On Industry Life-Cycles: Delay, Entry, and Shakeout in Beer Brewing *

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October 2000

Abstract

This paper proposes a new explanation for entry into a new industry and subsequent "shakeout". Based on an in-depth analysis of the shakeout in the United States beer brewing industry between 1880-1890, we propose that industry shakeouts naturally follow periods of mass-entry by firms. Similar patterns are evident in two other industries we briefly examine: the U.S. automobile and tire industries. While entry rates fluctuate broadly in all these industries, we find that the timing of exit for a given cohort of entrants is remarkably similar over time: the exit hazard rate is peaked in the first two years of every cohort's life and drops dramatically to low and stable levels for subsequent ages. We propose a theoretical model of information accumulation to explain this pattern of industry evolution. Entrepreneurs are uncertain about the profitability of the industry and this uncertainty is resolved through sufficient accumulation of information regarding the fortunes of incumbent firms. Delay in entry occurs if informational signals are sufficiently uninformative that it takes potential entrants time to accumulate information to support more entry. Shakeout occurs if informational signals are sufficiently informative to generate a period of mass-entry once entrants' optimism reaches a critical level. The resulting entry pattern from simulations of the model look much like that observed in the industries we study.

JEL Classification: D21, D83, L66

Keywords: Entry, Shakeout, Informational Cascade, Learning.

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†Financial support from the National Science Foundation (SBR-9507978) is gratefully acknowledged.

‡Support from Stanford Center for Organizations Research is gratefully acknowledged.

1 Introduction

This paper proposes a new explanation for a commonly observed pattern of industry evolution: exponential rise in entry into a new industry followed by a "shakeout" in which the number of firms drops significantly in a short interval of time. We document empirical evidence concerning industry evolution in the late nineteenth century U.S. beer brewing industry and provide similar but more cursory evidence for the early twentieth century U.S. automobile and tire industries. We then propose a theoretical model of information accumulation to explain these findings.

Briefly characterizing the data, the U.S. beer brewing industry exhibits a wave of entry between 1870-1879 in which the number of U.S. brewery firms more than doubles and an industry shakeout phase between 1880-1890 in which the number of firms in the industry drops by 40%. We find that a majority of the firms exiting during the shakeout entered the industry in the preceeding wave. A similar pattern is evident in the U.S. automobile and tire industries. In these industries, while entry rates fluctuate broadly, we find that the timing of exit for a given cohort of entrants is remarkably similar over time. In other words, the *shape* of the hazard function is similar across cohorts before and after shakeout; the exit hazard rate is peaked in the first two years of the cohort's life and drops dramatically in subsequent years.[1] However, we find that the *level* of the hazard function is not the same before and after the shakeout; latter entering cohorts exhibit higher probabilities of failure, especially in the first five years of existence, compared with cohorts entering prior to the shakeout.

A simple implication of the empirical findings on the stability of the shape of the hazard function over time is that if an unusually large cohort of firms enters an industry a large number of exits (both gross and net) will be observed in subsequent years. The industry will experience a shakeout even though exit rates for each cohort have not changed. In this sense, mass-exit naturally follows mass-entry and does not require a deep explanation. It is the mass-entry evident in the data for many industries that requires an explanation. In fact, we also find higher exit probabilities for the cohort entering just prior to shakeout which also contributes to the size of the exiting cohort during shakeout.

Across a broad selection of industries, many empirical studies fail to find a link between entry rates and conventional measures of profitability and entry barriers.[2] However, recent results by Geroski and Mazzucato (2000) lend empirical support for information accumulation as a main determinant of the path of industry evolution. We propose a theoretical model of information accumulation to explain mass entry into an industry. In our model, entrepreneurs are uncertain about the profitability of the industry and this uncertainty is resolved through sufficient accumulation of information regarding the fortunes of incumbent firms. Delay in entry occurs solely due to the fact that it takes time to accumulate sufficient information to support more entry. While delay and mass-entry are not a guaranteed outcome in the model, the resulting entry patterns from simulations of the model across a broad set of parameter values look much like those observed in the industries we study. Furthermore, the model predicts that early entrants will temporarily earn higher profits and experience higher probability of surviving after entry than later entrants. In the data we analyze, we find evidence that later-entering cohorts experience higher probabilities of exiting at any age, especially ages 1-5 years. Though we lack direct measure of profitability across cohorts, we interpret this as indicating an advantage to being an early entrant, consistent with our theoretical model.

We also highlight via simulation the characteristics of information accumulation responsible for

[1] Dunne, Roberts, and Samuelson (1989) and Mata (1995) present similar findings across a range of industries.

[2] See Geroski (1995) for a survey of the empirical literature. Also see Aldrich and Fiol (1994) and Bala and Goyal (1994).

matching empirically observed patterns of industry evolution, namely the information content of the signals provided by market incumbents. Delay in entry occurs if informational signals are sufficiently uninformative that it takes potential entrants time to accumulate information to support more entry. Shakeout occurs if informational signals are sufficiently informative to generate a period of mass-entry once entrants' optimism reaches a critical level. The model has many interesting implications for the emergence of markets which we are unable to explore within the scope of this paper.

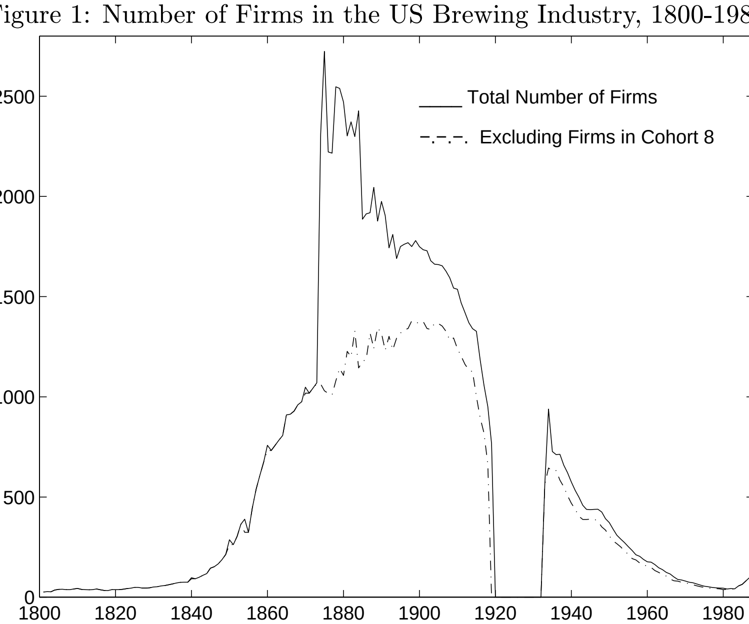
The rest of the paper is organized as follows. Section 2 carefully documents several empirical findings on exit and entry rates for the U.S. beer brewing industry. We also provide a limited analysis of the U.S. automobile and tire industries to show that our findings for beer brewing are not merely an isolated example. Section 3 contrasts our explanation for the empirical findings with existing literature on industry shakeouts. Section 4 presents the theoretical model of entry and exit behavior in an industry and section 5 explores the model's capabilities via simulation. Section 6 concludes.

2 Shakeout as an artifact: Exit follows Entry

In this section we present empirical evidence supporting our claim that the shakeout phase in the evolution of the U.S. beer brewing industry can be explained as a result of a massive wave of entry followed by otherwise normal exit rates. To do so we use a comprehensive dataset on all brewing firms with information on the entry and exit year of each firm, not merely the total number of entering and exiting firms each year. The dataset is described in more detail in the appendix B.

2.1 Evidence from the U.S. Beer Brewing Industry

Figure 1: Number of Firms in the US Brewing Industry, 1800-1988



The total number of firms producing legally in the U.S. beer brewing industry between 1800-1988 is depicted in Figure 1.[3] The anticipation of prohibition and the early enactment of temperance laws in

[3]The industry has existed in the United States since the pre-Colonial era. While we have data going back to 1633, the

individual states resulted in a rapid reduction in the number of operating firms between 1910 and 1919. No firms in the dataset openly produced during the years of prohibition (1919-1933); however, many firms that entered prior to prohibition resumed operations following the repeal of the 18th amendment.[4] After the repeal of prohibition, the number of firms continues to decay at rates seen in the 1880-1900 period, so that the process seems to have been undisturbed by the period of prohibition. We have mused over the implications of this finding for assessing the effectiveness of the constitutional ban on alcohol production.

