidelines set forth by the Antitrust Division of the Department of Justice (DOJ) and the Federal Trade Commission (FTC). The underlying objective of the Guidelines is stated as follows:

> The unifying theme of these Guidelines is that mergers should not be permitted to create, enhance, or entrench market power or to facilitate its exercise. For simplicity of exposition, these Guidelines generally refer to all of these effects as enhancing market power. A merger enhances market power if it is likely to encourage one or

> more firms to raise price, reduce output, diminish innovation, or otherwise harm customers as a result of diminished competitive constraints or incentives. In evaluating how a merger will likely change a firm's behavior, the Agencies focus primarily on how the merger affects conduct that would be most profitable for the firm. [*Horizontal Merger Guidelines*, 2010, p.2]

The Guidelines also recognize the fact that the potential creation of market power is to be weighed against any expected gain in efficiencies that a merger may generate:

> Competition usually spurs firms to achieve efficiencies internally. Nevertheless, a primary benefit of mergers to the economy is their potential to generate significant efficiencies and thus enhance the merged firm's ability and incentive to compete, which may result in lower prices, improved quality, enhanced service, or new products. For example, merger-generated efficiencies may enhance competition by permitting two ineffective competitors to form a more effective competitor, e.g., by combining complementary assets. In a unilateral effects context, incremental cost reductions may reduce or reverse any increases in the merged firm's incentive to elevate price. [*Horizontal Merger Guidelines*, 2010, p.29]

The computational model developed in this paper offers a fully dynamic setting in which one can examine these tradeoffs as they arise from the complex interactions between the recurrent shakeouts and merger waves. In line with the Guidelines, the merger policy is specified by two parameters in our model:[16] 1) ceiling value for the expected post-merger HHI; and 2) the ceiling value for the increase in the HHI resulting from the merger. If the expected post-merger HHI and the increase in the HHI are above the respective ceiling values, then the proposed merger is not allowed.

The experiments reported in the previous sections were performed under the condition that the ceiling values of the above two policy parameters are sufficiently high to allow *all* mergers proposed by the firms. In this section, I consider the impact of the antitrust enforcement policy on mergers by lowering these ceiling values such that they will be binding. In fact, I save on time and computational resources by restricting attention to the extreme case where all mergers are prohibited by the Agencies (DOJ and FTC). This entails setting the ceiling values so low that no proposed merger will ever meet the requirement. The impacts of mergers, or conversely the impacts of merger policies, on industry dynamics are then investigated by comparing the case of "no mergers" to that of "with mergers" in which all proposed mergers are permitted.

FIGURE 20 NEAR HERE

The first impact I examine is that on the degree of structural turbulence as captured by the degree of turnovers. First, I look at the number of entrants over time both with and without mergers. Figure 20(a) displays the mean time paths of the number of entrants under both scenarios. Allowing mergers clearly raises the number of entrants. The increase in the movement of firms into the industry is, however, matched by the increase in the total number of firm disappearances. In Figure 20(b), the solid curve represents the number of exits when there are no mergers. When mergers are allowed, the number of solo exits declines, as represented by the dashed curve. However, when the number of firm disappearances due to mergers is added to that of solo exits, the total number of firm disappearances uniformly increases, as captured by the dotted curve. Since mergers induce more firm entries and firm disappearance, we conclude: *The industry is more turbulent when mergers are allowed*.

[16] *Horizontal Merger Guidelines*, 2010, pp.18-19.

FIGURE 21 NEAR HERE

Recall from Figure 15 that the firms operating in the industry after the infant phase are mostly active firms when they are allowed to merge. In contrast, an industry in which mergers are completely prohibited displays quite a different composition of firms along the time path. Figure 21 captures the same set of information as in Figure 15, except that mergers are now strictly prohibited. Notice the substantial numbers of inactive firms that exist over the entire horizon. In fact, the total number of firms tends to increase after the initial shakeout to a steady-state, but this increase is purely due to the increase in the number of *inactive* firms. What is happening is that there are substantial number of entrants who enter the industry with technologies that are appropriate for the environment at the time of their entry. These firms tend to accumulate substantial amount of wealth until they are hit by an adverse technological shock. Even after an unexpected negative shift in the environment, the wealth they have accumulated in the past under more favorable conditions allows them to linger on even though they are no longer fit to operate in the industry. Because the technological shocks persist over time, an industry ends up carrying a substantial number of these inactive firms in the long run.

When mergers are allowed, many of the inactive firms (with their high marginal costs) become likely targets for mergers. Consequently, the technological shocks that drive some of the incumbent firms to relative inefficiency tend to intensify the merger activities that facilitate the acquisition of these firms by their more efficient counterparts. As shown in Figure 15, after the infant phase of the industry, one rarely finds firms that simply linger on till their eventual exit. Almost all firms that exist in the industry are active producers, because those firms that would have remained inactive are now mostly acquired by more efficient firms. The direct result of this process, as shown in Figure 22, is that the industry marginal cost is lower over time when firms are allowed to merge. Hence, *mergers improve average production efficiency within the industry*.

FIGURE 22 NEAR HERE

Mergers, by determining the number and efficiencies of the firms that operate in the market, influence the extent to which market shares are distributed among firms. Figure 23(a) shows the endogenous degree of industry concentration, as measured by the Herfindahl-Hirschmann Index (HHI), both with (dashed curve) and without (solid curve) mergers. It is clear that the presence of merger opportunities raises the degree of concentration. The increase in concentration due to merger has predictable implications for other aspects of the market performance. Figure 23(b,c,d) demonstrate that the market price, the industry price-cost margin, as well as the aggregate profits are all higher when mergers are allowed. In other words, *mergers induce an unambiguous increase in the market power of the firms.*

FIGURE 23 NEAR HERE

Are mergers then anti-competitive and, hence, reduce social welfare? To the extent that the market price rises as the result of mergers, the consumer surplus surely declines. However, as shown in Figure 22, mergers also improve the average efficiency of the firms by eliminating inefficient firms, thereby improving the profitability of the surviving firms. The mean time series of the consumer surplus and total surplus (consumer surplus plus aggregate profits), presented in Figure 24(a)-(b), show that mergers reduce the former as expected, but raise the latter. Hence, the increase in firm profits more than compensates for the loss of consumer surplus from the rising price.

FIGURE 24 NEAR HERE

Finally, Figure 25 shows the impact mergers have on the adaptiveness of the firms as captured by the degree of technological diversity and the intensity of the R&D activity within the industry. First, Figure 25(a) shows that mergers raise the industry-wide technological diversity (DIV^t). This can be explained on the basis of the fact that the industry is more turbulent – i.e., there are more entries and exits (via mergers) – when mergers are allowed. Consequently, the steady-state pool of firms, on average, includes more technologically heterogeneous firms when mergers are allowed.

Figures 25(b) shows that mergers reduce the aggregate R&D spending (TRD^t). The lower level of aggregate R&D would seem to indicate weaker incentives to perform R&D by firms. This is not the case. The aggregate R&D spending is heavily affected by the "number" of firms in the industry. Note that the number of firms operating at a given point in time, $|\Omega^t|$, is lower when mergers are allowed. When the aggregate R&D spending is divided by the number of firms, the average R&D spending per firm, $TRD^t/|\Omega^t|$, is higher along the steady-state path, if mergers are allowed – see Figure 25(c). [Though it is difficult to verify visually, the curves in Figure 25(c) cross each other at around $t = 50$, resulting in the average R&D spending being lower with *no mergers* than *with mergers* along the steady state.]

FIGURE 25 NEAR HERE

The higher level of average R&D spending is due to the higher rate of entry induced by mergers. Although there are less firms operating when mergers are allowed, these firms are relatively younger and more active in their R&D. Recall from our discussion of the result captured in Figure 22 that mergers tend to reduce the industry marginal cost, improving the production efficiency of the firms in general. It is important to note that the industry-wide level of production efficiency depends on two separate mechanisms. First, it is affected by the intensity of the firms' R&D activities, since it represents the extent to which firms are able to adapt to the technological environment. This is the *adaptation effect*. Second, it is affected by the capacity of the industry to weed out the inefficient firms through either competition or some other mechanism such as mergers. This is the *selection effect*. Given the positive impact that mergers have on the average R&D spending, the reduction in the industry marginal cost under mergers is due to the mutual reinforcement of the selection effect of mergers (which improves efficiency through the elimination-by-merger of the inefficient firms) and the adaptation effect of mergers (which improves efficiency through stronger R&D activities at the individual firm level).

7. Conclusion

The model presented here provides a potential mechanism for merger waves based on persistent shocks to the technological environment within which firms compete in a given industry. It builds on the base model of industry dynamics presented in Chang (2015) by allowing firms to make merger decisions as part of their attempt to survive in an industry in which they face unexpected changes in the technological environment.

With the computational model, I simulated an artificial industry and tracked its growth and development by collecting and analyzing the output data. In line with the empirical observations, mergers occur in waves in this setting. Interestingly, the wave-like merger pattern occurs simultaneously with the wave-like pattern in firm entries: Mergers and entries are correlated over time, and, hence, the recurrent mergers waves and the recurrent shakeouts tend to occur jointly.

Even with the persistent technological shocks, the industry eventually reaches a steady state, in which the distribution of a relevant endogenous variable becomes time-independent. Focusing on the steady-state means of the endogenous variables, I performed a number of comparative dynamics where the means are compared across various parameter configurations (industry-specific factors). Both the rate of entry and the rate of mergers decrease with the size of the market and increase with the size of the fixed cost. The rate of mergers is higher when the degree of technological turbulence is greater, both in terms of the rate and the size of the technological shocks.

Finally, a detailed examination of the impact endogenous mergers have on the evolving path of the industry indicated that they raise the degree of market turbulence (as represented by the rate of entry) as well as the market power of the incumbent firms. The latter effect is inferred from the rise in the price-cost margin and the aggregate profits of the firms, driven by the rise in the market price and the drop in the industry marginal cost. Mergers are seen to also increase the degree of technological diversity through the greater structural turbulence they induce. The overall intensity of R&D – measured by the average R&D spending per firm – is also higher when mergers are allowed.