Several forces, both technological and demographic, altered the economic landscape in which the beer brewing industry was situated around 1840. During the two centuries between 1640-1840, American brewing was a small, craft-based industry, as evidenced by the very low number of firms during this period. Expansion of individual breweries was severely limited by the technology of the time, especially the lack of alternatives to natural ice refrigeration. The second half of the nineteenth century was a period of vast and dramatic change for the industry with numerous factors affecting profitability in the industry and the size of the market. These included the country's increasing wealth, a growing abundance of domestically produced grain, the development of a national transportation system, and numerous technological refinements in the production process and in related fields.[5] These developments improved the reliability of the brewing process, allowed beer to be brewed in larger and more frequent batches and be delivered further distances, and disconnected the brewing cycle from any particular season. The influx of large numbers of German immigrants around 1850 also provided a pool of highly skilled producers and regular consumers, and served to shift consumer preferences away from porters and stouts to lighter lager beers which were more easily consumed in larger amounts.[6]

The nineteenth century developments on the supply and demand side suggest that the "modern" beer brewing industry in the United States dates back to the 1840's. We choose, therefore, to focus our attention on explaining the industry life-cycle of the U.S. beer brewing industry from 1840 onward. We shall seek to explain the three prominent features of figure 1 starting from this date: the slow but exponential rise in the number of firms until 1870, the nearly discontinuous jump in the number of firms in 1874, and finally, the precipitous drop in the number of firms (the shakeout) in the late 1870s and early 1880s.[7]

Figure 2 plots the time-path of the numbers of firms for four representative cohorts, excluding the years of definition of each cohort (*i.e.* for the 1839-43 cohort the plot start in 1843).[8] While it appears that there is a tendency for cohorts that are closer in birth-year to have more correlated high frequency movements, the differences are not overwhelming and the low frequency pattern of exits are strikingly similar. One difference is clear; the time profiles are steeper for later-entering cohorts.

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number of firms is quite low and stable until 1840 and is shown in the figure beginning only in 1800.

[4]We count the number of firms in the industry. Therefore we treat exits, mergers, and acquisitions equivalently since they all reduce the number of firms in the industry. Less than 1% of all firms in the sample were merged with or acquired by other firms. Temporary suspensions also reduce the number of firms. However, in the cohort analysis below, we associate reactivations of suspended firms with the cohort with which they first entered.

[5]Technological break-throughs relevant for the nineteenth century U.S. beer brewing industry included steam-driven machinery, mechanical refrigeration equipment, enhanced yeast cultivation, the saccharometer for measuring sugar content, and the keg.

[6]The production of lager beer required "bottom-fermenting" yeast which was unavailable in the United States prior to 1840 when John Wagner, a German brew-master, successfully transported a suitable yeast colony to his brewery in Philadelphia (Baron [1962]).

[7]Carroll and Swaminathan (1989) assume that the enormous entry wave did not occur solely in the year of 1874, but that it occurred in a small time interval around that year. Similarly, in our cohort analysis we ascribe the number of firm shown as entering in 1874 to a five year interval between 1874- 1878.

[8]Since we associate reactivations of suspended firms with the cohort with which they first entered, the number of firms in a given cohort need not be monotonically declining over time.

Figure 2: Evolution of Cohorts 1,4,6 and 10

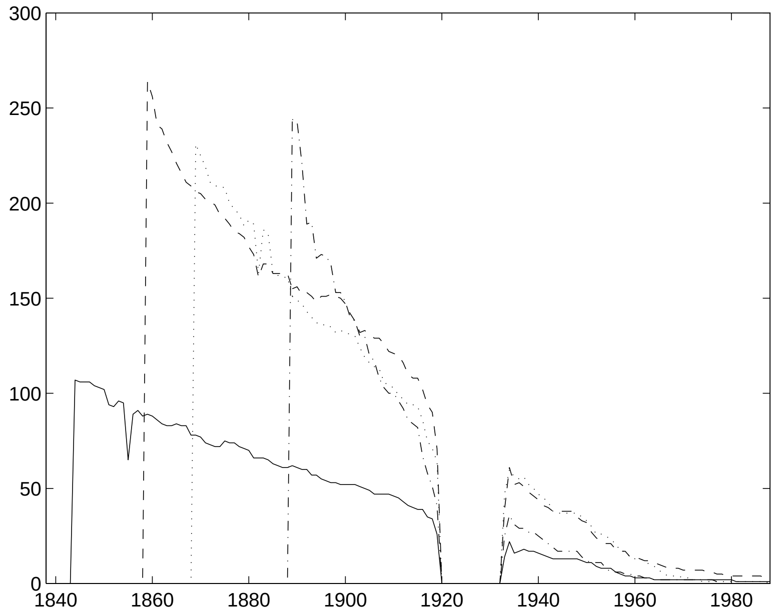


Table 1 presents data on the percentage of firms in each cohort from 1839-1919 that exit before reaching ages 2, 5, 10, 20 and 40 years. The data clearly indicate the existence of a structural break in firm survival rates: firms belonging to the pre-1859 cohorts display a remarkably lower probability of exiting the market within the first five years of start-up, compared with post-1859 cohorts. Within these two groups, exit rates by age are very similar across cohorts. In the earlier, pre-1859 cohorts roughly 7-13% of firms exit within their first 2 years and 11-17% within their first 5 years of operation. In the later, post-1859 cohorts, 15-61% of the firms exit within their first 2 years, and 25-77% within their first 5 years of operation.

From the cohort analysis we can ask the question: How similar are the evolutionary paths of cohorts that enter the industry at very different points in time? This question is interesting because it could illuminate the role differences in technology plays in shaping industry evolution. Cohorts that enter the industry several decades apart are likely to employ different technologies for production and distribution of their product. If technological inferiority and barriers to adoption of new technologies by existing firms are important determinants of failure, one would expect pre-shakeout cohorts to show elevated hazard rates[9] relative to post-shakeout cohorts for ages after shakeout has begun. We find, however, that the shape of the hazard rates for all cohorts (pre- and post- shakeout) are very similar. This can be seen in Figure 3 which shows estimated exit hazard rates for several representative cohorts (panels b-d) as well as the average hazard rates for all cohorts (panel a). For both pre- and post-shakeout cohorts the hazard rate peaks within the first two years and then declines to low and very stable levels. However, while the shape of the hazard function is the same across cohorts, its level is not; cohorts entering later in the industry life-cycle show elevated hazard rates, especially in the first five years of existence. The higher early exit hazard rate for post-shakeout cohorts is evident by comparing panels c and d with panel b, especially at ages 1-5.

A simple implication of the empirical findings on the stability of the shape of the hazard function

[9]Recall, the hazard rate is the conditional probability that a firm exits in period $\tau + \delta$ given that it has survived until period τ.

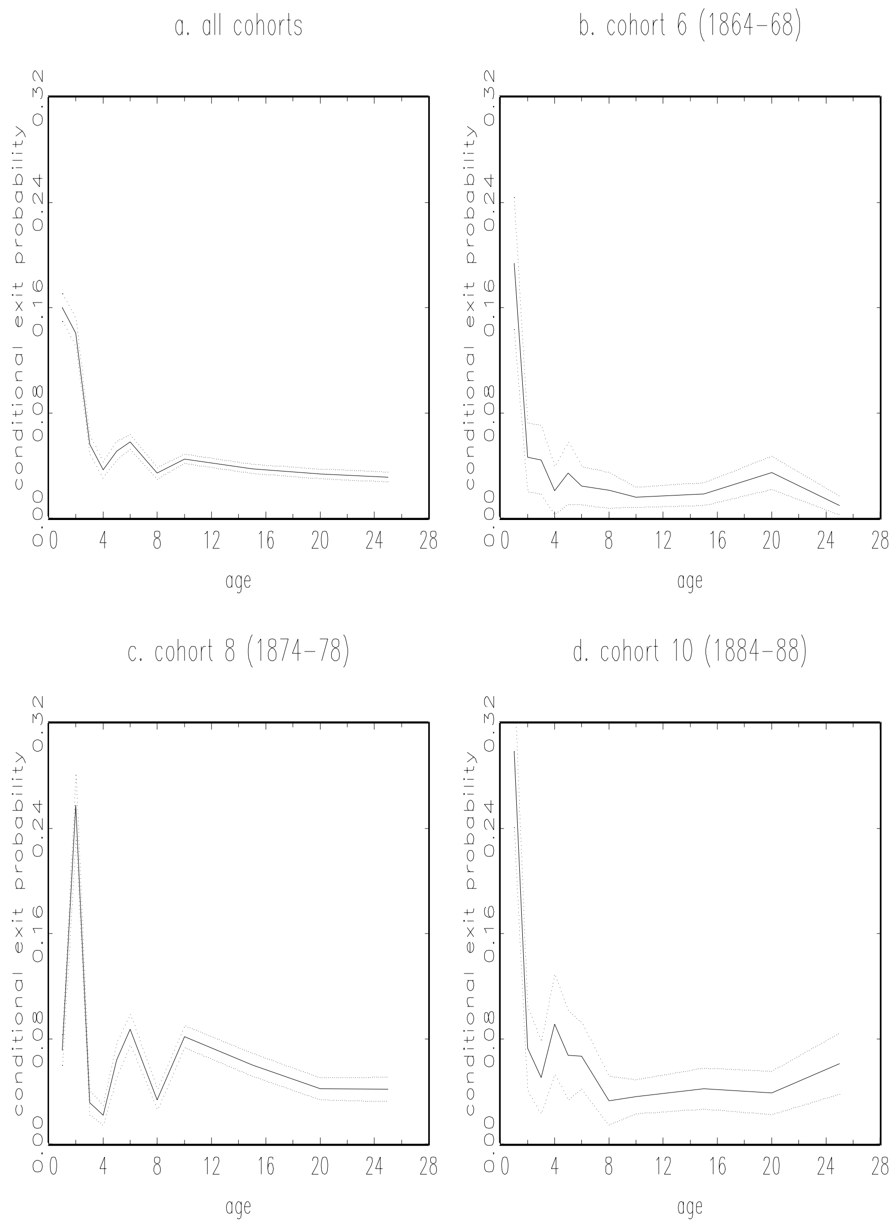


Figure 3: Hazard Rates with 95% C.I.

Table 1: Percentage of firms exiting within n years from entry, by cohort

Size	Entry Period (#)	n=2	n=5	n=10	n=20	n=40
127	1839-43 (1)	0.094	0.157	0.188	0.267	0.432
92	1844-48 (2)	0.087	0.109	0.196	0.283	0.435
230	1849-53 (3)	0.126	0.161	0.204	0.274	0.461
288	1854-58 (4)	0.069	0.163	0.260	0.347	0.465
289	1859-63 (5)	0.159	0.252	0.335	0.432	0.560
323	1864-68 (6)	0.213	0.287	0.358	0.485	0.633
257	1869-73 (7)	0.218	0.265	0.354	0.517	0.665
2060	1874-78 (8)	0.282	0.361	0.531	0.773	0.901
408	1979-83 (9)	0.279	0.541	0.661	0.764	0.930
385	1884-88 (10)	0.312	0.442	0.564	0.707	0.946
317	1889-93 (11)	0.384	0.450	0.532	0.677	0.895
248	1894-98 (12)	0.282	0.403	0.516	0.657	0.911
227	1899-03 (13)	0.242	0.317	0.449	0.735	0.964
213	1904-08 (14)	0.207	0.286	0.488	0.821	0.952
61	1909-13 (15)	0.410	0.574	0.771	0.869	0.935
26	1914-18 (16)	0.615	0.769	0.807	0.884	0.999
56	1919-23 (17)	0.232	0.519	0.858	0.912	0.984

over time is that if an unusually large cohort of firms enters an industry a large number of exits (both gross and net) will be observed in subsequent years. Of course, the elevated hazard rates we find for the cohort entering just prior to shakeout only serves to reinforce this effect. The dashed line in figure 1 drives home the point that the shakeout period in the U.S. brewery industry (1880-1890) can be explained as an artifact of the entry in the 1870s of a very large cohort. This line graphs the number of breweries operating between 1840-1988, excluding the cohort of firms entering in 1874-1878. The sharp decline in the total number of firms in the industry between 1880-1890 is almost entirely accounted for by exits from the 1874-1878 cohort.[10]

2.2 Evidence from other industries

It is important to determine whether the features of shakeout identified above are particular to the beer brewing industry. Two other industries that have received much attention in the literature on shakeout are the U.S. automobile and tire industries[11] and a similar pattern appears in these. The peak number of entering firms directly precedes shakeout and the largest contributors to the exiting firms during shakeout are the firms that entered just prior to shakeout.

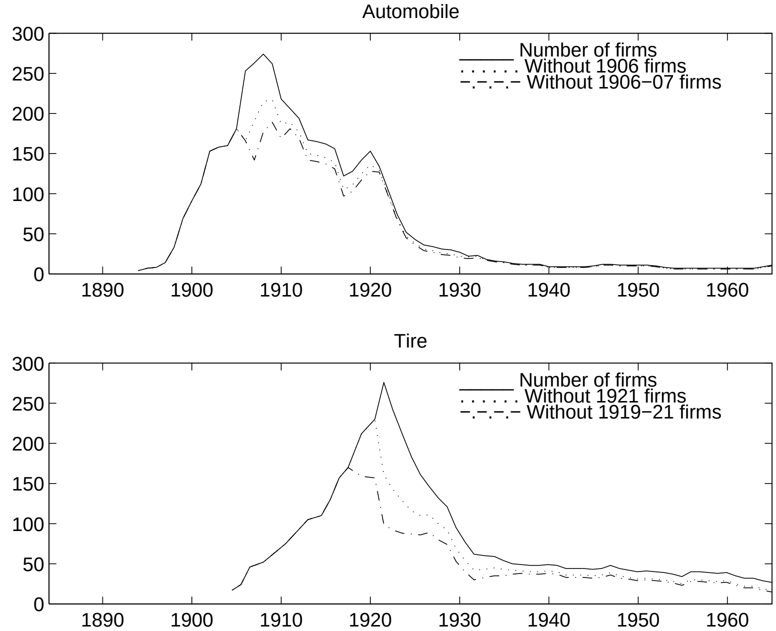
Figure 4 graphs the number of firms in the U.S. automobile and tire industries between 1894-1965.[12] The solid line in both panels graphs all operating firms in each year. The automobile industry (top panel) experienced a massive wave of entry in 1906-07 and a significant reduction in the number of

[10]It should be pointed out that these features of the data are replicated at a geographically disaggregated level as well. Plotting figure 1 by U.S. Census region yields the same picture as in figure 1 for each region. See Schivardi (1996).

[11]On tires, see Jovanovic and MacDonald (1994), Klepper and Simons (1993), and Klepper (1996b). On automobiles, see Klepper and Simons (1993) and Klepper (1996b).

[12]The data for these graph were taken from Klepper (1996b) Tables 1 and 2 which only reports the percent of firms entering in each year that survive more than 5 years, 15 years, and 25 years. From this data we compute the percent of each entering cohort that exit before age 5, 15, and 25 years. We assume that one-fifth of the 5-year exits for each cohort occur in each age 1-5 starting from the year after the cohort entered (the cohort is age 0 in the year it enters). We assume that the 15-year and 25-year exits occur in the 15th and 25th year of the cohort's life. This assumption is not crucial for the results. Calculations available from us by request.

Figure 4: Number of Firms in the US Automobile and Tire Industries: 1890-1965



firms between 1909-1912. The graph also shows the number of firms operating in the industry without the firms that entered in 1906 and 1906-07. While these lines still show a reduction in the number of operating firms between 1909-12, the drop is not nearly as precipitous. Roughly 40% of the exits during the shakeout period can be attributed to firms that entered between 1906-07, the years just prior to shakeout. The tire industry (bottom panel) experienced a shakeout beginning in 1921. While a weaker pattern is found than for either beer brewing or automobiles, a large portion of the exiting firms between 1921-1930 come from cohorts that entered in 1919-1921.

We acknowledge that evidence on three industries is insufficient to claim that delay, mass entry, and shakeout by new entrants is a universal pattern of industry-evolution. However, we are encouraged by the graphs of industry evolution of the 42 industries studied in Gort and Klepper (1982), most of which exhibit the an identical pattern to figures 1 and 4 for breweries, automobiles, and tires. While we do not have firm-level data on entry and exit dates for these industries, and thus can not identify the ages of the firms exiting during shakeout in other industries, these figures do *not* suggest that our characterization of the industry life-cycle is necessarily only limited to the three industries we study.

3 Explaining the Empirical Findings

Previous research has focused on explaining shakeout as a period in which firm exit rates increase and entry rates decrease due to either product or process innovation.[13] The earlier branch of the literature explains shakeout as a consequence of a technological innovation that rapidly forces existing firms to adopt new technologies or be driven out of the market.[14] However, Klepper and Simons (1993) examine

[13] Klepper (1996a), Klepper and Miller (1995), Jovanovic and MacDonald (1994), Lieberman (1990), Klepper and Graddy (1990), Jovanovic and Lach (1989), and Gort and Klepper (1982) posit such explanations for why industries undergo a period of mass net exit.

[14] Gort and Klepper (1982) analyze the entry and exit behavior of companies in 42 different product markets. They assume that the shakeout phase is triggered by "a rise in innovation [that] ... not only reinforces the barriers to entry but,

data from four industries and conclude that, while their evolutionary paths are remarkably similar, it is hard to identify a technological innovation with the shakeout period in each case. More recent research has focused on process refinement and the establishment of an industry standard as the cause of shakeout. Klepper and Simons (1993) and Klepper (1996a,b) offer an explanation for shakeout based on the assumption that, as an industry evolves, large firms will come to dominate the market due to a scale advantage in the area of process refinement. As long as demand is not ever expanding, profit margins of new entrants decline to zero over time while existing small firms become unprofitable and exit. Since the remaining firms are larger, there are fewer of them.