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APPENDIX-1

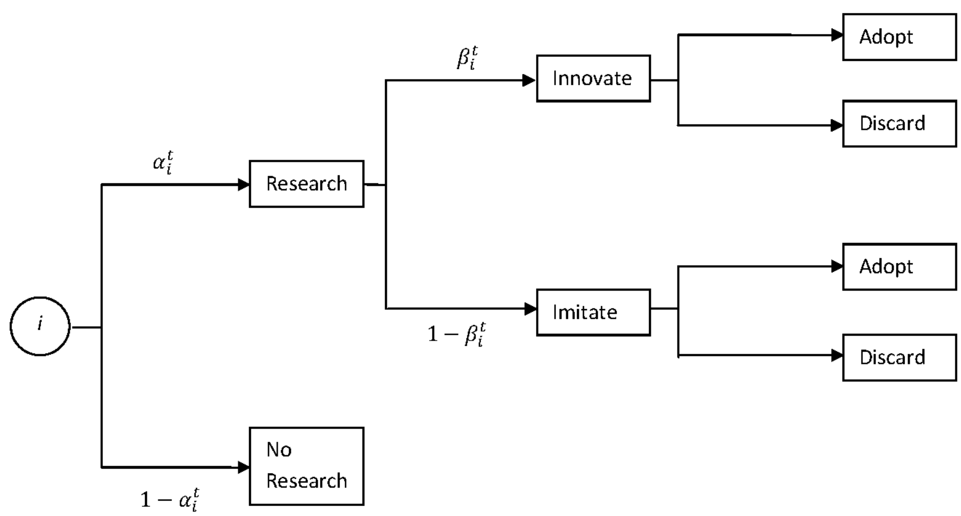
Stage-2 R&D Decisions

The process of R&D is made endogenous in this model. This process corresponds to the stage-2 process of transforming $\underline{z}_i^{t-1}$ to $\underline{z}_i^t$ as described in Section 2.3.2. I model the R&D-related decisions as being driven by 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 sufficient condition for a firm to engage in R&D is to have enough net wealth to cover the maximum R&D expense:

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

In the computational experiments reported here, I assume $K_{IN} > K_{IM}$.

The various stages of the R&D process are illustrated in the following figure:



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 the firm chooses not to pursue R&D, it simply keeps the old technology and, hence, $\underline{z}_i^t = \underline{z}_i^{t-1}$. However, if the firm chooses to pursue R&D, then it has a probability β_i^t with which it chooses to "innovate" and $1 - \beta_i^t$ with which it 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 other activities. [Hence, the imitating firm is capable of copying only a small part of the entire technology.]

Only those surviving firms which were profitable in $t-1$, i.e., $\pi_k^{t-1} > 0$, are considered as 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:

$$p_{ij}^t = \pi_j^{t-1} \Big/ \left(\sum_{\forall k \in S_+^{t-1}, k \neq i} \pi_k^{t-1} \right) \tag{A.2}$$

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 $\underline{\tilde{z}}_i^t$ denote firm *i*'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:

$$\underline{z}_i^t = \begin{cases} \underline{\tilde{z}}_i^t, & if\ and\ only\ if\ c_i\left(\underline{\tilde{z}}_i^t, \underline{\hat{z}}^t\right) < c_i\left(\underline{z}_i^{t-1}, \underline{\hat{z}}^t\right); \\ \underline{z}_i^{t-1}, & otherwise; \end{cases} \tag{A.3}$$

Firm *i* adopts the proposed technology 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. Hence, adoption 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, the only way that its profit is going to improve is if its marginal cost is reduced as the result of its R&D.

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

$$I_i^t = \begin{cases} 0 & if\ no\ R\&D\ was\ pursued; \\ K_{IN} & if\ R\&D\ was\ pursued\ and\ innovation\ was\ chosen; \\ K_{IM} & if\ R\&D\ was\ pursued\ and\ imitation\ was\ chosen; \end{cases} \tag{A.4}$$

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 (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.

Formally, the choice probabilities, α_i^t and β_i^t, are determined by the attraction measures, (A_i^t, $\bar{A}_i^t$) and (B_i^t, $\bar{B}_i^t$), as follows:

$$\alpha_i^t = \frac{A_i^t}{A_i^t + \bar{A}_i^t};\ \beta_i^t = \frac{B_i^t}{B_i^t + \bar{B}_i^t}, \tag{A.5}$$

where A_i^t is the attraction for *R&D* and $\bar{A}_i^t$ is the attraction for *No R&D*, while B_i^t is the attraction for *Innovation* and $\bar{B}_i^t$ is the attraction for *Imitation*. At the end of each period, α_i^t and β_i^t are adjusted on the basis of the changing values for these attraction measures. The table below shows the adjustment dynamics of these attractions for the entire set of possible cases.

Table A: Evolving Attractions

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

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, $\bar{A}_i^t$ 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, $\bar{B}_i^t$ 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.

Finally, all new entrants in E^t are endowed with the initial attractions that make them indifferent to the available options at the time of their entry. Specifically, I assume that $A_i^t = \bar{A}_i^t = 10$ and $B_i^t = \bar{B}_i^t = 10$ for new entrants 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 eventually diverge from one another as the firms go through different market experiences as the result of their R&D decisions made over time.

APPENDIX-2

Stage-4 Merger Decisions

Algorithm:

1. Set $n = 0$. Denote by B the set of all available buyer firms. Since every firm in the market could be considered a potential buyer, $B = \Omega^t = \Omega^t(0)$ at the beginning of stage 4.

2. BUYER LOOP: Routine for each potential buyer in B.

2.1. Is $B = \emptyset$? If so, then exit 2 and go to 3. Otherwise, continue.

2.2. Select the most efficient firm from B and designate it as BUYER. This is the firm with the lowest marginal cost. [Tie-breaking rule: If there are two or more firms with the lowest marginal cost, select the one with the largest current wealth.]

2.3. Define the set of all potential targets for the BUYER as G. The set, G, consists of all firms in B except for the BUYER.

2.4. Compute the gains from merger, $\Delta_{BUYER,j}$, for all $j \in G$, given $\Omega^t(n)$ where n is the number of mergers that have been consummated up to this point. Identify a subset of firms that will generate positive net gains from a merger with the BUYER such that $\Delta_{BUYER,j} - F_{MA} > 0$. Refer to this set of firms as the set of *viable targets* and denote it by $\hat{G}$.

2.5. TARGET LOOP: Routine for each viable target in $\hat{G}$.

2.5.1. Is $\hat{G} = \emptyset$? If so, then exit 2.5 and go to 2.6. Otherwise, continue.

2.5.2. Identify the firm in $\hat{G}$ that generates the biggest net gains for the BUYER as the TARGET. [Tie-breaking rule: In case of a tie, select the firm with the largest net wealth.]

2.5.3. Execute the merger between the BUYER and the TARGET: 1) Set $n = n + 1$. 2) the wealth of the TARGET is transferred to the BUYER; 3) the cost of the merger, F_{MA}, is incurred by the BUYER (the BUYER's net wealth is reduced to reflect the expense); 4) the TARGET is deleted from the set of potential targets, G, as well as from the set of potential buyers, B. $\Omega^t(n)$ is updated, given the disappearance of the TARGET. If the TARGET was previously an inactive firm, the market equilibrium remains the same as before. If the TARGET was an active firm, the elimination of the TARGET from the market requires the market equilibrium to be re-derived on the basis of $\Omega^t(n)$. This entails re-computing the outputs for all firms in $\Omega^t(n)$, the resulting market price, and the firms' profits.

2.5.4. The BUYER goes back to the set of potential targets, G, and revises $\hat{G}$ on the basis of $\Omega^t(n)$.

2.5.5. Repeat the TARGET LOOP by returning to 2.5.1.

2.6. No potential merger partner exists for the BUYER. Delete the BUYER from the set of potential buyers, *B*. Given the revised set, *B*, repeat the BUYER LOOP by returning to 2.1.

3. Terminate the merger process.

Table 1: US Manufacturing Sectors (2-digit SIC)

SIC	Two-Digit Sector	Total No. Mergers[1] (1948-1979)	Number of Firms (Establishments)[2] 1954	1958	1967	1972	Merger Intensity[3] (1948-1979)	CR-4[4] 1958	1982
20	Food and kindred products	164	42,373	41,983	32,518	28,183	0.00452	32.1	38.3
21	Tobacco products	20	627	1,004	329	272	0.03584	78.2	88.1
22	Textile mill products	73	8,054	7,675	7,080	7,201	0.00973	29.2	35.3
23	Apparel, other textile products	21	31,372	29,358	26,393	24,438	0.00075	14.8	22.5
24	Lumber and wood products	38	41,484	37,878	36,795	33,949	0.00101	12.5	19.5
25	Furniture and fixtures	8	10,273	10,179	10,008	9,233	0.00081	17.1	21.4
26	Paper and allied products	86	5,004	5,271	5,890	6,038	0.01549	31.4	31.1
27	Printing and publishing	32	32,530	35,456	37,989	42,103	0.00086	18.1	19.6
28	Chemicals and allied products	194	11,074	11,309	11,799	11,425	0.01701	37.6	34.1
29	Petroleum and coal products	85	1,262	1,608	1,880	2,016	0.05025	30.3	28.5
30	Rubber and miscellaneous plastics	28	3,845	4,462	6,456	9,237	0.00467	21.7	20.0
31	Leather and leather products	14	4,845	4,549	3,685	3,201	0.00344	22.7	28.2
32	Stone, clay, and glass products	59	N/A	15,055	15,580	16,015	0.00379	36.9	36.9
33	Primary metal industries	112	6,171	6,446	6,837	6,792	0.01707	44.3	37.4
34	Fabricated metal products	72	22,042	24,782	27,418	29,525	0.00278	31.4	24.3
35	Machinery (except electrical)	193	N/A	29,867	37,892	40,792	0.00533	36.1	32.1
36	Electrical equipment and supplies	201	N/A	8,091	10,706	12,270	0.01941	41.6	38.9
37	Transportation equipment	134	5,349	6,625	7,483	8,802	0.01897	65.7	64.0
38	Instruments and related products	33	3,141	3,526	4,453	5,983	0.00772	41.0	44.8
39	Miscellaneous manufactures	25	14,588	14,306	14,489	15,187	0.00171	23.0	27.9
	Total	1,592							

[1] The merger data are constructed from FTC *Statistical Report on Mergers and Acquisitions*, 1979.
[2] The establishment data are from the *Statistical Abstract of the United States*, 1965 and 1979 editions (Section 29: Manufactures).
[3] The merger intensity is obtained by dividing the total number of mergers in column 3 by the simple average of the number of firms from the 4 selected years in columns 4-7.
[4] The CR-4 (four-firm concentration ratio) data are from Table 1 of Pryor (1994).