Two characteristics of these technological explanations for shakeout are that gross entry slows prior to the peak in the number of firms in the industry and that older firms comprise a bulk of the exiting firms during shakeout. We have found little empirical support for either of these characteristics.

We wish to stress that our criticism of the technological explanations for shakeout focuses solely on their inconsistency with events in the period leading up to and immediately following shakeout. Furthermore, we do not claim to fully capture the gradual decline in the number of firms that occurs following shakeout in the industries we examine with the model presented here. Rather, we view these theories as complimentary since they apply to different time frequencies.

The model we offer in the next section is geared towards explaining all three aspects of industry evolution we highlighted in the previous section: a delay in entry, followed by a big wave of entry in a short interval of time, and a shakeout immediately following the wave. We suggest that the massive entry is the result of a process of information accumulation in which entrepreneurs must learn about the viability of a new market before entering. Even if the production of a new good is possible, the desirability of entering the market might be questionable due to uncertainty regarding the technology and/or consumers' tastes. Delay in entry comes from the belief that entry may prove to be unprofitable, *ex post*. One source of information that aids potential entrants in deciding whether to enter comes from observing the post-entry fortunes of others. The big wave of entry could then be explained as the result of an informational cascade: Entrepreneurs who are initially pessimistic (wrongly so) about the profitability of the market observe post-entry performance by others which improves their outlook.[15]

The model we propose has a very simple mechanism for generating cascade type behavior. Higher entry rates in the past makes information accumulation proceed at a faster rate since it provides more "data points" for potential entrants to gauge market profitability in future periods. More precisely, the quality of the signal that potential entrants receive from a set of historical observations on post-entry performance is proportional to the number of observations. When the unknown market prospects are indeed good, for example, the decision by a subset of entrepreneurs to enter the industry will supply the potential entrants with additional information. This, in turn, will induce more entry, setting in motion a process that may generate exponentially increasing entry rates. Linking this story to the industry data presented above, we suggest that brewers, automobile manufacturers, and tire makers entered *en masse* after updating their beliefs about industry profitability from observing the post-entry success of other firms.[16]

in addition, compresses the profit margins of the less efficient producers who are unable to imitate the leaders from among the existing firms. Consequently the exit rate rises sharply until the less efficient firms are forced out of the market." (p. 634)

[15]Also see the "legitimazation" theories in the literature on organizational ecology, *e.g.* Hannan and Carroll (1992) and Carroll and Hannan (1999).

[16]Given the state of communication technology at the turn of the 20th century, learning about entry was most likely a local phenomenon. While the model abstracts from geographical considerations, we appeal to the fact that results for the brewing industry (figure 1) are manifest at the regional level as well, as described above. We have no information on the location of firms in the automobile and tire industries and, therefore, are unable to investigate the shakeout effect at

4 A Model of Build-Up, Wave-entry, and Shakeout

The Environment

The environment is characterized by discrete time. The economic agents in this environment are also discrete and are called entrepreneurs. Since entrepreneurs start firms and each firm is associated with one and only one entrepreneur, we use the term entrepreneur and firm interchangeably. At time 0 a new industry is born producing a homogeneous good. The birth of the industry presents entrepreneurs with the opportunity to pay a sunk cost k to enter and begin producing and selling the good. Each entrepreneur can produce only one unit of the good in each period. Entrepreneurs differ in their ability to produce; we implement this by assuming that at the time of entry an entrepreneur draws a variable cost parameter c from the distribution $F(c)$. For simplicity, we assume that entrants learn their drawn value of c upon entry and that, once drawn, the entrepreneur's cost is fixed for all time.[17] Having entered, entrepreneurs must choose between staying in the market and exiting. We assume the scrap value upon exiting is zero and point out why this is not an innocuous assumption below. Formally, for firms that have not entered the market yet, the action space is $\{enter, wait\}$ while for firms in the market, the action space is $\{stay, exit\}$.[18] All entrepreneurs have a one-period discount factor of β. Free entry ensures that, at each point in time, the equilibrium value of entry is non positive and determines the evolution of the market. Finally, there exists a continuous, decreasing demand function $P(N)$, with $\lim_{N\to\infty} P(N) = 0$, where N is the number of firms that decide to stay in the market. We assume that price is a function of the number of firms in the market since each firm has the capacity to produce and sell one unit of the good. Hence, N is equivalent to potential supply.

The fundamental assumption in the model is that there is uncertainty about profitability and that potential entrants resolve this uncertainty from observing the experiences of incumbent firms. We formalize this idea by assuming that not all the incumbents receive an order for the good every period: rather, firms are matched with customers with some unknown probability q and incumbents and potential entrants must learn the "true" value of q.[19] The number of matches each period is observeable. At time 0 entrepreneurs hold initial beliefs about q summarized by the probability density function $g_0(q)$. Through observing the experiences of operating entrepreneurs, all agents learn about the true value of q in a Bayesian fashion. Matches, or orders, are independently distributed both within a period and across time. Firms that do not receive an order are inactive for that period and do not pay variable cost. For a given price, the higher the value of q, the higher the expected stream of profits that accrue to a firm. Given free entry, this implies that the market will be characterized by a higher equilibrium number of firms, were the higher value of q known with certainty. Effectively, revelation of the true value of q over time through observation of incumbent firms drives entry and exit in the model.

A period of time is comprised of a sequence of events. First, $y \geq 0$ new entrepreneurs enter; these, together with the N firms that were already in the market from the previous period, constitute the number of *gross* incumbents, denoted by $M = N + y$. Second, the equilibrium price is determined and exit decisions are made according to an equilibrium rule discussed below. The remaining N' firms

a geographically disaggregate level for these two industries

[17] Jovanovic (1982) presents a model in which the process of learning one's type occurs over time. The present analysis could be modified in a similar fashion, at the expense of considerable complication, without altering the tenor of the results.

[18] In principle, the exit decision is irreversible. However, in equilibrium, the same results would obtain if entrepreneurs were permitted to re-enter the industry, so long as they re-entered with the same cost parameter, c, drawn on their first entry.

[19] An interesting modification of this set-up would have q changing over time in response to entry. In this case, firms would be learning about an endogenous variable rather than a fixed parameter. This modification is complicated and left for future research.

are referred to as *net* incumbents, or simply incumbents. Third, orders are distributed randomly across incumbents. Firms that receive an order pay their (firm specific) cost c and get a price $P(N')$. Finally, agents update their beliefs over q on the basis of the number of order that were distributed relative to the total number of incumbents.

At each point in time, all agents in the economy can observe the number of entering entrepreneurs, y_t, and exiting entrepreneurs, x_t, as well as the number of incumbents receiving orders, l_t. Let the history of observables be denoted $H^t = (y_i, x_i, l_i)_{i=1}^{t-1}$. We concentrate on *stationary Markov equilibria*, in which agents only consider payoff relevant information. The state of the market can be summarized by three statistics: the number of incumbents at the beginning of the period, N_t, the total number of firm-period observations up to time t, G_t, and the total number of orders received by entrepreneurs, L_t.[20] We can define the state variables $\{N, L, G\}$ in terms of the observed history H^t as follows:

$$N_t = \sum_{i=0}^{t-1}(y_i - x_i), \quad G_t = \sum_{i=0}^{t-1} N_i, \quad L_t = \sum_{i=0}^{t-1} l_i \qquad . \tag{1}$$

The first equation says that the number of incumbents at the beginning of a period is equal to the sum of net entry in all previous periods (since $N_0 \equiv 0$). The second equation says that the number of firm-period observations prior to period t is equal to the sum of the number of incumbents in each period prior to period t. The third equation determines the total number of orders received. These variables summarize all the information needed to asses the opportunity of entering the market: while N represents the information relevant for the price determination, $\{L, G\}$ are sufficient statistics to form the posterior over the probability of receiving an order, q. In fact, given that incumbents receive an order with a certain probability, they constitute, respectively, the number of successes and of trials for a binomial random variable with success probability q. Such a binomial representation of uncertainty makes the firm's decision into a type of "*one-armed bandit*" problem. It has the advantage of allowing a parsimonious representation of information, and has been used by, among others, Rothschild (1974) who studies the optimal pricing policy for a monopolist facing an unknown demand and Schivardi and Schneider (1997), who analyze a game of R&D with uncertainty regarding the value of an innovation. Given the independence of the realizations across firms and over time, the order in which the successes occur bears no informational value for the calculation of the posterior distribution of q.

The Exit Decision

Once M gross incumbents are in the market, it is necessary to determine who will stay and who will exit. Assume that M is such that, if all firms remained in the market, some of them would be making losses at the resulting price $P(M)$. Then, the determination of the exiting firms gives rise to some ambiguities. Consider the simple example of a one-shot game with only two incumbents firms (1,2) with costs $c_1 < c_2$. Assume that the market is such that $P(2) < c_i < P(1),\ i = 1, 2$ which means that the market cannot sustain both firms, but either firm earns positive profits as a monopolist. This setting is familiar from the work of Fudenberg and Tirole (1986), Ghemawat and Nalebuff (1985, 1990), and Lieberman (1989). The payoff matrix from $\{stay, exit\}$ is given by

[20] We assume that the ex-post distribution of c, $\hat{F}(c)$, coincides with $F(c)$. Without this shortcut it would be necessary to include $\hat{F}(c)$ in the description of the state, greatly complicating the analysis without altering the spirit of the model.

		firm 2: *stay*	firm 2: *exit*
firm 1	*stay*	$P(2) - c_1$, $P(2) - c_2$	$P(1) - c_1$, 0
	exit	0, $P(1) - c_2$	0, 0

This simple game has three Nash equilibria, namely $(stay, exit)$, $(exit, stay)$ and a mixed strategy equilibrium. Our case is complicated by the fact that we have an arbitrary and changing number of players, and by the fact that strategies need to take into account future occurrences as well. This suggests that, if we allow firms to engage in strategic behavior to determine exit, the problem might become intractable.

Because the number of firms involved in the industries studied in section 2 is quite large, it seems reasonable to abstract from strategic behavior with regard to exit decisions in order to achieve a tractable model. Consequently, we bypass all these issues by selecting the most natural of the equilibria, the one in which the least efficient firms exit the market first (the $(stay, exit)$ equilibrium in the previous example). This selection criterion is based on the presumption that market competition will induce the survival of the most efficient production units.[21]

We extend this logic to our multiperiod model with many players by assuming firms get to commit to staying in the market each period in a sequential fashion with the lowest cost firm moving first, the second-lowest moving second, and so on. Formally, for a given number of gross incumbents M, define c_i as the cost of the i^{th} firm when firms are ranked in efficiency terms, so that c_1 is the cost of the most efficient firm in the industry while c_M is that of the least efficient. Since the value of continuing in the market is bounded below by zero due to the zero scrap value assumption, any firm with cost below the equilibrium price will decide to stay in the market, regardless of expectations of profitability in future periods. Define the marginal firm as the i for which $c_i > P(i)$ and $c_{i-1} \leq P(i-1)$. If firms $1, ..., i-1$ have committed to staying in the market this period then it is optimal for firm i to leave. This follows from the fact that firms $1, ..., i-1$ are guaranteed to be among the gross incumbent firms next period and therefore the marginal firm this period will have an index at least as high as i next period if it did not exit. Given this assumption of sequential, ordered exit, the market-clearing equilibrium prices will be weakly decreasing over time, as shown below. Hence, in equilibrium, the optimal exit strategies of firms have the characteristic that the marginal firm will exit and firms with index $1, ..., i-1$ will remain in the market. Then the equilibrium number of net incumbents N' is determined as a function of M by

$$\phi(M) = \text{Max}\{N' \text{ such that } c_{N'} \leq P(N'),\ N' \leq M\} \tag{2}$$

Clearly, given that $c_i > c_{i-1}$ and $P(\cdot)$ is decreasing, the two curves cross at most once, so that the value of N' is *uniquely* determined each period.

Taking stock of the assumptions made above to achieve model tractability, it is clear that some richness of the environment has been lost. We acknowledge that it would be interesting to study the interplay between the the war-of-attrition problem and the associated armed-bandit problem but this presents a much more formidable modeling task and is left for future research. Bulow and Klemperer (1999) offer an environment in which to study strategic exit behavior or "wars of attrition" when the

[21] In the example above, it is trivial to show that, in the mixed strategy equilibrium, the most efficient firm plays *exit* with a higher probability than the less efficient one, so that this equilibrium will tend to select the inefficient unit. Moreover, the higher c_2 the higher the probability that firm 1 will exit the market.

number of players is large but the entry decision and armed-bandit problem are not present. Extending their work by combining it with the armed-bandit problem described here seems like a fruitful path to pursue.

The distribution of exit between new entrants and previous period incumbents is determined as follows. While entrants draw costs from the whole distribution $F(c)$, previous period incumbents have cost lower than $P(N)$ because those firms with costs above $P(N)$ have already left the market. The fraction of entrants and of previous period incumbents that stay in the market, denoted by μ and θ respectively, is therefore given by:

$$\mu(N') = \int_0^{P(N')} dF(c), \quad \theta(N') = 1 - \int_{P(N')}^{P(N)} dF(c) \tag{3}$$

Equilibrium

We use a recursive representation of the value of entering the market, which is the discounted expected value of the stream of profits that occur after entry. Define $v(y; N, L, G)$ as the value of entering the market at $\{N, L, G\}$ when y other firms do so. This value can be decomposed into the sum of the current payoff plus the expected value of continuation. The current payoff π depends on the probability of staying in the market μ, as determined in eq. (3), the probability of obtaining an order, which depends on the current evaluation of q, and the cost level that the firm will draw:

$$\begin{aligned} \pi(y; N, L, G) &= \int_0^{P(N')} E[q \mid L, G](P(N') - c)dF(c) \\ &= \mu(N')E[q \mid L, G](P(N') - \int_0^{P(N')} cdF(c)) \quad , \end{aligned} \tag{4}$$

where $N' = \phi(y + N)$ as determined in equation (2). The expectations over q are formed using the posterior distribution given the values of $\{L, G\}$:

$$g(q|L, G) = \frac{Pr\{L|G; q\}g_0(q)}{\int_0^1 Pr\{L|G; q\}g_0(q)dq} \tag{5}$$

where $Pr\{L|G; q\}$ is the probability of L successes out of G trials for a binomial random variable with probability of success q:

$$Pr\{L|G; q\} = \binom{G}{L} q^L (1-q)^{G-L} \quad .$$

Potential entrants need to form expectations over the value of being in the market next period, which in turn depends on the value of the state that will be realized. Once N' is determined, so is G'; however, L' will depend on the number of orders, l', received in the current period by the N' incumbents: $L' = L + l'$. Agents form expectations over l' using their current beliefs over q, so that the probability of observing $L' = L + l'$ total successes next period given N' trials and given $\{L, G\}$ is calculated as:

$$Pr\{L'|N'; L, G\} = Pr\{l' + L|N'; L, G\} = \int_0^1 \binom{N'}{l'} q^{l'} (1-q)^{N'-l'} g(q|L, G)dq \quad . \tag{6}$$

These probabilities are used to calculate the expected value of being in the market next period, $V(N', L', G')$.

Let $\mathcal{Z}_+$ be the set of nonnegative integers. We are ready for the following definition of equilibrium and theorem proving its existence.

Definition 1 *An equilibrium is a function:*

$V : (N, L, G) \in \mathcal{Z}_+^3 \rightarrow \Re$

and a correspondence:

$y : (N, L, G) \in \mathcal{Z}_+^3 \rightarrow \mathcal{Z}_+$

such that:

(i) $V(N, L, G) \leq k$

(ii) $V(N, L, G)$ *satisfies the functional equation:*

$$V(N, L, G) = \int_0^{P(N')} E[q \mid L, G](P(N') - c)dF(c) + \beta \sum_{L'=L}^{L+N'} V(N', L', G')Pr\{L' \mid N'; L, G\} \quad (7)$$

where $N' = N + \phi(N + \tilde{y})$ *with* $\tilde{y} \in y(N, L, G)$.

The next theorem establishes existence of the equilibrium.

Theorem 1 *Given a state* $\{N, L, G\} \in \mathcal{Z}_+^3$*, there exists an equilibrium* $\{V, y\}$.

Proof: see appendix A.

Before discussing the results of the computations, we note that the definition is stated in terms of a policy *correspondence* because we have not been able to prove the uniqueness of the equilibrium; in particular, we could not show that for any $\{N, L, G\}$ the value of entering the market is monotonically decreasing in the number of entrants. Difficulties arise from the informational structure of the model. While the price effect of more entry goes clearly in the direction of reducing the value of entering the market, it is much harder to ascertain the net effect on the value of entry of additional information gained from more entry. Stronger assumptions would be needed to assure uniqueness.