Table 2: List of Parameters and Their Values

Notation	Definition	Baseline Value	All Values
N	Number of tasks	96	96
r	Number of potential entrants per period	40	40
b	Start-up wealth for a new entrant	0	0
$\underline{W}$	Threshold net wealth for survival	0	0
a	Demand intercept	300	300
f	Fixed production cost	200	{200, 300, 400, 500}
F_{MA}	One-time cost of a two-firm merger	10	10
K_{IN}	Fixed cost of innovation	100	{100, 300, 500, 700}
K_{IM}	Fixed cost of imitation	50	{50, 150, 250, 350}
A_i^0	Initial attraction for R&D	10	10
$\bar{A}_i^0$	Initial attraction for No R&D	10	10
B_i^0	Initial attraction for innovation	10	10
$\bar{B}_i^0$	Initial attraction for imitation	10	10
T	Time horizon	5,000	5,000
s	Market size when demand does not fluctuate	4	{3, 4, 5, 6}
γ	Rate of change in technological environment	0.1	{0.01, 0.05, 0.1, 0.2}
g	Maximum magnitude of change in technological environment	8	{4, 8, 16, 32}

Table 3: Steady-State Means of the Endogenous Variables With and Without Mergers*

Variable	With Mergers	Without Mergers
$\lvert E^t \rvert$	1.492 (0.1142)	0.684 (0.0606)
$\lvert L^t \rvert$	0.225 (0.0255)	0.683 (0.0606)
$\lvert \Omega^t \rvert$	23.981 (0.1972)	41.170 (0.4837)
NM^t	1.267 (0.0913)	---
RM^t	0.052 (0.0066)	---
ER^t	0.060 (0.0042)	0.016 (0.0015)
XR^t	0.009 (0.0009)	0.016 (0.0015)
P^t	47.269 (0.1771)	45.924 (0.2108)
Q^t	1,010.930 (0.7082)	1,016.300 (0.8433)
Π^t	5,844.660 (161.01)	-53.840 (113.46)
PCM^t	0.238 (0.0029)	0.198 (0.0019)
WMC^t	36.048 (0.2558)	36.842 (0.2335)
H^t	444.024 (4.0401)	357.458 (2.6171)
TRD^t	702.469 (10.220)	1,051.320 (17.279)
NRD^t	0.641 (0.0034)	0.644 (0.0025)
CS^t	127,752.000 (179.34)	129,114.000 (214.60)
TS^t	133,596.000 (310.39)	129,060.000 (261.66)
DIV^t	0.455 (0.0020)	0.453 (0.0027)
$GINI^t$	0.127 (0.0020)	0.379 (0.0091)

*These are the descriptive statistics of the steady-state means from the 500 independent replications. Each steady-state mean is the average over the 2,000 periods between t = 3,001 and 5,000. The standard deviations are provided inside the parenthesis.

Figure 1: Merger Waves

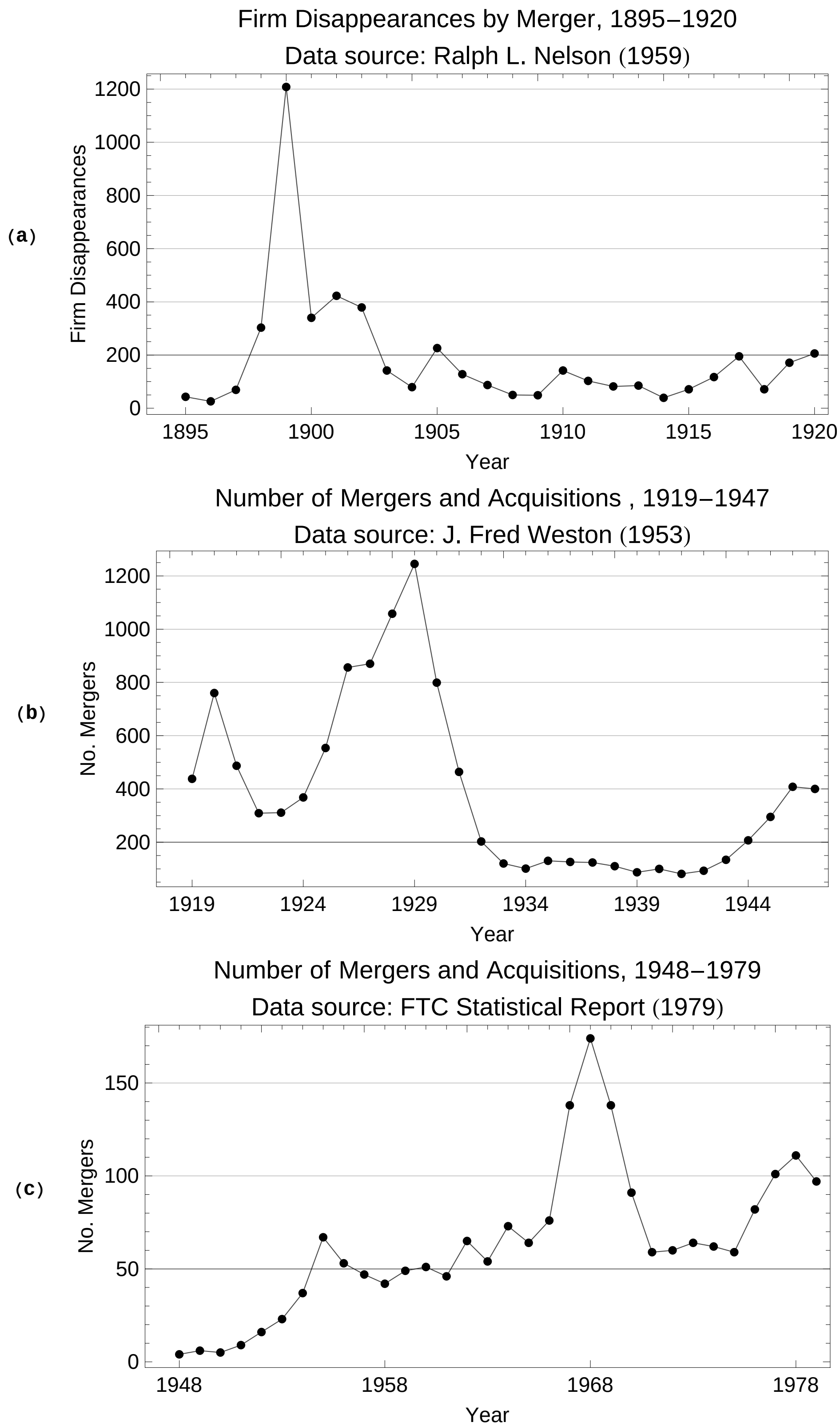


Figure 2: Mergers and Acquisitions, 1948-1979, US Manufacturing Sectors

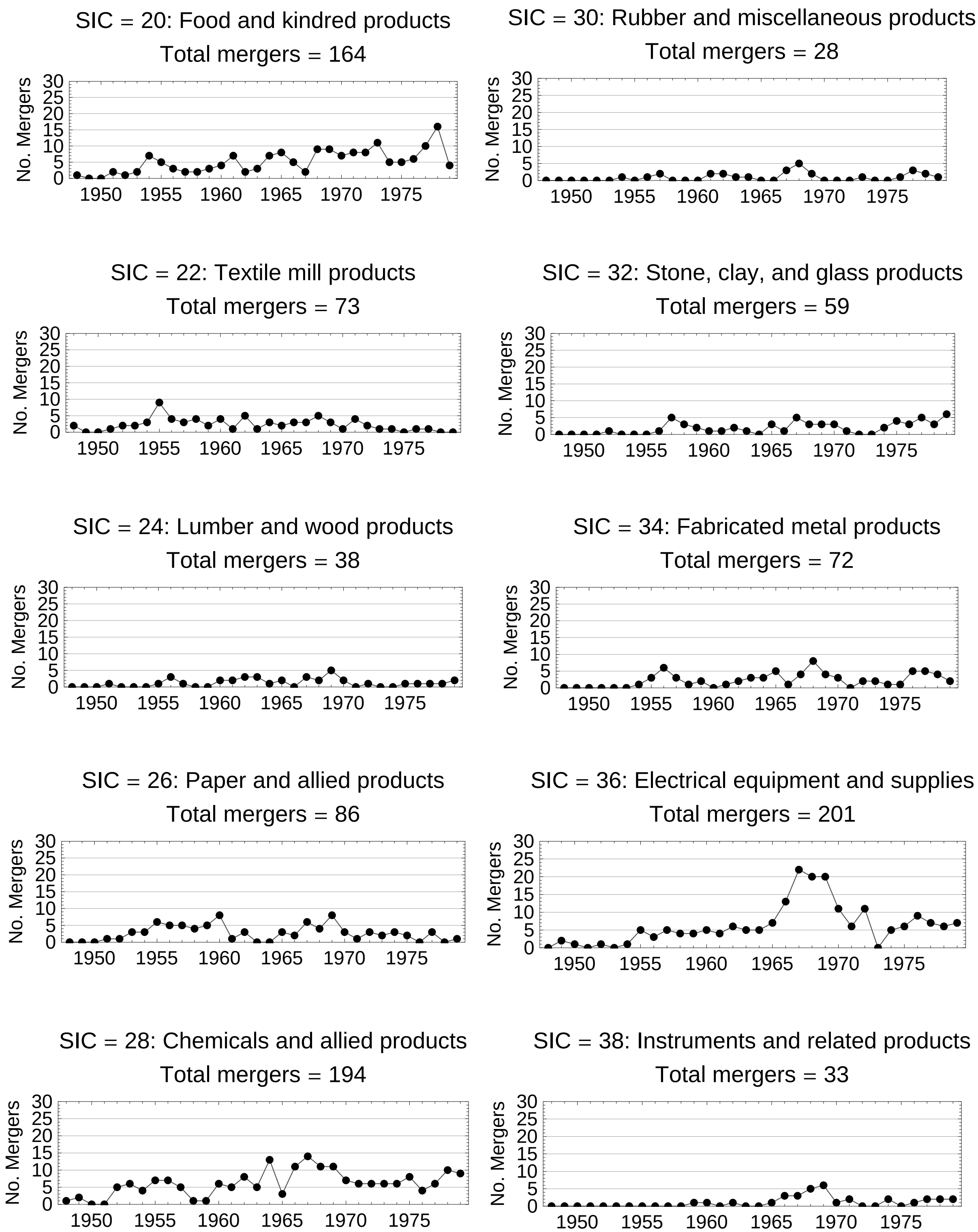
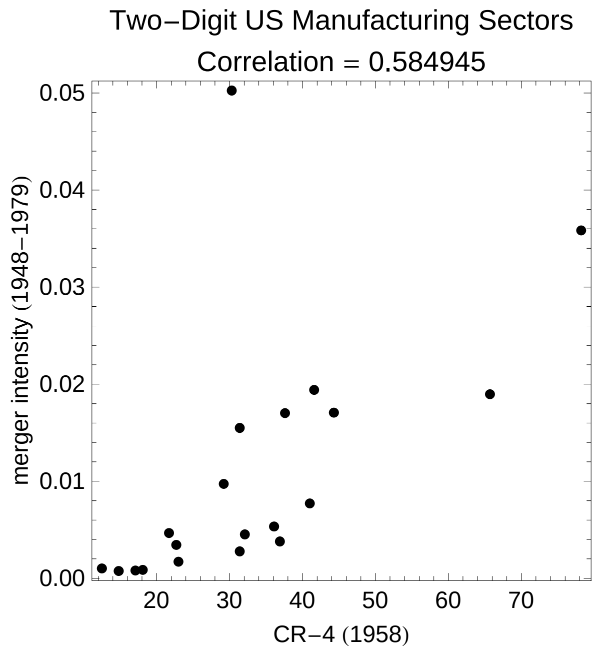