5 Simulation Results

We solve the model numerically, using a method based on backward induction which closely follows the existence proof of Theorem 1. We first solve the problem for the case in which q is known, determining the equilibrium number of incumbents as a function of the value of q. This number is determined as

$$\text{Max}\{N \text{ s.t. } q \int_0^{P(N)} (P(N) - c)dF(c) \geq (1 - \beta)k\} \quad . \quad (8)$$

The upper value for N, N_{max}, is determined by the number of firms that the market can sustain for the highest possible value of the support of the prior distribution of q. In addition to the equilibrium value, we can similarly determine the value of entering the market for any possible value of N. This set of values constitutes the starting point for the backward induction algorithm. The grid of points at which V is evaluated is determined by choosing a value G_{max} large enough so that the estimates of q based on such a number of trials can be thought of as arbitrarily accurate. Then, for each possible realization $L = 0, 1, ...G_{max}$, we compute the corresponding estimate of q and values of V. We then step backward

Table 2: Parameter values for fig. 5

	Cases	
	$q_l = .35, q_h = .65$	$q_l = .3, q_h = .7$
Parameters		
$P(N)$	$1 - .007N$	$1 - .007N$
α	.1	.1
k	1.715	1.47
β	.9	.9
G_{max}	300	300

to $G_{max} - 1$ and evaluate the functional equation (7) using as continuation values those calculated in the previous step. This process is repeated until $G = 0$. At each step, we compute $V(N, L, G)$ for $N = 1, ...N_{max}$. For each $\{S, G\}$, the equilibrium value of N is determined by taking the value preceding that at which $V(N, L, G) - k$ first becomes negative.

We compute a policy function that gives the equilibrium value of incumbents for each couple $\{L, G\}$; together with previous number of incumbents, this uniquely determines entry. The policy function can then be used to perform simulations in which the number of orders received by incumbents is drawn from a binomial with the probability of success set to a pre-specified value (the "true" value of q).

The method is simple but computationally intense due to the curse of dimensionality in the state space. For our baseline case we choose the following specification: q can only take two values, q_l, q_h, in which case the prior is $Pr\{q = q_l\} = \alpha$. Moreover, we assume that c is distributed uniformly over $[0, 1]$ and that demand is linear.

The crucial parameter driving the results of the simulations is the distance between q_l and q_h, defined as $d \equiv (q_h - q_l)$. This parameter controls the informational content of the signal: while low values of d imply that a given realization for entry will be nearly as likely under either value of q, high values will imply substantially different assessments from the same realization. As a consequence, beliefs are updated faster with the latter. As a result, we expect that the market, on average, will fill up faster and that the paths of entry will be less variable when d is large. To verify this conjecture, we solve the model for different sets of values of q, and report the results for the case of $(q_l = .35, q_h = .65)$ and $(q_l = .3, q_h = .7)$. The other parameter values are reported in table 2. We then run 5000 simulations using the policy function obtained from the solution of the model to generate paths of industry evolution when the true value of q is q_h. The results go in the expected direction: the average number of periods to reach the peak number of firms in the market is 4.74 for $d = .4$ and 7.04 for $d = .3$ and the maximum number of periods is 24 and 36 respectively. Figure 5 plots the *gross* number of incumbents for the two cases, selecting the paths in which the peak number of firms is reached respectively after 7 and 13 periods and plotting the same number of paths for each period length. Again, the low d case (lower graphs) have a more disperse pattern.

Figure 5 also makes clear that the model is indeed able to generate a shakeout: the life-cycle plotted closely resembles those of the industries studied in section 2. This is particularly true for the $q = \{.3, .7\}$ case, where around 30% of the firms that are in the market in the peak period of exit one period later, but a shakeout is evident in the lower graphs as well. We stress that the shakeout is the result of two phenomena: on one side, the process of information accumulation induces a "snowball" effect on entry for which the revelation of a certain quantity of information induces agents to take actions

Table 3: Percentage of first-period exit for subsequent years: 8 Period Market Case

Period	$q = \{.35, .65\}$	$q = \{.3, .7\}$
1	.021	.021
2	.029	.024
3	.036	.026
4	.053	.033
5	.090	.055
6	.166	.144
7	.266	.340
8	.273	.349

thus causing more information to be revealed, and so on. The second phenomenon of the shakeout is the exit of a substantial number of firms; this is due to the fact that the massive wave of entry induces a substantial reduction in the equilibrium price, so that, ex post, entry is unprofitable for a large proportion of firms.

Certain paths in figure 5 display fals-starts and temporary crashes. These arise from the random-draws nature of the simulations. While the true value of q is "high", the actual number of matches in each period of each simulation is drawn from a binomial distribution with parameters (q_l, q_h). These realized draws cause reversals in the path of M when they disagree with the current priors held by firms. This said, it should be stressed that the number of incumbents or "stayers" in the market, N', is weakly increasing throughout all simulations and the path of equilibrium prices is weakly decreasing. The difference between M and N' each period represents the number of firms choosing to exit.

The model also replicates the evolution of the hazard rates in the beer brewing industry. Table 3 reports the percentage of new firms that leave the market in the first period after entry when the market reached the peak number of firms in 7 periods. This table shows strong similarity with table 1 (column "n=2") reporting the actual exit rates, for firms aged 2 years or less, for different cohorts of firms in the beer brewing industry. In both tables the exit rates rise with industry age. We therefore offer an explanation of the "first mover advantage", that is of the fact that early entrants have lower hazard rates. According to the model, early entrants bear a risk in exploring the market and are rewarded by a lower level of competition and therefore higher profits and survival rates. As the information they produce reduces the risk of entry, more entry takes place thus generating stronger competition and a lower exit cutoff point in terms of efficiency.[22]

The last experiment we perform considers the time period length. In this model, the discount factor determines the length of the period after which new observations become available and agents can act. If we assume a yearly discount factor of .95 , then our parameterization of $\beta = .9$ sets the interval length slightly above two years. To investigate the effects of the interval length, we run the model for the $q_l = .3$ case for $\beta = .95$ and $\beta = .99$.[23] The mean period to reach the peak number of firms is 4.74 for the .9 discount, 5.5 for the .95 and 7.03 for the .99. This means that shortening the period makes agents more willing to wait in terms of *number of periods*: the loss of current profit from not entering this period becomes in fact smaller, given that one will have the possibility to reconsider

[22] Table 3 also shows that, as evidenced in figure 5, this process generates a stronger shakeout, on average, in the second parameterization, where the supports of the distribution of priors is more spread out. The first-period exit rates in the second column remain below those of the first column until age 7 and 8.

[23] We vary the fixed cost of entry in such a way that the equilibrium number of firms is the same in all experiments.