Figure 3: Merger Intensity and Industry Concentration Ratio
US Manufacturing Sectors

(**a**)



(**b**)

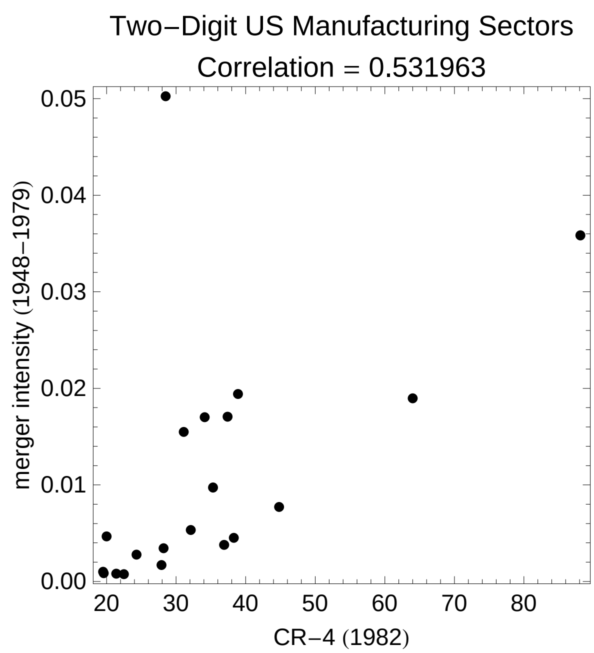


Figure 4: Timeline of Firm Decisions

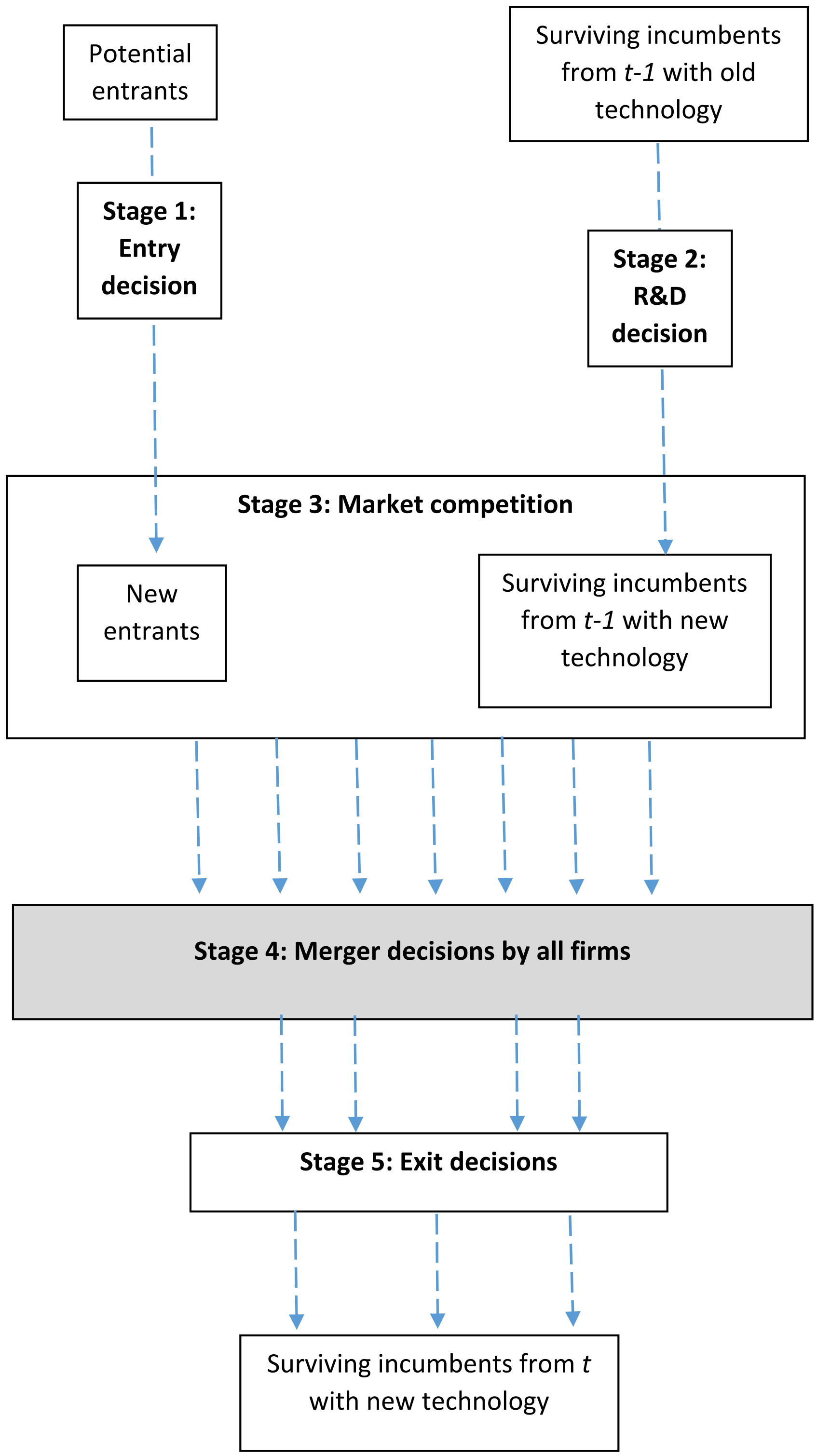


Figure 5: Number of firms
(single replication)

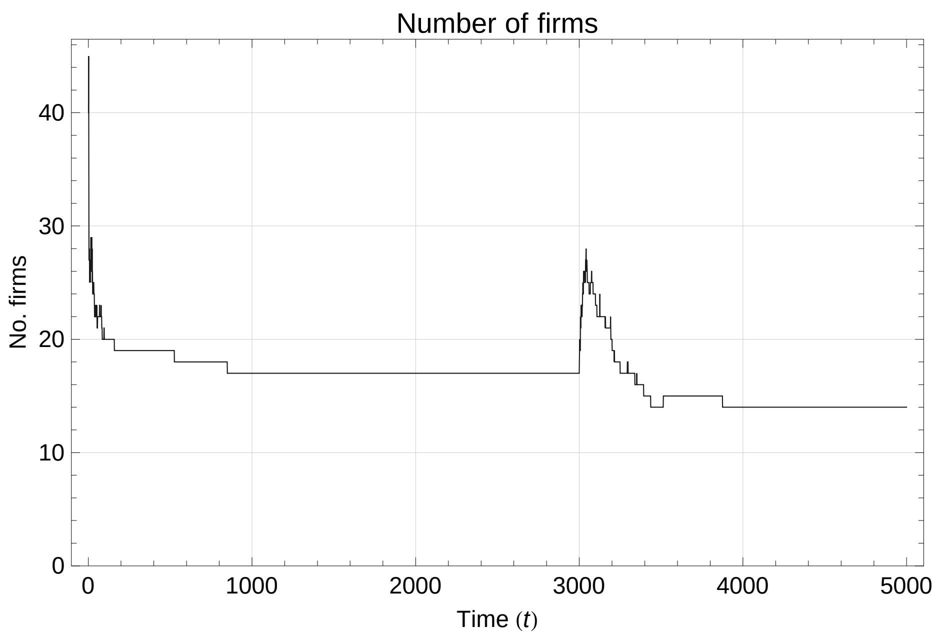


Figure 6: Mergers and entries
(single replication)

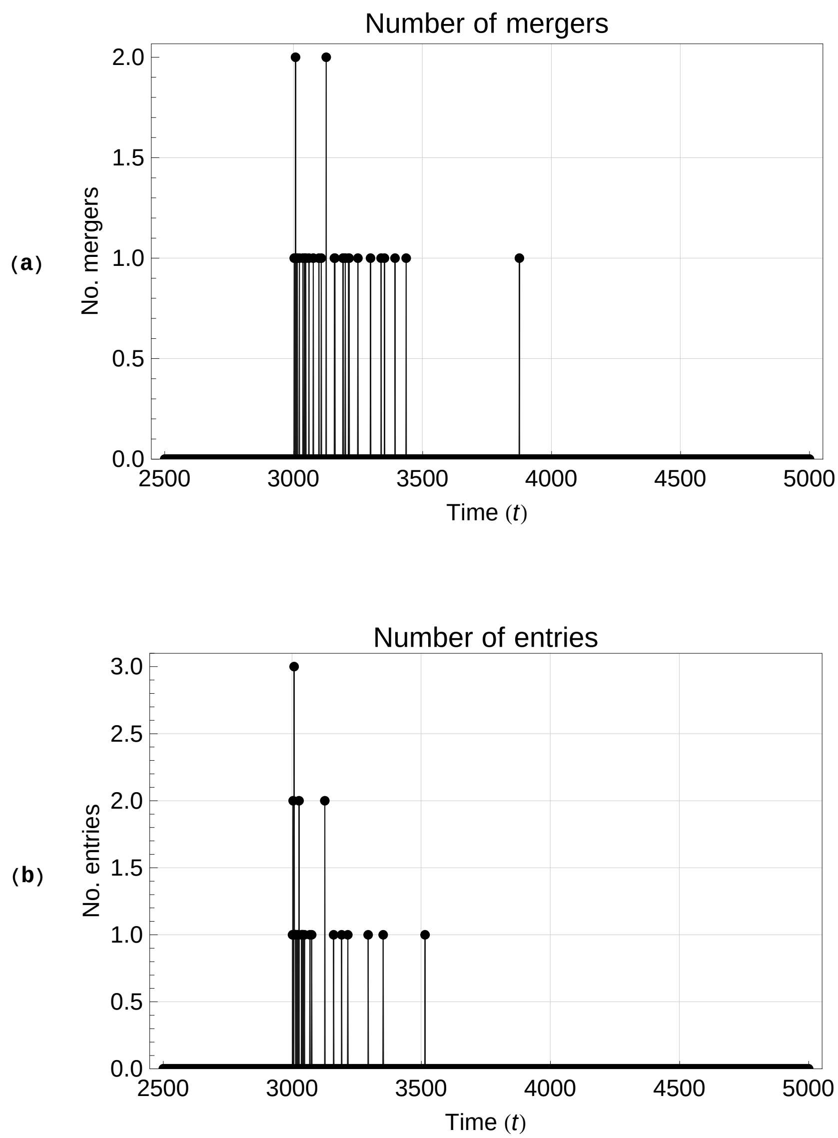
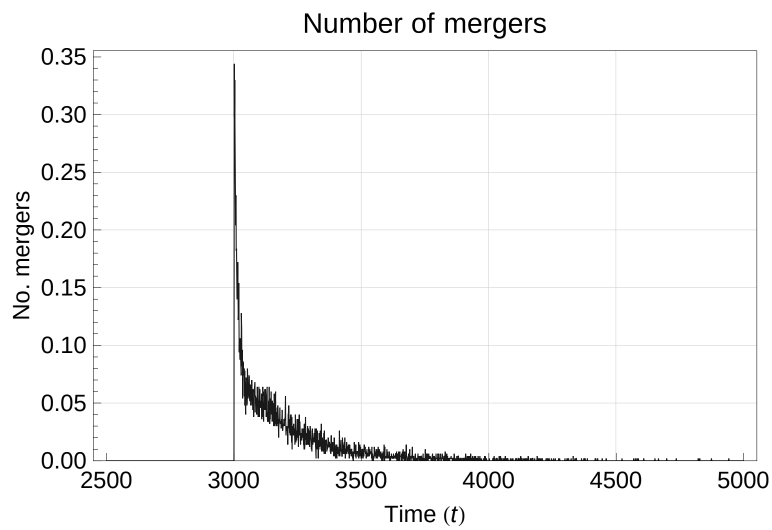


Figure 7: Mergers and entries
(average over 500 replications)

(**a**)



(**b**)

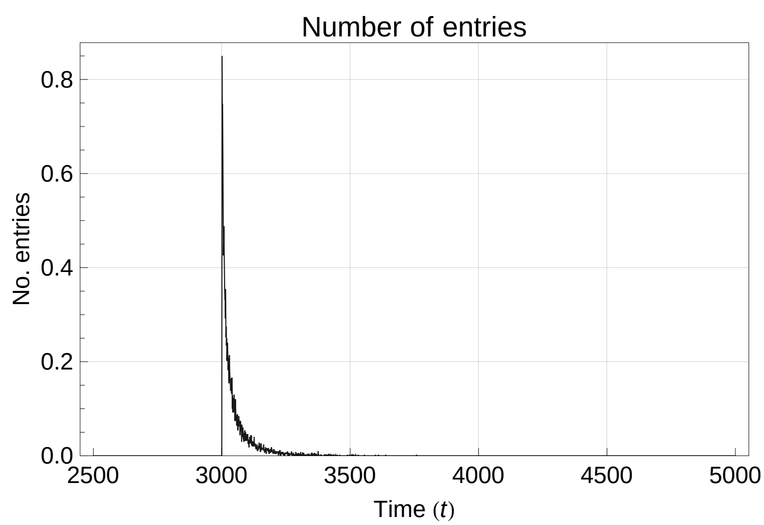
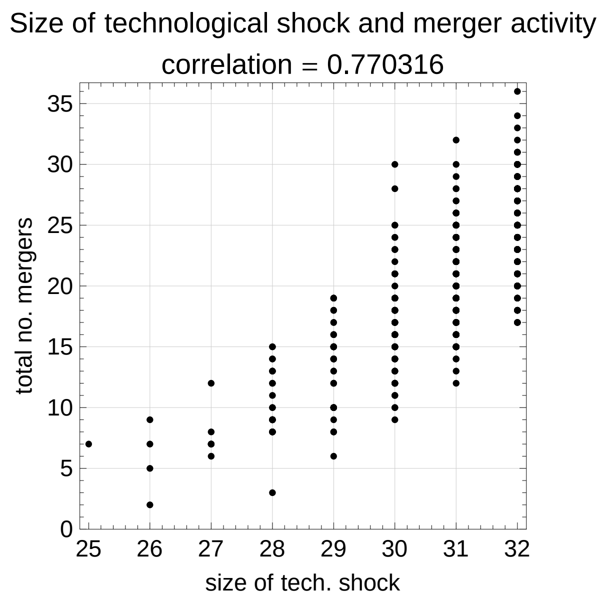


Figure 8: Impact of the size of technological shock (500 replications)

(a)



(b)

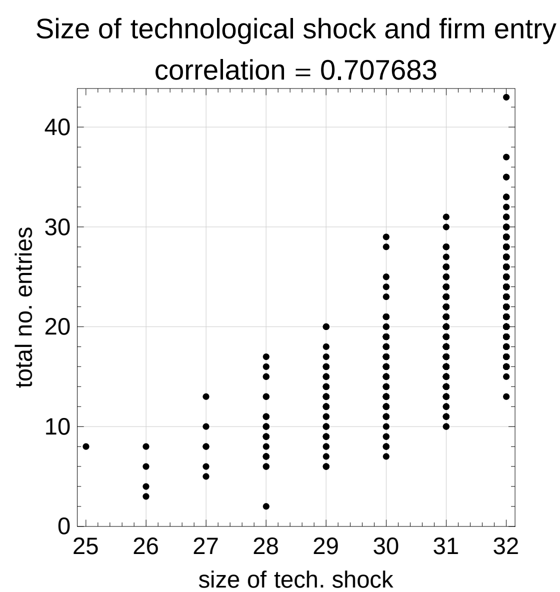


Figure 9: Intra-industry diversity

(a), (c), (d): average over 500 random replications
(b): average over 20 random replications

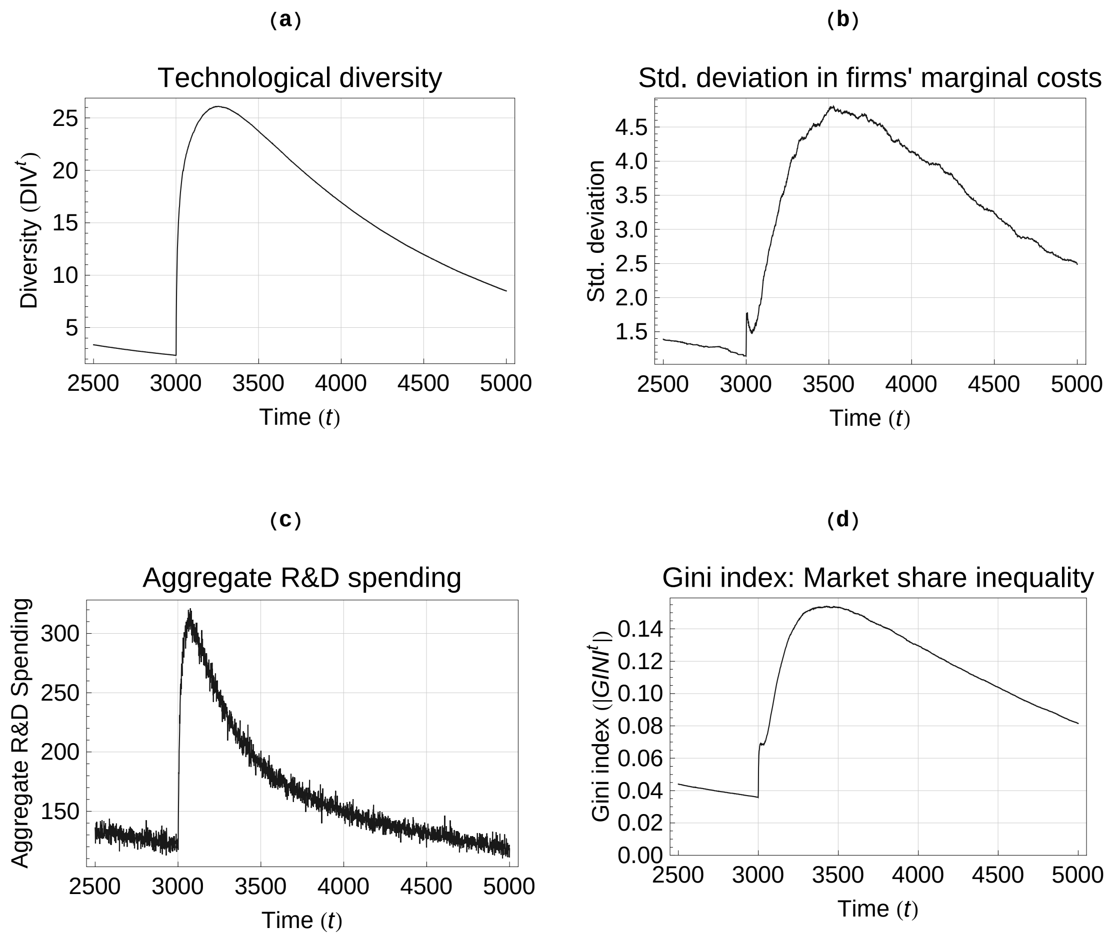


Figure 10: Number of firms and mergers over time
(single replication)