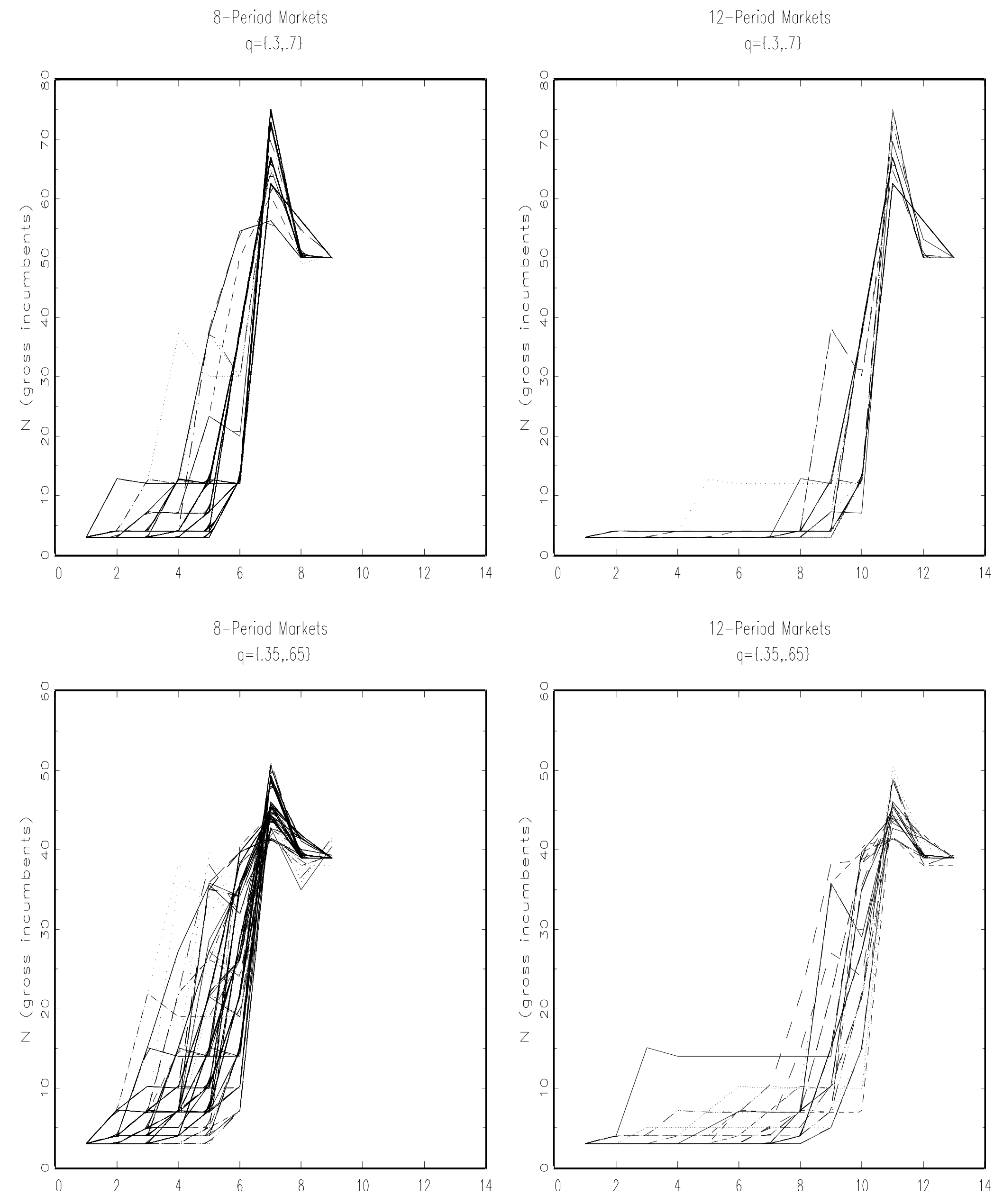


Figure 5: Simulations Results: Gross Number of Firms

this decision in a shorter period of time. However, in *time* terms, the effect is more than compensated by the shorter intervals: average emergence time is in fact 9.7, 5.5 and 1.4 years for the .9, .95 and .99 cases respectively. With shorter intervals new information becomes available more frequently and this effect more that counterbalances the higher willingness to wait, reducing the average emergence time. The result is due to the fact that in the model new information is always produced by incumbents even when no new firms enter the market, and it is not obvious that it would carry over to a model where inaction (zero entry) would imply no additional information.

5.1 Entry Pattern and Informational Structure

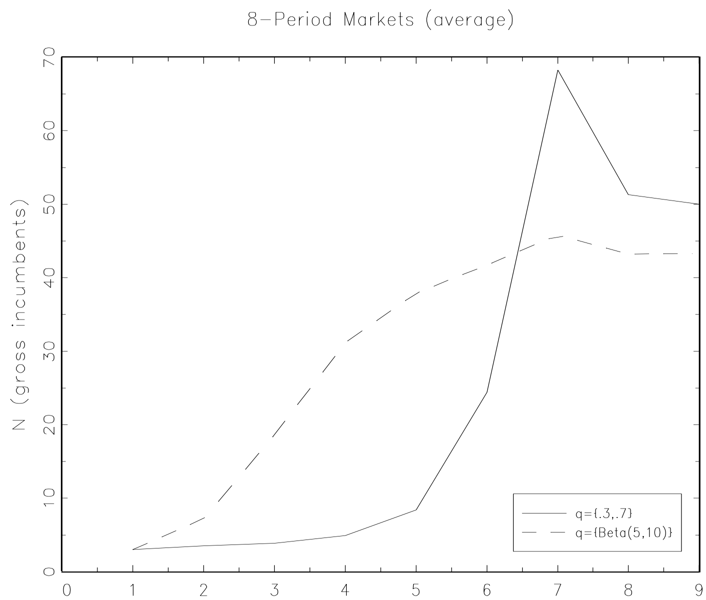
In the preceding simulations we have shown that our model is indeed capable of generating a discontinuous pattern of entry induced by the process of information accumulation. This is an important point, given the interest of economic and social phenomena that are characterized by this type of behavior, such as bank runs, market crashes and revolutions. This result is not new in the literature. One line of research has concentrated on "herd" behavior (Banerjee, 1992; Bikhchandani et al., 1992). These models study the possibility that agents might disregard their own private signal and base their decisions only on public information, thus not revealing to others what they know and potentially generating socially inefficient outcomes with respect to a situation in which agents' private information is fully revealed.

In contrast to this literature, in our model the presence of firms in the market always reveals new information. Our approach is more similar to the work of Rob (1991), Caplin and Leahy (1994, 1996) and Chamley and Gale (1994), in which actions always increase the amount of public information available. The models of Caplin and Leahy (1994,1996) also give rise to a discontinuous pattern of actions, with no activity for some time and all the information revealed as soon as some agents act. In those models, however, the result is based on the particular formalization of uncertainty. In Caplin and Leahy (1994), it is assumed that there is a *continuum* of agents that receive private signals about the state of the market; given the continuity assumption, it turns out that when a set of agents first acts (thus revealing their private information) the state of the market is fully revealed. In Caplin and Leahy (1996) it is *assumed* that the first action taken by any agent reveals the state of the market. Our model is different in that there is some level of activity taking place over time, without implying the immediate resolution of uncertainty.[24] This result is obtained by assuming a finite number of agents and a noisy signal on the underlying state of the market.

It is important to understand what drives the exponential entry pattern: why does the market fill up in such a short period of time? The answer to this question lies in the choice of the prior distribution of q. When q can only take two values even a small number of trials can move the posterior dramatically in one direction or another. As a result, for any given number of trials the equilibrium number of incumbents is quite sensitive to the number of successes. With a more diffuse prior, one would instead expect a smoother path of entry. To investigate this issue we simulate the model when the prior distribution is a continuous function over $[0, 1]$. We choose a Beta distribution with parameters $(5, 10)$ to match the mean and the variance of the $q = \{.3, .7\}$ case, and we run a simulation starting with the same number of firms in the market at time zero. In figure 6 we report the average entry path for the 8-period market in the two cases. The figure makes clear the different shape of entry, strongly convex in one case and concave in the other. With a Beta distribution the discontinuous shifts in beliefs are

[24] From this respect, our model is more similar to Rob (1991) and Chamley and Gale (1994). The latter do not characterize the shape of the "entry" function, but rather concentrate on related problem of the possibility of delays in taking actions.

Figure 6: Average path of entry, 8-Period market case



smoothed out, so that a little new information typically does not translate into a large updating.[25]

This example suggests that, to obtain a discontinuous pattern for actions in these types of models, the beliefs of the agents must be highly sensitive to the arrival of (at least certain) news. A shift in the posterior must induce a sizable portion of agents to act which will in turn reveal new information. In some sense, the models of Caplin and Leahy (1994, 1996) constitute extreme applications of this principle in which a single action resolves all uncertainty, thus inducing a once-for-all change in beliefs. Our dichotomous representation of reality is a way to model this characteristics of the learning process without resorting to this extreme assumption. However, the principle is more general than our particular choice. The preceding analysis makes clear that the fundamental characteristic of phenomena involving delay followed by mass activity is an informational setting where small amounts of additional information induce large shifts in posterior beliefs.

6 Concluding Remarks

This paper has presented empirical evidence on the industry life-cycle. We have shown that in the evolution of the U.S. beer brewing, automobile, and tire industries most of the shakeout is due to exit by the most recently entered firms and that entry rates increase rather than decrease prior to shakeout. Our empirical evidence suggests that the *shape* of exit hazard rates are qualitatively similar across the life span of an industry; regardless of when a cohort enters, the highest conditional probability of exit is

[25]This feature is similar to the role of d in the previous section: lower values of d imply smaller shifts in beliefs for given realizations of the observables.

in age 1-2 years. By age 5, hazard rates decline markedly to low levels and remain low for the remainder of the cohort's life. However, we document the *elevated* hazard rates for cohorts that enter later in an industry's life cycle.

To capture the gradual exponential rise in the number of firms followed by a massive wave of entry characteristic of the industries we study, we propose a theoretical model of information accumulation. In the model, potential entrants are uncertain about the profitability or viability of the industry and this uncertainty is resolved through sufficient accumulation of data regarding the post-entry performance of firms. A subset of agents delay entering if they are too pessimistic regarding the profitability of the industry. The few that do enter serve to resolve the uncertainty, regardless whether additional firms enter in future periods. The more firms that are in the market, however, the stronger the signal from their performance, whether good or bad. As more firms enter the market, more information gets released to potential entrants by their operations, speeding up the resolution of uncertainty and triggering additional entry whenever the likelihood of a good market increases.

While our information accumulation story surely is not the only possible explanation for the patterns of industry evolution we highlight, we are encouraged by the model's ability to generate these patterns in simulation. We show that the information content of signals controls the resulting entry patterns in simulations of the model. When the informative value of a firm-period observations is low, delay is long but entry is roughly constant and declines prior to market emergence. When signals are very informative, there is little or no delay. When signals are somewhat informative, the simulations generate industry life- cycles that closely resemble the experiences in the U.S. beer brewing and automobile industries. Extending the one-armed-bandit nature of the model by including strategic behavior with regard to the exit decision through a war-of-attrition mechanism, as proposed by Bulow and Klemperer (1999) is left for future research.

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Appendixes

A Proof of Theorem 1

We offer a constructive proof of the theorem based on the idea that, as the number of trials goes to infinity, q is estimated with an arbitrary level of accuracy. For G "sufficiently large" the model can be solved as if q were known and then backward induction can be used to compute the implied values of (V, y) for each $\{N, L, G\}$. While more direct proofs could be obtained, this approach has the advantage of suggesting a natural way to solve the model numerically.

We first assume that the value function V exists. We need to show that the equilibrium correspondence is nonempty. For $m \in \mathcal{Z}_+$ and for fixed $\{N, L, G\}$ consider the function

$$v(y; N, L, G) = \int_0^{P(\hat{N})} E[q \mid L, G](P(\hat{N}) - c)dF(c) + \beta \sum_{L'=L}^{L+\hat{N}} V(\hat{N}, L', G')E[Pr\{L' \mid \hat{N}, q\} \mid L, G] \tag{A-1}$$

where $\hat{N} = \hat{N}(y, N)$ as determined in eq. (2). It is immediate to verify that N' is decreasing in y.

This equation represents the gross value of entering the market at $\{N, L, G\}$ when y firms enter (so that the equilibrium number of incumbent after exit will be $\hat{N}$) and it is known that tomorrow the zero profit condition will hold. As observed by Rob (1991), this representation is analogous to the principle of optimality in dynamic programming in the sense that the zero profit condition pins down the continuation value. This ensures that the elements of the sum on the r.h.s. of eq. (A-1) are all at most k so that

$$v(y; N, L, G) \leq \hat{v}(y; N, L, G) \equiv \equiv \int_0^{P(\hat{N})} E[q \mid L, G](P(\hat{N}) - c)dF(c) + \beta k \tag{A-2}$$

But then, given that $P'(\cdot) < 0$ and $\lim_{m \to \infty} P(m) = 0$, and recalling that N' is decreasing in y, the first term of $\hat{v}$ also converges to zero as y increases, so that there exists a $\bar{y}$ s.t.

$$\hat{v}(y; N, L, G) \leq k \ \ \forall \ y \geq \bar{y} \tag{A-3}$$

This in turns implies that

$$v(y; N, L, G) \leq k \ \ \forall \ y \geq \bar{y} \tag{A-4}$$

which establishes the nonemptyness of the equilibrium correspondence.

We now show existence of a function V satisfying (7). If q were known, then the value of L, G would be irrelevant and we could determine V directly as a function of (N, q) (abusing notation) as

$$V(N, q) = \min\{k, q\frac{\int_0^{\hat{c}}(P(N) - c)dF(c)}{1 - \beta}\} \tag{A-5}$$

First, note that in any equilibrium N will not exceed the number of firms that the market can sustain for the highest possible value of q; call this upper bound N_{max}. Moreover, given that firms can always exit, the value of V is bounded below by 0.

Now consider the modified economy in which it is known that the value of q will be fixed at its estimated value when a sufficiently large amount of information has been collected, say G^*; this defines a sequence of economies indexed by G^*. Define $W_{G^*} : (N, L, G) \to \Re$ to be the corresponding value function for this economy, subject to the same free-entry condition as in the original one. Then, $\forall G \geq G^*$ the value of q is fixed and known at $q^* = q(G^*)$, where $q(G^*) = E[q \mid L(G^*), G^*]$ with L^* denoting the value of L when G first reaches (or exceeds) G^*. Therefore, the gross value of entering the market after reaching G^* is determined by:

$$W_{G^*}(N, L, G) = \min\{k, q^* \frac{\int_0^{\hat{c}}(P(N) - c)dF(c)}{1 - \beta}\}, \quad G \geq G^* \tag{A-6}$$

These values can then be used as the starting point for the backward induction, and compute $W_{G^*}(N, L, G)$ for all triple (N, L, G). We want to show that, for any (N, L, G), the sequence $\{W_{G^*}\}_{G^*=1}^{\infty}$ converges, in which case we define $V(N, L, G)$ as the limit of this sequence. By construction (i.e. by the use of backward induction), the resulting function will satisfy eq. (7).

To do this, we consider two economies with two different ending points, G^* and $G^* + T$, $T \geq 0$; we want to show that $W_{G^*}(N, L, G^*) \overset{a.s.}{=} W_{G^*+T}(N, L, G^*)$ as $G^* \to \infty$: if this holds, in fact, the economies represented by W_{G^*} and W_{G^*+T} are almost surely identical at G^*, so that the process of backward induction will generates almost surely equal values for $W_{G^*}(N, L, G)$ and $W_{G^*+T}(N, L, G)$: the sequence converges.

The remainder of the proof is an application of the Law of Large Numbers (LLN). Define $\bar{q}$ as the true value of q; then, by the LLN,

$$\lim_{G^* \to \infty} W_{G^*}(N, L, G^*) \overset{a.s.}{=} \min\{k, \bar{q} \frac{\int_0^{\hat{c}} (P(N) - c) dF(c)}{1 - \beta}\}$$

and the same holds for $W_{G^*+T}(N, L, G^* + T)$. But then,

$$\begin{aligned} \lim_{G^* \to \infty} W_{G^*+T}(N, L, G^* + T - 1) &\overset{a.s.}{=} \bar{q} \int_0^{\hat{c}} (P(N') - c) dF(c) \\ &+ \beta \min\{k, \bar{q} \frac{\int_0^{\hat{c}} (P(N') - c) dF(c)}{1 - \beta}\} \end{aligned} \tag{A-7}$$

But then, given that the free-entry condition holds, we have

$$\begin{aligned} \lim_{G^* \to \infty} W_{G^*+T}(N, L, G^* + T - 1) &\overset{a.s.}{=} \begin{cases} k & if\, N' > N \\ \bar{q} \frac{\int_0^{\hat{c}} (P(N) - c) dF(c)}{1 - \beta} & N' = N \end{cases} \\ &= \min\{k, \bar{q} \frac{\int_0^{\hat{c}} (P(N) - c) dF(c)}{1 - \beta}\} \end{aligned} \tag{A-8}$$

where the last equality follow from the fact that, for any $a, b > 0, \beta \in (0, 1)$,

$$a + \beta \min\{b, \frac{a}{1 - \beta}\} < b \;\Rightarrow\; \frac{a}{1 - \beta} < b$$

Therefore,

$$\lim_{G^* \to \infty} W_{G^*+T}(N, L, G^* + T - 1) \overset{a.s.}{=} W_{G^*+T}(N, L, G^* + T) \tag{A-9}$$

This equation states that, as the amount of information grows indefinitely, the arrival of new information becomes insignificant in assessing the value of entering the market. But the we can apply the same argument at $T-2, T-3$... to obtain

$$\lim_{G^* \to \infty} W_{G^*+T}(N, L, G^*) \overset{a.s.}{=} W_{G^*+T}(N, L, G^* + T) = W_{G^*}(N, L, G^*)$$

which proves that $\lim_{G^* \to \infty} W_{G^*}(N, L, G)$ exists for any $G = 0, 1, 2, ...$ Therefore we define

$$V(N, L, G) = \lim_{G^* \to \infty} W_{G^*}(N, L, G) \tag{A-10}$$

This concludes the argument.

B Brief Description of the Breweries Dataset

We analyze the Unites States beer brewing industry between 1800-1987. In order to perform the cohort analysis presented in the paper we require information on the entry and exit year of each firm, not merely the total number of entering and exiting firms each year. The two datasets we describe below satisfy this requirement. Bull *et al.* (1984) *American Breweries* constitutes the primary source of data on the population of brewing firms. Bull *et al.* claim to have recorded information on *all* American beer producers from the colonial period to the present day.[26] The dataset contains starting year, ending year, and any suspensions of operation of length one

[26] This definition excludes contract brewers who sell under contract to other brewers.

year or more for each brewery.

Carroll *et al.* (1989) extended historical coverage up to the autumn of 1988, coded the dataset into a machine readable format, and changed some of the coding in the case of brewery suspensions. Because the listings in the Bull *et al.* volume pertain to plants rather than to firms, Carroll *et al.* also aggregated the histories for all plants belonging to the same firm. That is, the data record firm-level event histories on foundings and deaths. For a more detailed description of the dataset see Carroll, *et al.*(1989).