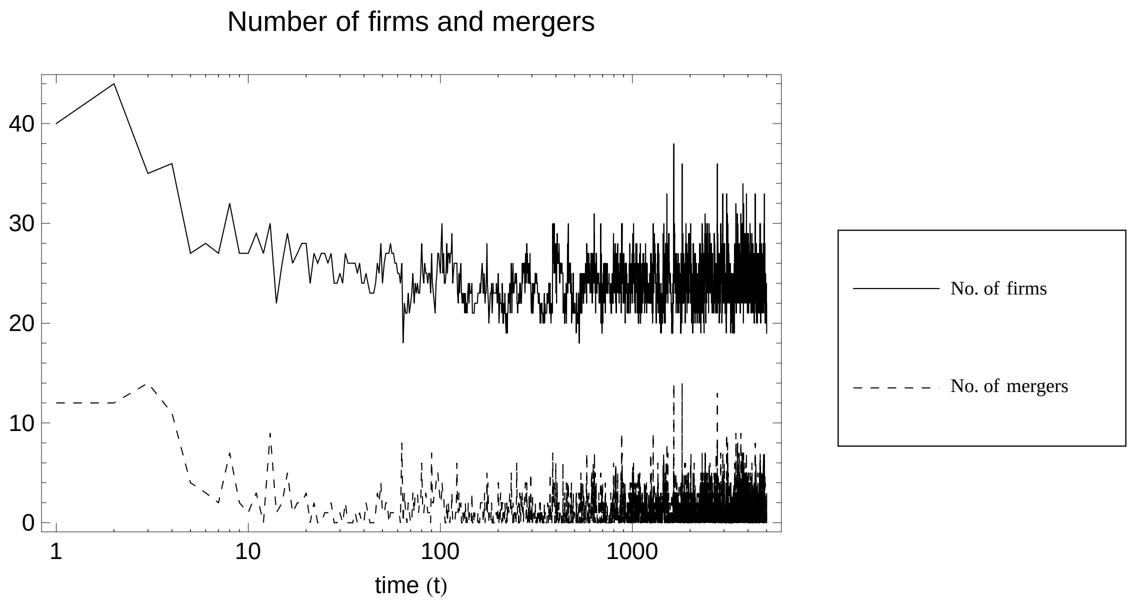


Figure 11: Rate of mergers over time
(single replication)

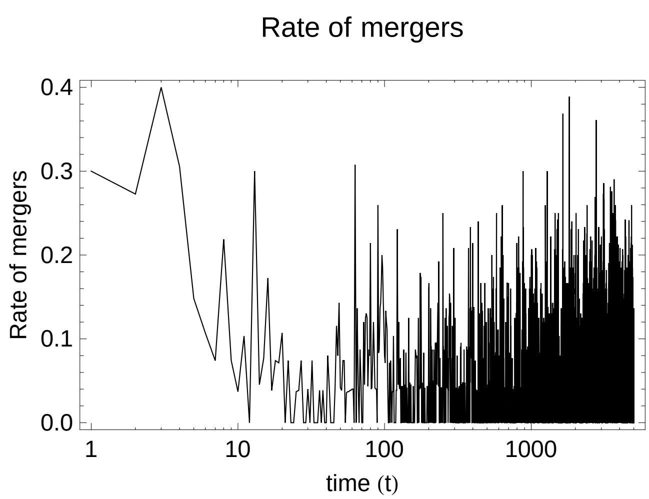


Figure 12: Rate of mergers since the last technological shock over $1{,}001 \leq t \leq 5{,}000$

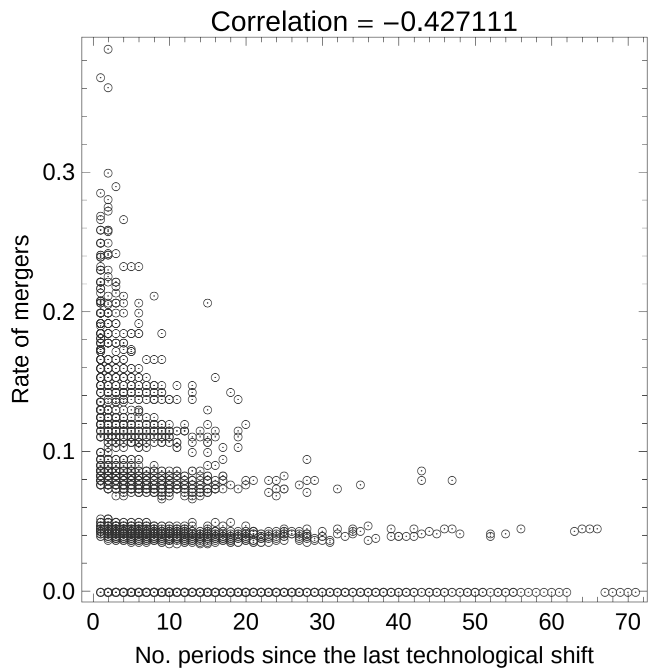


Figure 13: Rate of entry since the last technological shock over 1,001 ≤ t ≤ 5,000

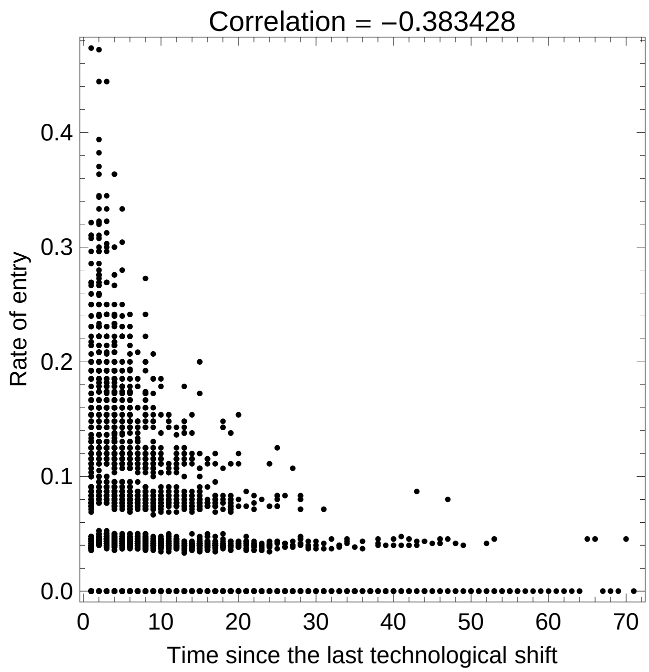


Figure 14: Endogenous number of mergers over time
(average over 500 replications)

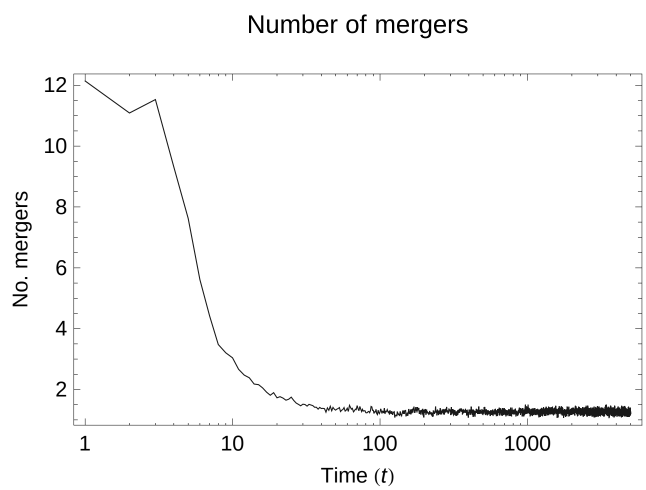


Figure 15: Number of firms over time
(average over 500 replications)

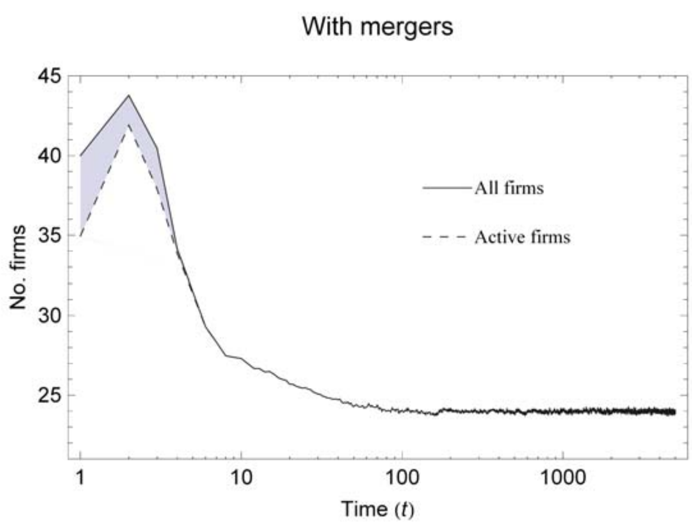


Figure 16: Steady-State Market Structure

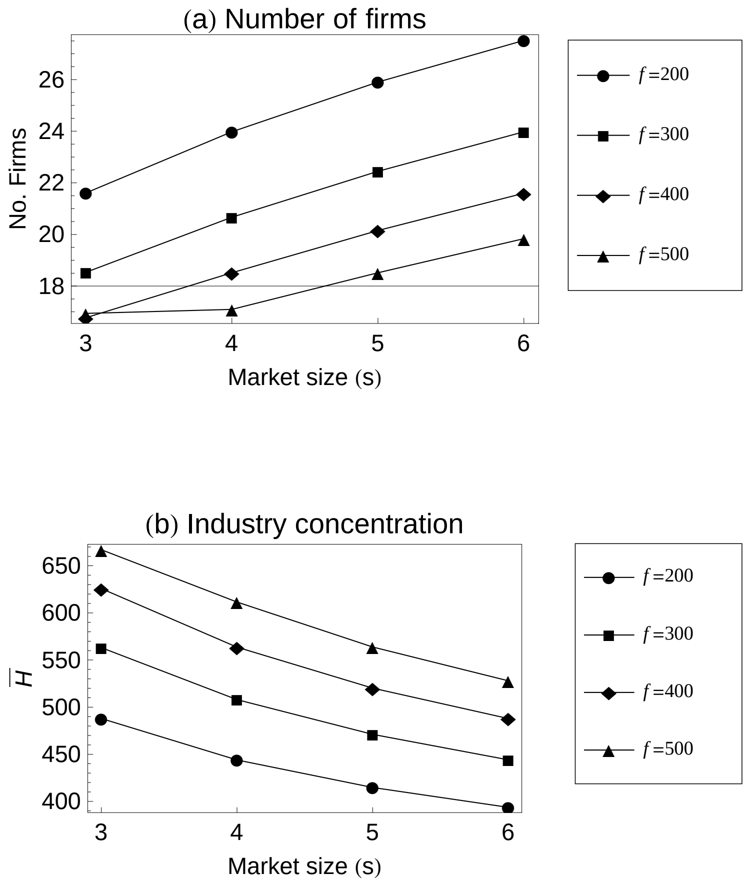


Figure 17: Steady-State Rates of Turnover and Mergers

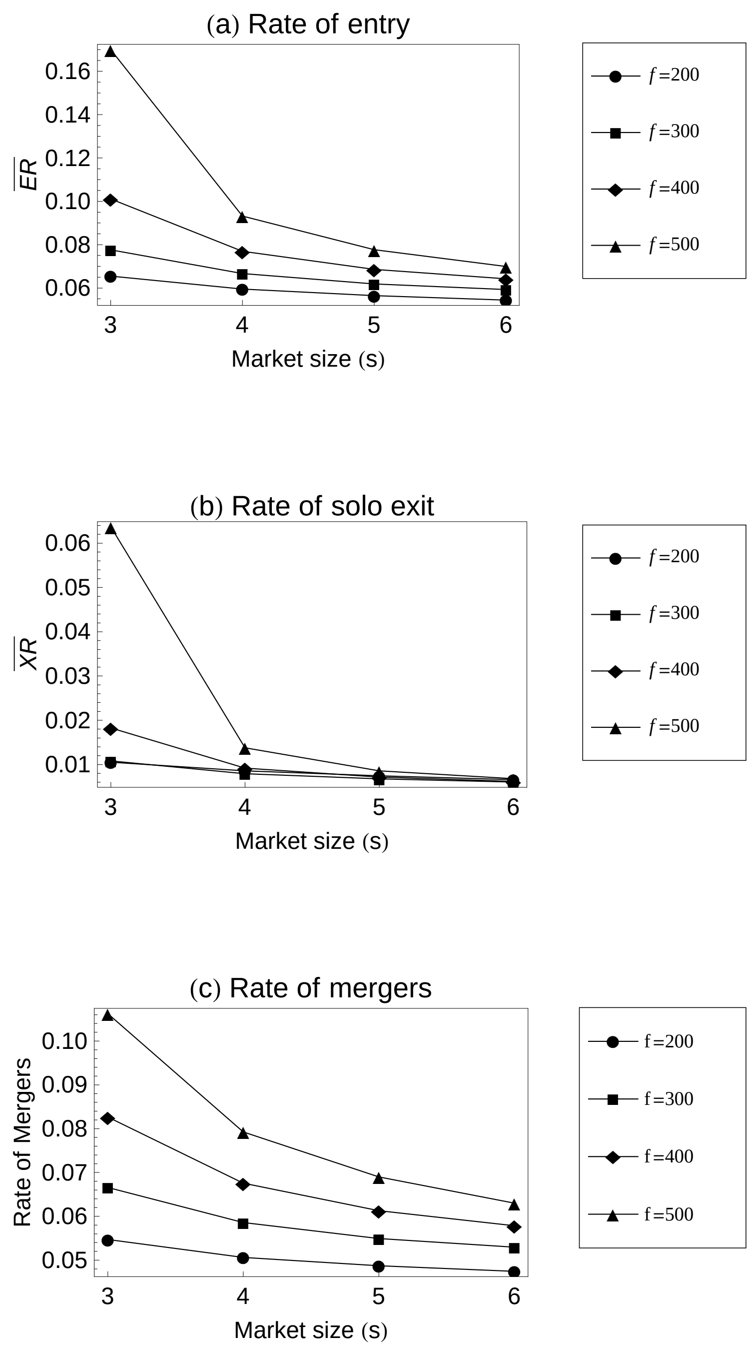


Figure 18: Impact of Technological Turbulence (γ, g) on the Rate of Mergers

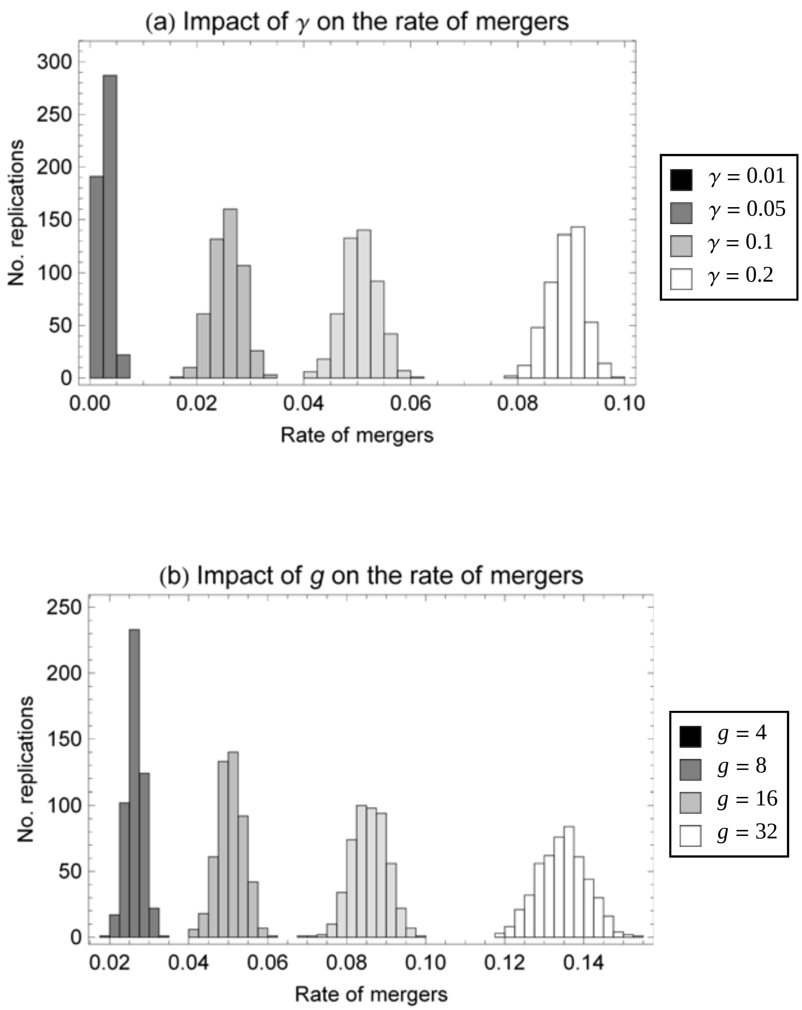
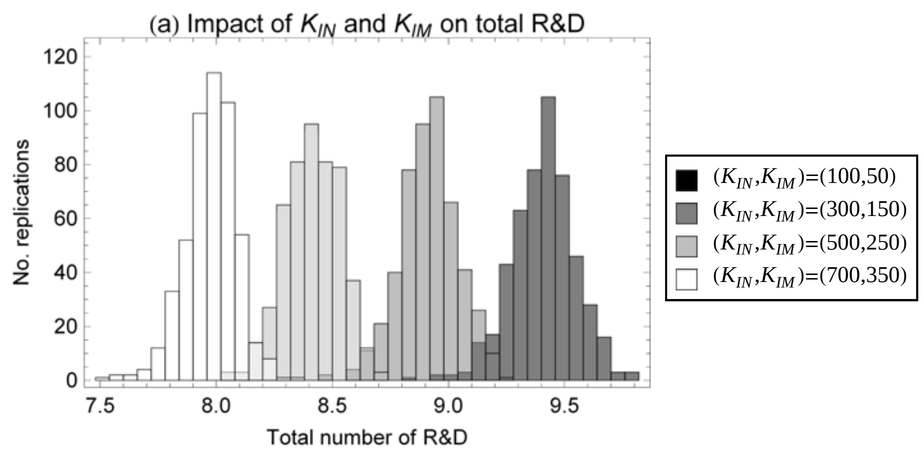


Figure 19: Impact of R&D Cost on the Intensities of R&D and Mergers



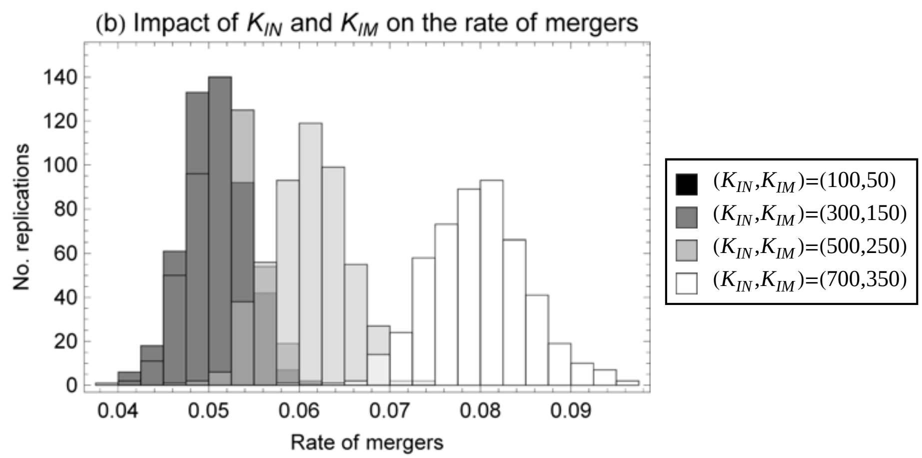


Figure 20: Turnover of firms over time with and without mergers
(average over 500 replications)

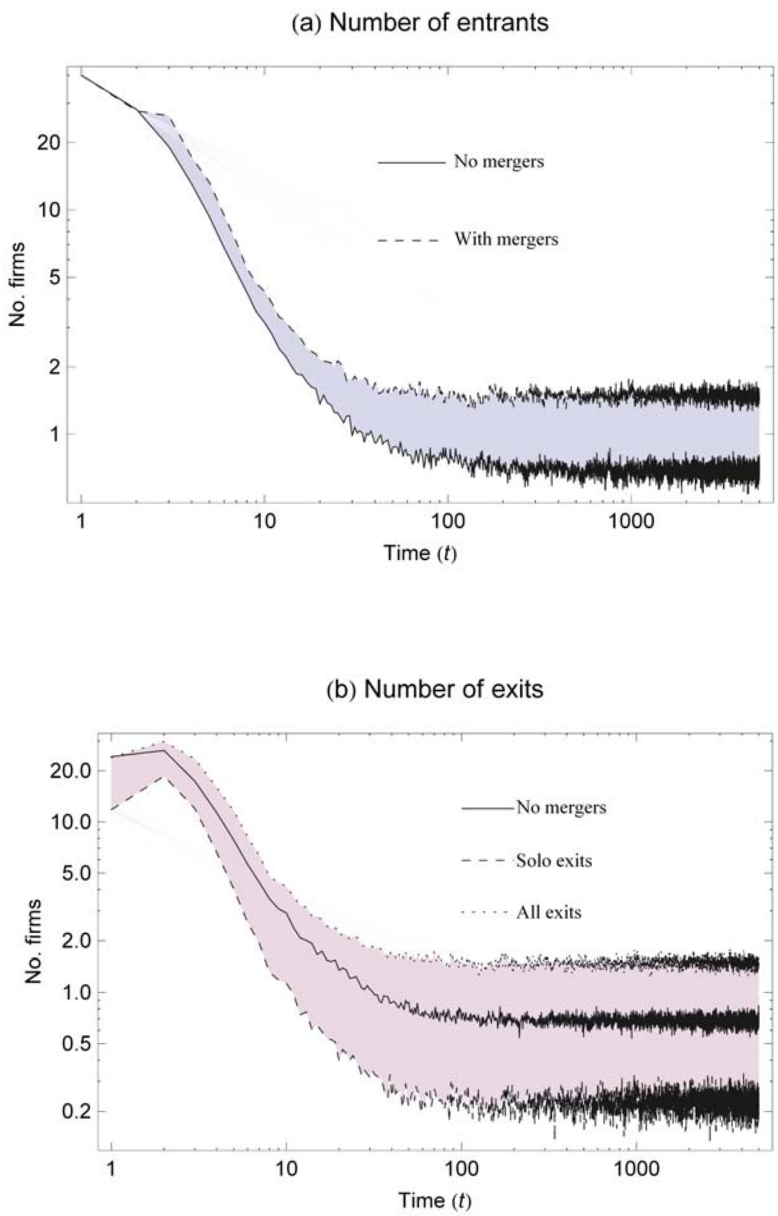


Figure 21: Number of firms over time without mergers
(average over 500 replications)

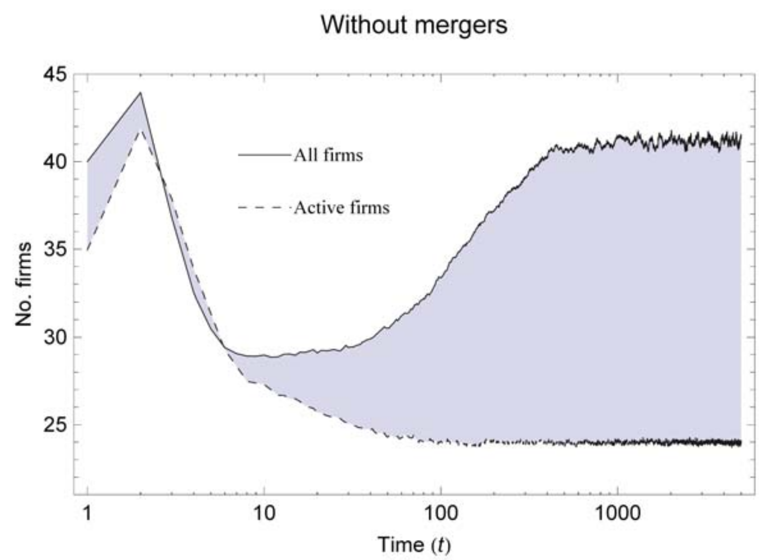


Figure 22: Industry marginal cost over time with and without mergers
(average over 500 replications)

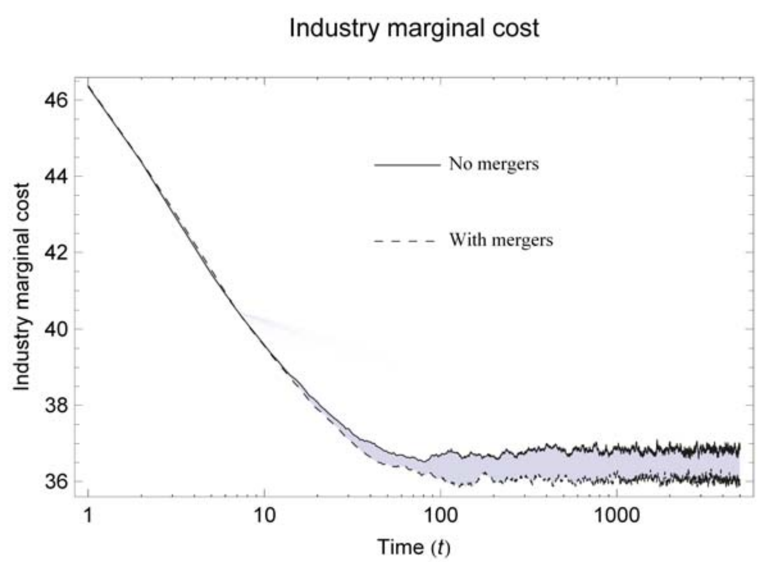


Figure 23: Industry concentration over time with and without mergers
(average over 500 replications)

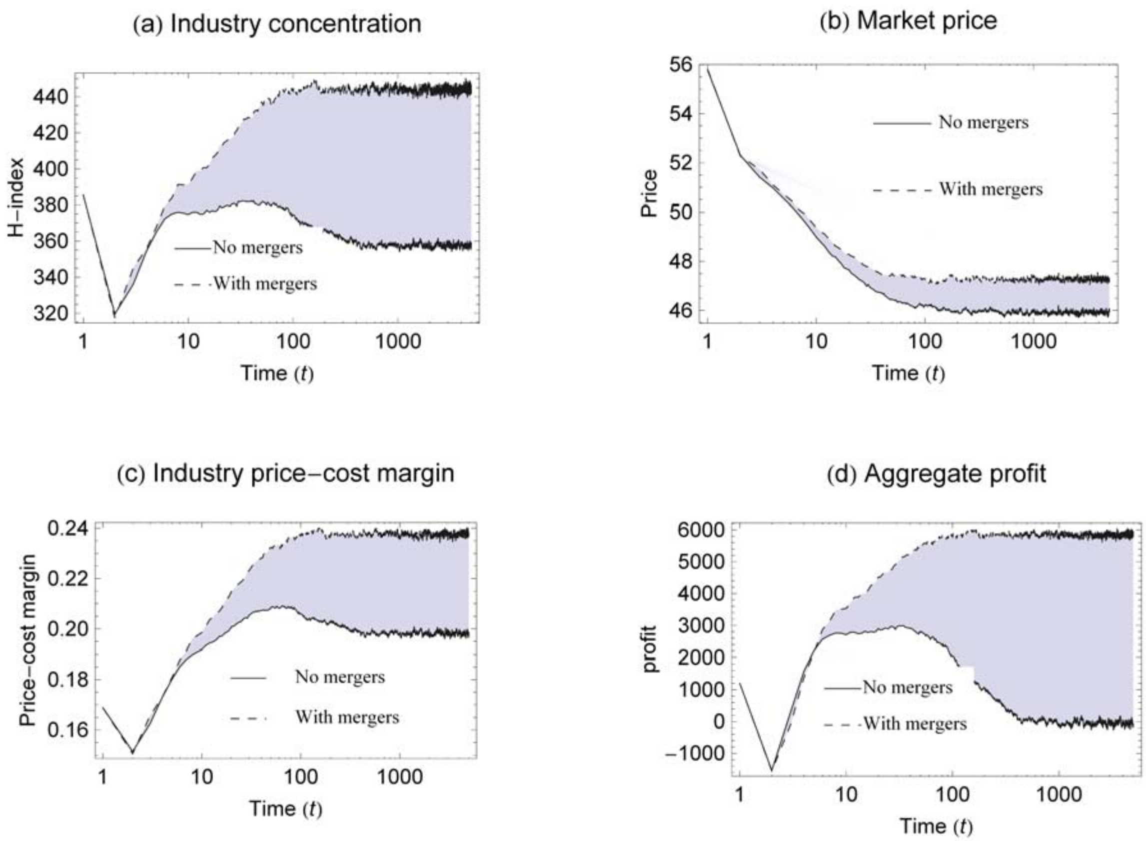


Figure 24: Impact of endogenous mergers on welfare
(average over 500 replications)

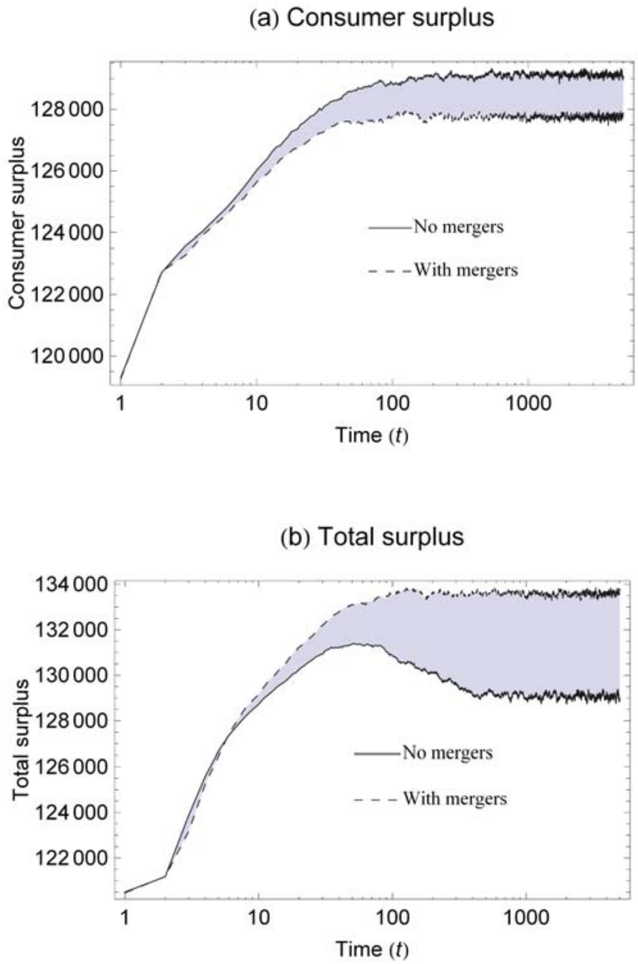


Figure 25: Impact of endogenous mergers on technology
(average over 500 replications)